



Neurobiomechanics Characterization of Postural Control in Chronic Stroke – A Linear and Non-linear Approach

Academic thesis submitted for obtaining a doctoral degree in Physiotherapy by Faculty of Sport of the University of Porto according to the Decree-Law nº 74/2006, March 24th, amended by Decree-Law nº 65/2018, August 16th.

Supervisor: Maria Augusta Silva, Ph.D.; Physiotherapy, ESS, Polytechnic of Porto

Co-Supervisors: João Paulo Vilas-Boas, Ph.D.; Porto Biomechanics Laboratory and CIFI2D, Faculty of Sport, University of Porto; Francisco Pinho, Ph.D.; Department of Physiotherapy, Health School, Vale do Ave Polytechnic Institute.

Marta Sofia Nicolau Gonçalves de Freitas

Porto, Janeiro de 2025

Reference

Freitas, M. (2024). *Neurobiomechanics Characterization of Postural Control Chronic Stroke – A Linear and Non-linear Approach*. Porto: M.S.N.G. Freitas. Doctoral Thesis in Physiotherapy presented to the Faculty of Sport of the University of Porto.

KEY-WORDS: STROKE; POSTURAL CONTROL; ASSESSEMENT; NON-LINEAR ANALYSIS; GAIT INITIATION; BIOMECHANICS

This thesis was supported by the Porto Biomechanics Laboratory (LABIOMEPE) from the Faculty of Sport of the University of Porto (FADEUP) and by the Center for Rehabilitation Research (CIR).



Acknowledges

First and foremost, this thesis would not have been possible without the support and trust of my participants, whose contributions have been essential to the success of this research.

I would like to express my heartfelt gratitude to Dr. António Conceição, President of Portugal AVC, for his invaluable support and willingness to assist in securing the sample for this study. Your dedication to promoting awareness and research in the field of stroke has been truly inspiring, and your availability and collaboration have been fundamental to the development of this work. Thank you for your generosity and for believing in the importance of advancing knowledge in this area.

A special thank you to the members of the CIR for their collaboration, stimulating discussions, and invaluable assistance.

I would also like to extend my sincere gratitude to Pedro Fonseca from Labiomep for his invaluable help and constant availability. Your expertise and support have been crucial to overcoming many challenges along the way, and I am truly grateful for your dedication and generosity.

I wish to express my deepest gratitude to my supervisor, Professor Augusta Silva, for her unwavering guidance, expertise, and encouragement throughout this challenging journey. Her insightful advice and constructive feedback have been instrumental in shaping the work presented here.

To my co-supervisor, Professor João Paulo, thank you for your generosity with your time, knowledge, and advice. Your input has enriched both my research and my personal development in countless ways.

To my co-supervisor and friend, Professor Francisco Pinho, I want to take this opportunity to express my deepest respect and gratitude. Your guidance, generosity, and friendship have been a cornerstone of this journey. Thank you for your unwavering support and for always believing in my potential. Your wisdom and dedication have left an indelible mark on both this thesis and my personal growth.

To Liliana, Sandra, Vânia, Manuela, and Sílvia – my family at work – thank you for your encouragement, kindness, and for always being there to uplift me. Your support has been invaluable, and I am truly fortunate to have shared this journey with you.

To my friends – you know who you are – thank you for bringing joy and lightness to arduous days of work. Your companionship has been a much-needed reminder of the importance of balance and happiness, even during the most challenging times.

To my beloved mother, I owe a debt of gratitude that words cannot fully express. Your unconditional love, unwavering support, and endless encouragement have been the foundation of everything I have achieved. Thank you for being my rock, my confidante, and my greatest inspiration. Your sacrifices, wisdom, and belief in me have carried me through even the most challenging moments of this journey. This accomplishment is as much yours as it is mine, and I dedicate it to you with all my love.

To my dear parents-in-law, thank you for your kindness, support, and encouragement throughout this journey. Your generosity and understanding have meant so much to me, and I am deeply grateful for the love and care you have shown. This achievement is a testament not only to my efforts but also to the strength of the family that has surrounded and supported me.

I am deeply thankful to my husband, Jorge, and my children, Maria Clara and António, for their endless patience, love, and unwavering support. Jorge, your steadfast belief in me and your encouragement during moments of doubt have been my anchor. Thank you for taking on countless responsibilities and for always finding ways to lighten my load, even when it meant sacrificing your own time and energy. To my dear children, thank you for your understanding and resilience during the times I could not be fully present. Your smiles, hugs, and boundless energy have been a constant reminder of why this journey was worth pursuing. Each of you has been my source of strength and inspiration, and I could not have reached this milestone without your love and faith in me. This accomplishment is as much yours as it is mine.

To all those who have shared in my journey, directly or indirectly, thank you for being a part of this meaningful chapter in my life.

List of Publications

The present Thesis was based on three original studies identified below:

Article I

Freitas, M., Pinho, F., Pinho, L., Silva, S., Figueira, V., Vilas-Boas, J. P., & Silva, A. (2024). Biomechanical Assessment Methods Used in Chronic Stroke: A Scoping Review of Non-Linear Approaches. *Sensors*, 24(7), 2338. <https://doi.org/10.3390/s24072338>

Article II

Freitas, M., Pinho, F., Cruz-Martins, N., Pinho, L., Silva, S., Figueira, V., Vilas-Boas, J. P., & Silva, A. (2024). European Portuguese version of the Mini-BESTest: a cross-cultural adaptation and psychometric measurements in individuals with sensorimotor impairments. *Disability and rehabilitation*, 1–11. Advance online publication. <https://doi.org/10.1080/09638288.2024.2402085>

Article III

Freitas, M.; Fonseca, P.; Alves, L.; Pinho, L., Silva, S., Figueira, V.; Félix, J.; Pinho, F.; Vilas-Boas, J. P., & Silva, A. (2024). Neurobiomechanical Characterization of Feedforward Phase of Gait Initiation in Chronic Stroke: A Linear and Non-linear Approach. Submitted for publication in *Applied Sciences*.

Table of Contents

Acknowledges	IV
List of Publications.....	VI
Table of Contents	VII
List of Figures.....	IX
List of Tables.....	XI
List of Appendices	XIII
List of Equations.....	XIV
List of Abbreviations and Symbols.....	XV
Abstract.....	XIX
Resumo	XX
 CHAPTER I: GENERAL INTRODUCTION.....	 1
General Introduction	2
Research Problem I.....	5
Research Problem II.....	6
Research Problem III	7
 CHAPTER II: METHODOLOGICAL CONSIDERATIONS	 10
Scoping Review	11
Research Studies	13
 CHAPTER III: ORIGINAL STUDIES	 20
Study I	21
Abstract	22
1. Introduction	23
2. Materials and Methods	25
3. Results	27
4. Discussion	45
5. Conclusions	56
6. References	57
Study II.....	71
1. Introduction	73
2. Methods	75
3. Results	81
4. Discussion	87
5. Conclusion.....	91
6. References	92
Study III.....	101
Abstract	102
1. Introduction	103
2. Methods	105

3. Results	114
4. Discussion	129
5. Conclusion.....	146
6. References	147
CHAPTER IV: GENERAL DISCUSSION	168
General Discussion.....	169
<i>Study I: Addressing Methodological Gaps.....</i>	<i>169</i>
<i>Study II: Cross-Cultural Adaptation and Validation of a Robust Clinical Tool....</i>	<i>171</i>
<i>Study III: Neurobiomechanical Characterization of PC During GI.....</i>	<i>172</i>
Clinical Contributions.....	178
Limitations and Future Studies	179
CHAPTER V: CONCLUSION	182
CHAPTER: VI REFERENCES.....	184
APPENDICES	207

List of Figures

CHAPTER I: GENERAL INTRODUCTION

Figure 1. Graphic presentation explaining the rationale of this Thesis.	5
---	---

CHAPTER II: ORIGINAL STUDIES

Study I

Figure 1. Flow diagram for the scoping review process adapted from the PRISMA-ScR statement.....	28
Figure 2. Characterization of the tasks.....	40
Figure 3. Types of assessment instruments.....	42
Figure 4. Kinetic variables.....	43
Figure 5. EMG variables.....	43
Figure 6. Kinematic variables.....	43
Figure 7. Non-linear measures.....	44

Study II

Figure 1. Stages of cross-cultural adaptation of the European Portuguese Mini-BESTest.....	77
Figure 2. Distribution of sum scores on Mini-BESTest_EP.....	83
Figure 3. Bland–Altman analysis of differences between EP_Mini-BESTest and BBS.....	84
Figure 4. Bland & Altman graphs presenting the Mini-BESTest_EP for inter-rater A) and intra-rater B) reliability.....	86

Study III

Figure 1. Scatter Plot of CoP representative of the CoP total displacement trajectories in the mediolateral (X-axis) and anteroposterior (Y-axis) directions for healthy and stroke groups.....	116
Figure 2. Median, 25th and 75th percentiles of position (°), total displacement (°), mean displacement (°) and amplitude (°) values of linear outcome of head, trunk and pelvis joints.....	119
Figure 3. Median, 25th and 75th percentiles of position (°), total displacement (°), mean displacement (°) and amplitude (°) values of linear outcome of lower limb joints.....	120
Figure 4. Median, 25th and 75th percentiles of position (°), total displacement (°), mean displacement (°) and amplitude (°) values of linear outcome of upper limb joints.....	122
Figure 5. Non-linear analysis of position and mean displacement of head, pelvis and trunk joints.....	124
Figure 6. Non-linear analysis of position and mean displacement of swing lower limb joints.....	126

Figure 7. Non-linear analysis of position and mean displacement of stance lower limb joints.....	127
Figure 8. Non-linear analysis of position and mean displacement of swing upper limb joints.....	129
Figure 9. Non-linear analysis of position and mean displacement of stance upper limb joints.....	130
Figure 10. Significant results of linear and non-Linear CoP Analysis, between healthy and stroke groups.....	131
Figure 11. Significant results of linear and non-Linear joints analysis in sagittal plane, between healthy and stroke groups.....	135
Figure 12. Significant results of linear and non-linear joints analysis in frontal plane, between healthy and stroke groups.....	139
Figure 13. Significant results of linear and non-linear joints analysis in transverse plane, between healthy and stroke groups.....	141

Não foi encontrada nenhuma entrada do índice de ilustrações.

List of Tables

CHAPTER II: ORIGINAL STUDIES

Study I

Table 1. Eligibility criteria according to PCC.....	25
Table 2. Characteristics of the participants, study design, and tasks.....	29
Table 3. Assessment instruments, kinematic, kinetic and EMG variables, non-linear measures and their parameters.....	32

Study II

Table 1. Participant demographics and clinical characteristics.....	82
Table 2: Item-total correlation of Mini-BESTest_EP from n = 100.....	85
Table 3: Mean±SD and intra and inter-rater reliability of Mini-BESTest_EP from n = 30.....	85

Study III

Table 1: Participants' characteristics (sociodemographic and clinical)	107
Table 2: Median (MED), 25th (P25) and 75th (P75) percentiles of position... (POS), mean displacement (DISP), and mean velocity (MVEL) values of linear outcome of CoP.....	116
Table 3: Median (MED), 25th (P25) and 75th (P75) percentiles of position (POS), mean displacement (MDISP) and mean velocity (MVEL) values of non-linear outcomes of CoP.....	117

Appendix I

Table 1: Initial search for different databases.....	207
--	-----

Appendix III

Table 1: Anatomical Reference Points for Marker Placement.....	212
Table 2: Interpretation table to the meaning of the positive and negative values of joint angles.....	214
Table 3. Median (MED), 25th (P25) and 75th (P75) percentiles of position (POS), total displacement (TDISP), mean displacement (MDISP) and amplitude (AMP) values of linear outcome of the head, trunk, and pelvis....	215
Table 4. Median (MED), 25th (P25) and 75th (P75) percentiles of position (POS), total displacement (TDISP), mean displacement (MDISP) and amplitude (AMP) values of linear outcome of lower limb joints.....	216
Table 5. Median (MED), 25th (P25) and 75th (P75) percentiles of position (POS), total displacement (TDISP), mean displacement (MDISP) and amplitude (AMP) values of linear outcome of upper limb joints.....	218

Table 6. Median (MED), 25th (P25) and 75th (P75) percentiles of position (POS) and displacement (DISP) values of non- linear outcome of head, trunk and pelvis.....	219
Table 7. Median (MED), 25th (P25) and 75th (P75) percentiles of position (POS) values of non-linear outcome of lower limb joints.....	221
Table 8. Median (MED), 25th (P25) and 75th (P75) percentiles of displacement (DISP) values of non-linear outcome of lower limb joints.....	222
Table 9. Median (MED), 25th (P25) and 75th (P75) percentiles of position values of non-linear outcome of upper limbs joints.....	224
Table 10. Median (MED), 25th (P25) and 75th (P75) percentiles of displacement (DISP) values of non-linear outcome of upper limbs joints.....	225

List of Appendices

Appendix I: Search strategy for the study I.....	207
Appendix II: Ethics committee's deliberation.....	208
Appendix III: Informed Consents.....	210
Appendix IV: Supplementary data from study III.....	212

List of Equations

CHAPTER II

Study II

Equation 1: $SEM = SD \times \sqrt{(1-ICC)}$	80
Equation 2: $MDC_{95} = SEM \times 1.96 \times \sqrt{2}$	80
Equation 3: $MDC\% = (MDC_{95}/mean) \times 100$	80

Study III

Equation 1: $SE(m, r, N) = -\ln \frac{Um+1(r)}{Um(r)}$	113
Equation 2: $y_j^{\tau m} = \left(\frac{1}{\tau m}\right) \sum_{i=(j-1)\tau m+1}^{j\tau} x_1, 1 \leq j \leq \frac{N}{\tau m}$	113
Equation 3: $C_1 = \sum_{j=1}^N S_E(i)$	114
Equation 4: $\lambda(i) = \frac{1}{M} \sum_{K=K_{min}}^{K_{max}} \left(\frac{1}{K.t} \ln \frac{L_{i+K}}{L_i}\right)$	114

List of Abbreviations and Symbols

ABD	Abduction
AD	Adduction
ADLs	Activities of daily living
AMP	Amplitude
AP	Anteroposterior
APAs	Anticipatory postural adjustments
ApEn	Approximate entropy
BBS	Berg balance scale
BIC	Biceps brachii
BMI	Body mass index
CCL	Contralesional left
C FuzzyEn	Cross fuzzy entropy
CI	Confidence interval
CIFI2D	Centre for Research, Training, Innovation, and Intervention in Sport
CIR	Centre for Rehabilitation Research
CLR	Contralesional right
CNS	Central nervous system
COM	Centre of mass
CoP	Centre of pressure
COSMIN	Consensus based Standards for the Selection of Health Status Measurement Instruments
CPGs	Central pattern generators
CRS	Corticoreticular system
CSS	Corticospinal system
DF	Dorsiflexion;
DISP	Displacement
EMG	Electromyographic
EPAs	Early postural adjustments

ER	External rotation;
EU	Upper extremity
EV	Eversion
EXT	Extension
F	Female
fApEn	Fuzzy approximate entropy
FLE	Flexion
GBD	Global Burden of Disease
GI	Gait initiation
H ² M	Health and Human Movement Unit
Hemo	Hemorrhagic
HMS	Human movement system
ICC	Intraclass correlation coefficient
iC-FuzzyEn	Instantaneous cross fuzzy entropy
IEEE	Institute of Electrical and Electronics Engineers®
i-FuzzyEn	Fuzzy entropy
IMUs	Inertial measurement units
IPAQ-SF	International Physical Activity Questionnaire short form
IPSN	Instituto Politécnico de Saúde do Norte
IR	Internal rotation
Isch	Ischemic
ITC	Item total correlation
IV	Inversion;
JB	Joanna Briggs Institute
LABIOME	Porto Biomechanics Laboratory
LDE	Local divergence exponent
LE _{FM}	Fugl–Meyer assessment lower extremity
LL	Lower limb
LOA	Limits of Agreement

LR	Left rotation
LT	Left tilt
M	Male
M	Mean
MAL	Motor activity log
MAS	Modified Ashworth Scale
maxFM	Maximum Floquet multiplier
MCA	Middle cerebral artery
Md	Median
MDISP	Mean displacement
MF DFA	Multifractal detrended fluctuation analysis
Min	Minutes
Mini-BESTest	Mini balance evaluation systems test
Mini-BESTest_EP	European Portuguese Mini balance evaluation systems test
MIVE	Maximum isometric voluntary extension
MIVF	Maximum isometric voluntary flexion
ML	Mediolateral
MLyE	Maximum Lyapunov exponent
MMSE	Mini mental state examination
mMSE	Multivariate multiscale entropy
MS	Multiple sclerosis
MSE	Multiscale entropy
MVC	Maximal voluntary contraction
MVEL	Mean velocity
NIHSS	National Institutes of Health Stroke Scale
OG	Overground
PC	Postural control
PCC	Population, concept and context
PD	Parkinson's disease

PerFOMs	Performance based outcome measures
PIP	Proximal interphalangeal
POS	Position
PRISMA ScR	Preferred Reporting Items for Systematic Reviewers and Meta Analysis extension for Scoping Reviews
PV	Peak velocity
Q	Quartile
RMI	Rivermead mobility index
ROM	Range of motion
RR	Right rotation;
RV	Retroversion;
SampEn	Sample entropy
SD	Standard deviation
SEM	Standard Error of Measurement
sEMG	Surface electromyography
SIS	Stroke impact scale
StL	Stance limb
STROBE	Strengthening the Reporting of Observational Studies in Epidemiology
SwL	Swing limb;
TDISP	Total displacement
TRI	Triceps
TUG	Timed Up and Go
UB	Upper body
UD	Ulnar deviation;
UE_FM	Fugl–Meyer assessment upper extremity
UL	Upper limb
V	Volts

Abstract

Introduction: Postural control reflects the dynamic balance between stability and adaptability, which is often compromised following a stroke. The Human Movement System theory highlights the need for advanced tools to capture the complexity of motor systems. However, non-linear analyses and culturally adapted instruments remain underutilised in clinical contexts.

Main Objectives: To investigate non-linear methods for analysing motor variability in individuals' post-stroke, adapt and validate a culturally relevant clinical assessment tool, and characterise the complexity and adaptability of the feedforward phase of gait initiation using linear and non-linear approaches.

Methods: Three studies were conducted. The first study consisted of a scoping review analysing non-linear measures applied to kinematic, kinetic, and electromyographic data in post-stroke populations across different motor tasks. The second, a cross-sectional study, involved the cross-cultural adaptation and validation of the Mini-BESTest for European Portuguese by evaluating its psychometric properties in 100 individuals with sensorimotor impairments. The third cross-sectional study analysed the feedforward phase of gait initiation in 17 individuals' post-stroke and 16 healthy controls, employing motion capture systems and force platforms to assess the dynamics of the CoP and joint angle variability using linear and non-linear measures.

Results: The complexity of movement patterns was analysed in 14 studies, with entropy emerging as the most used non-linear measure across tasks such as reaching, arm tracking, elbow flexion, wrist and knee extension, and gait (Study I). The Mini-BESTest demonstrated excellent psychometric properties, confirming its suitability for clinical use in Portuguese-speaking contexts (Study II). Study III identified, post-stroke, greater CoP displacement, lower velocity, and reduced complexity in CoP dynamics, alongside increased displacement and amplitude of body segments (head, trunk, pelvis, and limbs) in all planes. Exacerbated rotational patterns in the transverse plane were also observed, reflecting reduced complexity in non-linear parameters and greater variation in linear measures.

Conclusions: Postural control dysfunctions after stroke highlight the importance of non-linear approaches, which provide insights into the adaptability and complexity of motor control. The validated Mini-BESTest has proven to be an effective clinical assessment tool. These advancements underpin the development of more innovative and effective rehabilitation strategies, with significant potential to enhance stability and adaptability in post-stroke individuals.

KEYWORDS: STROKE; POSTURAL CONTROL; ASSESSMENT; NON-LINEAR ANALYSIS; GAIT INITIATION; BIOMECHANICS.

Resumo

Introdução: O controlo postural reflete o equilíbrio dinâmico entre estabilidade e adaptabilidade, frequentemente comprometido após AVC. A teoria do Sistema de Movimento Humano enfatiza a necessidade de ferramentas avançadas para capturar a complexidade dos sistemas motores. Contudo, análises não lineares e instrumentos culturalmente adaptados ainda são pouco aplicados em contextos clínicos. **Objetivos Principais:** Investigar os métodos de análise não linear da variabilidade motora em indivíduos após AVC, adaptar e validar um instrumento de avaliação clínica culturalmente relevante, e caracterizar a complexidade e adaptabilidade da fase de feedforward do início da marcha, através de abordagens lineares e não lineares. **Métodos:** Foram realizados três estudos. O primeiro consistiu numa scoping review, na qual se analisaram as medidas não-lineares aplicadas a dados cinemáticos, cinéticos e eletromiográficos em populações pós-AVC, em diferentes tarefas motoras. O segundo estudo, de carácter transversal, envolveu a adaptação transcultural e a validação do Mini-BESTest para o Português Europeu, através da avaliação das propriedades psicométricas em 100 indivíduos com comprometimento sensoriomotor. O terceiro estudo transversal analisou a fase de feedforward do início da marcha em 17 indivíduos após AVC e 16 controlos saudáveis, utilizando sistemas de captura de movimento e plataformas de força para avaliar a dinâmica do CoP e a variabilidade dos ângulos articulares, por meio de medidas lineares e não lineares. **Resultados:** A complexidade dos padrões de movimento foi analisada em 14 estudos, com a entropia sendo a medida não linear mais utilizada em tarefas como alcance, seguimento com o braço, flexão do cotovelo, extensão do punho e do joelho e marcha (estudo I). A Mini-BESTest demonstrou excelentes propriedades psicométricas, confirmando sua adequação para contextos clínicos em língua portuguesa (estudo II). O estudo III identificou, após o AVC, maior deslocamento, menor velocidade e menor complexidade na dinâmica do CoP, além de maior deslocamento e amplitude dos segmentos corporais (cabeça, tronco, pélvis e membros) em todos os planos, com padrões rotacionais exacerbados no plano transversal, refletindo redução da complexidade não linear e maior variação nas medidas lineares. **Conclusões:** As disfunções no controlo postural após AVC destacam a importância das abordagens não lineares, que fornecem insights sobre a adaptabilidade e complexidade do controlo motor. O Mini-BESTest, validado, confirma-se como uma ferramenta eficaz na avaliação clínica. Esses avanços fundamentam o desenvolvimento de estratégias de reabilitação mais inovadoras e eficazes, com potencial para melhorar significativamente a estabilidade e adaptabilidade em indivíduos pós-AVC.

PALAVRAS-CHAVE: AVC; CONTROLO POSTURAL; AVALIAÇÃO; ANÁLISE NÃO LINEAR; INICIAÇÃO DA MARCHA; BIOMECÂNICA.

CHAPTER I: GENERAL INTRODUCTION

General Introduction

The most recent data from the Global Burden of Disease (GBD) report for 2019 indicate that stroke remains the second leading cause of death worldwide (Feigin et al., 2022). It is also one of the most prevalent causes of disability in the European regions of the World Health Organization (Deuschl et al., 2020). Moreover, the global burden of stroke is projected to increase in the coming decades due to aging populations and the rising prevalence of modifiable risk factors such as hypertension and diabetes (Katan & Luft, 2018). Each year, over 62% of strokes occur in individuals under the age of 70, with 16% affecting those aged 15 to 49 years (Ekker et al., 2019; Thayabaranathan et al., 2022). Beyond the acute phase, stroke survivors often face profound long-term effects: more than 75% experience significant disability, limiting their ability to regain functional independence in activities of daily living (ADLs) (Fathi azar et al., 2018; Gil-Salcedo et al., 2022). Functional limitations typically diminish in the sub-acute phase (Wafa et al., 2020), stabilize in the chronic phase (Rejnö et al., 2019), and may worsen due to progressive impairments in subsequent years (Blomgren et al., 2018).

From a neurobiological perspective, stroke represents an acute disruption of an individual's connectome, caused by a focal or widespread loss of blood flow, interrupting the brain's structural and functional networks (Li et al., 2022). The neurophysiological impact of stroke extends beyond directly affected regions. It disrupts structurally intact but functionally connected network areas too, including the contralesional hemisphere (Lundy-Ekman & Weyer, 2022). Strokes affecting the middle cerebral artery (MCA)—the most common location—have a distinct impact on both cortical and subcortical structures. This region encompasses the corticospinal and cortico-reticular systems, essential for integrating motor commands and postural adjustments (Jang & Lee, 2019). Disruptions in this area upset the balance between dorsolateral systems, which control voluntary movements, and ventromedial systems, which govern postural control (PC), leading to impairments on both the contralesional and ipsilesional sides (Seo & Koo, 2023; Yoo et al., 2023).

PC and voluntary movement are inherently intertwined, as all motor tasks require postural adjustments to maintain stability and facilitate movement (Shumway-Cook & Woollacott, 2017). This interdependence is particularly evident in complex tasks

requiring simultaneous postural and motor control. The central nervous system (CNS) must coordinate multiple degrees of freedom to preserve stability without constraining movement (Vaughan-Graham & Cott, 2016). Post-stroke PC dysfunctions often manifest through consequences such as asymmetric postures, reduced stability, increased sway, and forward body tilt (Tasseel-Ponche et al., 2015). These impairments may arise from dysfunctions inherent to anticipatory postural adjustments (APAs), alongside a reduced capacity for sensory integration and verticality perception (Cho et al., 2014). Furthermore, these challenges are further influenced by disruptions in the visual, vestibular, and somatosensory systems, exacerbating the challenges (Cabanas-Valdés et al., 2021). The overarching goal of post-stroke rehabilitation is to restore function, improve participation, and enhance quality of life through targeted interventions (Ghamari et al., 2023). Accurate and comprehensive assessment methodologies are pivotal, forming the foundation of clinical reasoning to achieve therapeutic objectives (Sahrmann, 2022).

The Human Movement System (HMS) framework, formally introduced by the American Physical Therapy Association (APTA) in 2015 (APTA, 2015), underscores the integrated nature of movement variability and adaptability, particularly in rehabilitation science (Hedman et al., 2018; Sahrmann, 2022). The HMS is a multidimensional construct encompassing the musculoskeletal, nervous, cardiovascular, pulmonary, and endocrine systems to facilitate coordinated movement and postural control (Gorniak, 2019; Harbourne & Stergiou, 2009). Its adaptability and functional capacity are governed by intrinsic variability, enabling dynamic responses to environmental and contextual demands (Stergiou & Decker, 2011). According to the HMS framework, optimal movement is characterised by a balance between excessive variability and complete repeatability, fostering both stability and adaptability (Harbourne & Stergiou, 2009). This concept provides a robust scientific foundation for understanding optimized movement, supporting targeted interventions to address impairments and improve function (APTA, 2015).

The dynamic complexity of the HMS makes conventional linear measures—such as averaged metrics—insufficient to capture the nuanced variability of human movement (van Emmerik et al., 2016). Non-linear analyses provide a robust framework for quantifying the complexity, adaptability, and stability of dynamic systems (Cavanaugh

et al., 2017). These approaches are particularly relevant in stroke rehabilitation, as they can detect subtle changes in movement patterns frequently overlooked by linear methods (Jagroop et al., 2023). Integrating linear and non-linear measures offers a more comprehensive understanding of PC and human movement, delivering valuable insights for clinical practice (da Costa et al., 2013; Stergiou & Decker, 2011). Instrumental approaches that combine clinical tools with kinetic, kinematic, and electromyographic (EMG) analyses enable precise quantification of movement patterns, facilitating tailored and effective interventions (Lencioni et al., 2019).

Despite growing recognition of their utility, non-linear measures remain underutilised in clinical settings, particularly for post-stroke populations (Stergiou & Decker, 2011). This underutilisation underscores the need for further research to validate and integrate non-linear methodologies into routine clinical assessments and intervention planning. By exploring the magnitude of variation and complexity of PC in stroke survivors, this thesis aims to advance the field of neurorehabilitation by bridging the gap between theoretical constructs and practical applications. This approach aligns with the broader goals of the HMS framework, which emphasises adaptability and variability as key factors in promoting functional recovery and enhancing quality of life (Altenburger et al., 2023; Guccione et al., 2019; Hedman et al., 2018).

Understanding motor recovery mechanisms post-stroke through precise measurement and robust interpretative methods is essential for guiding effective rehabilitation programmes (Saladin & Voight, 2017). The **research question**, “How can neurobiomechanical linear and non-linear approaches characterise the complexity and variability of the human movement system in post-stroke individuals, providing valuable insights into their adaptive postural and movement strategies and informing the development of targeted rehabilitation interventions?” highlights a critical gap in current knowledge and practice. The **main objective** of this thesis is to advance the understanding and assessment of neurobiomechanical parameters in chronic stroke through the integration of linear and non-linear approaches. This overarching objective is addressed through three interconnected research problems, each addressing a critical dimension of assessment and rehabilitation, as outlined below (Figure 1).

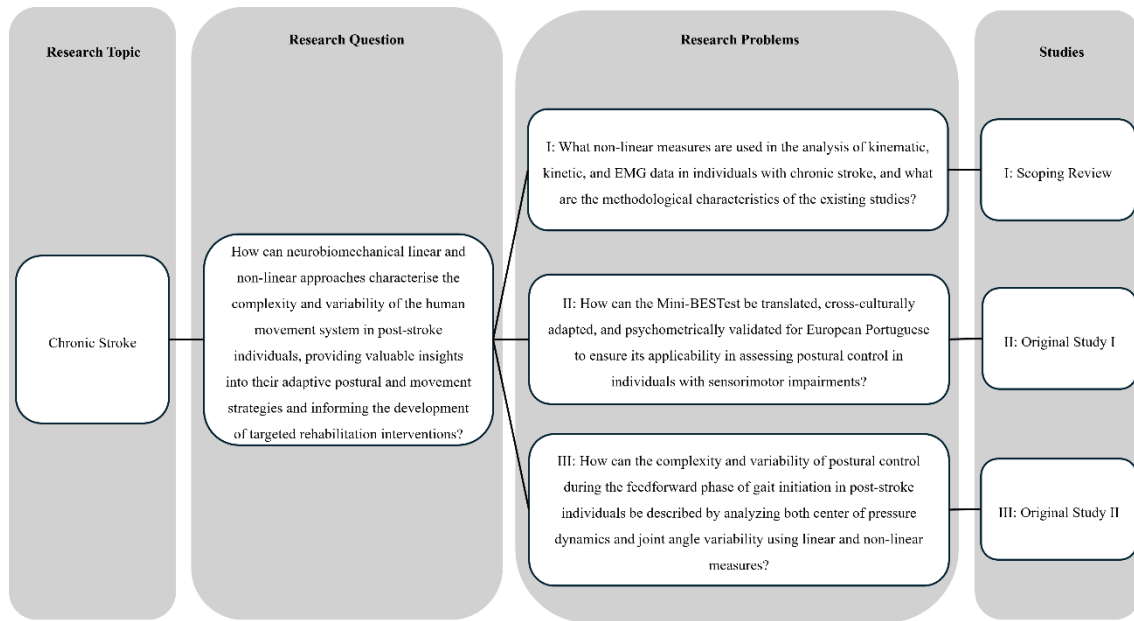


Figure 1. Graphic presentation explaining the rationale of this Thesis.

Research Problem I

Motor variability is an inherent feature of the HMS, enabling a variety of solutions and strategies during a single task (Stergiou & Decker, 2011), and providing flexibility to adapt to environmental changes and contextual demands (Cavanaugh et al., 2017). Human movement is characterised by complexity, allowing the execution of specific tasks through varying strategies while maintaining regularity in variability patterns over time (Bisi & Stagni, 2018). These features enable functional movements to respond to perturbations and task demands without rigidity (da Costa et al., 2013; Stergiou & Decker, 2011), striking a balance between high variability and complete repeatability (Harbourne et al., 2009).

Stroke disrupts this dynamic complexity, leading to impairments in movement variability and complexity. These deficits result in functional limitations and reduced autonomy due to motor and PC impairments (Adegoke et al., 2012; Hartman-Maeir et al., 2007). Non-linear methods have emerged as valuable tools for analysing movement variability, offering deeper insights into neuromotor control that conventional linear measures cannot capture (Stergiou & Decker, 2011). Despite their potential, further evidence is needed to understand the role of non-linear approaches in complementing linear measures for assessing HMS dysfunction.

To address the need for improved characterisation of human movement post-stroke, research problem I investigates the use of non-linear measures in the analysis of kinematic, kinetic, and EMG data in individuals with chronic stroke. Study I aims to provide a comprehensive scoping review of the non-linear methods employed to analyse motor variability in post-stroke individuals. It identifies the most assessed variables, the tasks performed in these studies, and the laboratory instrumentation employed. By establishing a comprehensive overview of non-linear approaches, Study I provides a solid foundation for advancing research in this domain. By identifying methodological gaps, it informs the selection of tools and techniques applied in later studies. This groundwork is essential for exploring novel approaches and refining assessment methodologies (Altenburger et al., 2023).

The findings from **research problem I** underscore the need for accurate and comprehensive tools to characterise PC and motor variability in stroke survivors. Building on this foundation, **research problem II** addresses a critical gap in clinical practice: the absence of culturally adapted and validated tools for assessing the multifaceted components of PC in Portuguese-speaking populations. This approach aligns with the evolving paradigm of the HMS, which emphasises the integration of dynamic and complex sensorimotor processes in evaluating PC (Gill-Body et al., 2021).

Research Problem II

According to the HMS framework, PC is a complex sensorimotor behaviour involving the integration of multiple systems (Gill-Body et al., 2021). PC enables individuals to maintain verticality and stability, facilitating the motor control required for activities of daily living (ADLs) (Horak et al., 2009; Le Mouel & Brette, 2017; Shumway-Cook & Woollacott, 2017). Impairments in PC are associated with significant declines in quality of life and functional independence, particularly among stroke survivors (Halmi et al., 2020). These challenges highlight the need for reliable and comprehensive assessment tools to guide intervention planning and clinical reasoning (Altenburger et al., 2023; Saladin & Voight, 2017).

Among the various Performance-Oriented Functional Outcome Measures (PerFOMs), the Mini Balance Evaluation Systems Test (Mini-BESTest) is a highly recommended tool for assessing impaired PC (Dos Santos et al., 2023; Sibley, Beauchamp, et al.,

2015; Sibley, Howe, et al., 2015). Rooted in the HMS framework, it evaluates eight key components of PC, including *quasi*-static stability, anticipatory and reactive adjustments, dynamic stability, sensory integration, and cognitive influences (Gill-Body et al., 2021; Sibley, Beauchamp, et al., 2015; Sibley, Howe, et al., 2015). The Mini-BESTest has demonstrated strong psychometric properties across diverse populations, such as individuals with chronic stroke, Parkinson's disease, and older adults (Alqahtani et al., 2022; Cramer et al., 2020; Lampropoulou et al., 2018; Lemay et al., 2019; Tsang et al., 2013). Compared to other dynamic balance assessment tools, it is one of the most responsive (Godi et al., 2013; Niklas Löfgren et al., 2014) and is particularly suitable for individuals with higher functional abilities (Potter & Brandfass, 2015), addressing limitations like the ceiling effect observed in the Berg Balance Scale (BBS) (Blum & Korner-Bitensky, 2008).

Prior to this study, the Mini-BESTest had not been validated for the European Portuguese population, leaving a significant gap for clinicians and researchers in Portuguese-speaking regions. To address this, **research problem II** focused on the translation, cross-cultural adaptation, and psychometric validation of the instrument, ensuring it retained the reliability, validity, and conceptual equivalence of the original version. The aim of **Study II** was to adapt the Mini-BESTest into European Portuguese and evaluate its psychometric properties in individuals with sensorimotor impairments, confirming its relevance for both clinical and research use.

Building on the foundations of **Study I**, **research problem III** shifts the focus towards a deeper exploration of the mechanisms underlying PC. This problem highlights the importance of integrating linear and non-linear measures to comprehensively analyse the dynamic interplay between postural stability and adaptability in stroke survivors.

Research Problem III

PC relies on dynamic and continuous interactions between the sensorimotor system and environmental stimuli (Vaughan-Graham & Cott, 2016). It encompasses two core components: postural stability—maintaining the centre of mass within the base of support—and postural orientation—aligning body segments with gravity and the environment (Horak, 2006; Sibley, Beauchamp, et al., 2015). These mechanisms are

essential for functional movements and for maintaining postural stability during dynamic activities (Shumway-Cook & Woollacott, 2017).

Feedforward mechanisms of PC, including early postural adjustments (EPAs) and anticipatory postural adjustments (APAs), play a crucial role in preparing the body for movement and ensuring stability (Farinelli et al., 2021; Maeda et al., 2020). EPAs occur 600–450 milliseconds before movement initiation, activating postural muscles independently of the disturbance direction (Klous et al., 2012; Latash & Zatsiorsky, 2015). APAs, closer to movement onset, generate forces to counter destabilising effects, enabling efficient and safe movement (Kanekar & Aruin, 2015; Klous et al., 2012). Both mechanisms reflect the adaptability of the sensorimotor system (Harbourne & Stergiou, 2009; Moreno et al., 2022).

Stroke survivors often exhibit deficits in EPAs and APAs, leading to compensatory strategies that compromise stability and efficiency (Halmi et al., 2020; Hugues et al., 2019). Despite the recognised importance of these mechanisms, research has predominantly focused on APAs, with limited attention given to EPAs. Additionally, existing studies often emphasise centre of pressure (CoP) dynamics while overlooking joint angle variability, which provides critical insights into segmental coordination and adaptive strategies (Kilby et al., 2015).

Research Problem III aims to address these gaps by analysing the feedforward phase of gait initiation (GI) (-600ms to +50ms relative to movement onset) using both linear and non-linear measures. By integrating CoP dynamics and joint angle variability, this study seeks to offer a comprehensive understanding of postural adjustments in stroke survivors. The findings allow to inform the development of advanced rehabilitation strategies, enhancing stability, adaptability, and functional independence in this population.

Together, these studies provide a multi-dimensional perspective on PC and motor variability in post-stroke individuals. By integrating linear and non-linear methodologies, the thesis advances the understanding of neurobiomechanical mechanisms, facilitating the creation of innovative assessment tools and rehabilitation strategies tailored to this population, ultimately bridging critical gaps in stroke rehabilitation research.

The work presented in this thesis is organised into seven chapters. **Chapter I** provides a general introduction, contextualising and explaining the relevance of the research, while offering an overview of the research question and specific research problems. **Chapter II** outlines the methodological considerations related to the various studies included in the thesis. **Chapter III** comprises three studies: **Study I** addresses **research problem I** by presenting a scoping review that summarises the existing evidence on non-linear measures used in processing kinematic, kinetic, and EMG data to assess human movement after chronic stroke; **Study II** tackles **research problem II**, focusing on the cross-cultural adaptation and validation of the Mini-BESTest for European Portuguese; and **Study III** analyses the feedforward phase of GI using non-linear methods, examining both stroke survivors and healthy subjects to address **research problem III**. An integrated discussion of the main findings, overall limitations, and implications for future research and clinical practice is presented in **Chapter IV**, followed by the main conclusions of the thesis in **Chapter V**. Finally, **Chapter VI** outlines the bibliographic references used throughout the work.

CHAPTER II: METHODOLOGICAL CONSIDERATIONS

Three studies, employing distinct methodological designs, were conducted to address the objectives of this thesis. This chapter provides a concise overview of the methods applied in each study. A comprehensive description of these methods is available in the individual studies presented in the subsequent chapter.

Scoping Review

Study Design

The Study I was conducted as part of the present thesis to address the need for broader research on biomechanical assessment methods in chronic stroke populations. Specifically, this review aimed to explore and summarize the application of non-linear approaches in analysing kinetic, kinematic, and EMG data, filling gaps in the literature related to motor variability, complexity, and adaptability post-stroke. The findings provided a foundational understanding of existing methodologies, supporting a more informed approach to subsequent empirical investigations in this thesis.

Methods

This study was registered at Open Science Framework (<https://doi.org/10.17605/OSF.IO/R3PE9>). The Preferred Reporting Items for Systematic Reviews and Meta-Analysis extension for Scoping Reviews (PRISMA ScR) framework was used to ensure a transparent, systematic, and replicable review process (Tricco et al., 2018). By providing clear guidelines for identifying, selecting, and reporting studies, it enhanced the reliability and credibility of findings while minimizing selection bias. This structured approach was critical for scoping reviews, as it facilitated a comprehensive mapping of existing evidence and highlighted gaps in the literature, ensuring that the study's conclusions were robust and well-grounded.

The PCC strategy was defined as follows:

Population: Chronic stroke adults (>19 years old six months post-stroke) were chosen because the chronic phase is characterized by a stabilization of motor impairments, allowing for more consistent and reliable assessments of non-linear motor control adaptations (Bernhardt et al., 2017). Additionally, individuals in this phase often experience significant and persistent motor deficits, such as reduced movement

variability and adaptability, which are crucial for understanding the complexity of motor patterns (Biryukova & Sirotkina, 2020; Stergiou & Decker, 2011). The chronic phase provides a window where biological processes have plateaued, enabling a clearer analysis of the intrinsic capacity of the motor system to cope with long-term sequelae (Bernhardt et al., 2017). These characteristics make this population particularly suitable for cross-sectional studies investigating neurobiomechanical adaptations after stroke.

Concept: Non-linear measures for processing kinetic, kinematic, or EMG data. The focus on non-linear measures reflects their growing recognition as robust tools to capture the complexity and adaptability of human movement. Unlike linear methods, non-linear approaches provide insights into the dynamic and often irregular patterns of motor behaviour, making them particularly suitable for studying populations with neurological impairments, such as chronic stroke patients (Altenburger et al., 2023).

Context: The selection of studies from 2013 to 2023 ensures the inclusion of contemporary and methodologically advanced research for this scoping review. This timeframe reflects significant progress in biomechanical analysis techniques, particularly in non-linear approaches, over the past decade (Kedziorek & Blazkiewicz, 2020). It captures the latest advancements in understanding postural control mechanisms post-stroke, aligning with current clinical and research priorities. By focusing on the most recent 10 years (January 2013 to 12 April 2023), the review balances comprehensiveness with manageability, avoiding outdated methodologies while maintaining relevance to modern scientific and clinical practices.

Limiting the inclusion to experimental or epidemiological studies ensures a focus on high-quality, data-rich, and evidence-based sources. By excluding narrative reviews or letters, the methodology avoids redundancy, reduces the risk of subjective bias, and emphasizes studies with replicable and well-documented data. This focus strengthens the reliability and applicability of the findings to neurobiomechanical research.

The databases consulted included PubMed®, Web of Science®, IEEE, Science Direct®, and Google Scholar®. These were strategically chosen to ensure comprehensive coverage of relevant literature spanning multiple disciplines, including biomechanics, neuroscience, and clinical neurorehabilitation.

The search strategy incorporated terms such as "stroke," "non-linear," "entropy," and "variability," which were selected to align with the study's objective of identifying research employing advanced non-linear analysis techniques (Appendix I). This focus enhances the ability to capture studies addressing complexity and adaptability in motor control.

To ensure methodological rigor and reduce the risk of oversight or duplication, two independent reviewers conducted the search and screening processes (Aromataris & Munn, 2020).

These methodological justifications ensure that the review comprehensively captures the state of the art in non-linear biomechanical analysis of chronic stroke, providing a solid foundation for future research and clinical applications.

Research Studies

One cross-sectional validation study (Study II), and one cross-sectional study (Study III) were developed.

Ethics

Study II was approved by the Ethics Committee of the Instituto Politécnico de Saúde do Norte, with the reference 8CE-IPSN2023 (Appendix II). Additionally, Study III included in this thesis received ethical approval from the Ethics Committee of the School of Health (ESS) at the Polytechnic of Porto under the reference CE0054D (Appendix II).

All participants provided informed consent after being fully informed about the nature and objectives of the research (Appendix III).

Study II

The study was designed as a cross-sectional, cross-cultural adaptation, and validation research, following the COSMIN (Consensus-based Standards for the Selection of Health Measurement Instruments) guidelines and the STROBE (Strengthening the Reporting of Observational Studies in Epidemiology) statement (Elm et al., 2007; Mokkink et al., 2010). These frameworks were selected to ensure a systematic, transparent, and replicable process throughout the study, providing methodological rigor and reducing the potential for bias.

Participants:

A convenience sample of 100 participants was recruited following COSMIN recommendations to ensure sufficient statistical power for psychometric evaluations. Inclusion criteria specified adults aged 18 years or older, of Portuguese nationality, with sensorimotor impairments affecting PC (e.g., stroke, Parkinson's disease, or musculoskeletal conditions) (Cramer et al., 2020). Participants were required to walk 6 meters (with or without assistive devices) and complete assessments without excessive fatigue, ensuring their ability to perform the European Portuguese Mini-BESTest (Mini-BESTest_EP) tasks accurately (Cramer et al., 2020; Dominguez-Olivan et al., 2020). Exclusion criteria included acute or unstable medical conditions, pregnancy, and cognitive impairments, which were assessed using the Mini-Mental State Examination and Portuguese normative data (Lampropoulou et al., 2018; Lemay et al., 2019). These criteria were established to minimize confounding factors that could compromise the reliability of the findings.

Although the primary focus of this thesis is on stroke populations, the inclusion of individuals with diverse sensorimotor impairments was intentional, as it allowed for the validation of the Mini-BESTest_EP in a heterogeneous population. This approach complements the thesis's central objective by ensuring that the adapted tool is applicable not only to stroke survivors but also to a broader spectrum of clinical populations. Validating the Mini-BESTest_EP in a diverse group enhances its utility and generalizability, ultimately supporting its relevance in the assessment of PC across various conditions, including stroke.

Translation and Cultural Adaptation:

The study employed a six-step process for cross-cultural adaptation: translation, synthesis, back-translation, expert review, pretesting, and finalization. This methodology, widely recommended for adapting measurement tools, ensured both linguistic accuracy and cultural relevance (D. E. Beaton et al., 2000; De Vet et al., 2011; Mokkink et al., 2010). Adjustments to clinical terminology were made in consultation with Portuguese physiotherapists, ensuring that the language used was aligned with local clinical practices. To preserve the tool's conceptual integrity, the back-translation was reviewed by the original authors of the Mini-BESTest, confirming equivalence

while making the tool suitable for Portuguese-speaking professionals (D. E. Beaton et al., 2000). This rigorous process ensured the adaptation maintained the validity and reliability of the original instrument.

Data Collection Procedures:

Assessments were conducted under standardized conditions by two experienced physiotherapists, each with over 16 years of clinical practice, ensuring consistency in administration and scoring. To reduce potential bias and random effects, all assessments were randomized, and participants performed the Mini-BESTest_EP along with a comparator scale (Bergström et al., 2012; Nakhostin-Ansari et al., 2022). Additionally, a subset of 30 participants was video-recorded while performing the Mini-BESTest_EP. These recordings allowed for detailed reliability analysis, minimized potential observer bias, and enhanced scoring objectivity by enabling evaluations from multiple independent raters (Wong, 2014).

Validation of the Mini-BESTest:

The study focused on the total score of the Mini-BESTest, rather than the validity and reliability of individual items, to align with its primary objectives. This decision was supported by evidence indicating the unidimensionality of the Mini-BESTest, confirming that it measures a single construct—dynamic balance (Franchignoni et al., 2015). Prior research highlights the total score as the most accurate and reliable representation of overall balance ability, capturing clinically meaningful changes that individual sections or items may not detect (Franchignoni et al., 2015; Franchignoni et al., 2010). By focusing on the total score, the study ensured a comprehensive evaluation of the tool's applicability and sensitivity in assessing dynamic balance in clinical settings.

Study III

This study integrates linear and non-linear biomechanical analyses to characterise PC in stroke survivors during the feedforward phase of GI. The design combines traditional linear measures, such as displacement and velocity, with advanced non-linear metrics like Lyapunov exponent (LyE) and multiscale entropy (MSE), to capture both stability and adaptability dimensions of PC.

The chosen methods reflect a deliberate response to limitations in traditional linear approaches, which often fail to consider the complexity and temporal dynamics of PC (Caballero et al., 2014). This combination allows for a nuanced understanding of post-stroke PC deficits, balancing insights into motor stability with indicators of neuromuscular adaptability.

Participants

The inclusion criteria—chronic unilateral ischemic stroke and independent ambulation—ensure a homogenous sample capable of safely participating in the experimental tasks (Kedziorek & Blazkiewicz, 2020; Silva et al., 2015; Walcott et al., 2014). Exclusion criteria, such as cognitive impairment and recent surgeries, were implemented to eliminate confounding variables that could obscure results (Sousa et al., 2013). This approach balances the need for experimental control with the ecological validity of studying a clinically relevant population.

Data Collection Protocol

Feedforward Window: The selected time frame of -600ms to +50ms relative to movement onset focuses on capturing early postural adjustments critical for anticipatory control (Kanekar & Aruin, 2015; Klous et al., 2012; Latash & Zatsiorsky, 2015). This aligns with the study's emphasis on feedforward mechanisms, offering a detailed understanding of pre-movement dynamics in PC.

Task: GI was selected for its high sensitivity in identifying deficits in PC mechanisms. This transition from a static to a dynamic posture challenges the balance between anticipatory adjustments and stability, which are often impaired in stroke survivors (Halmi et al., 2020). By analysing this phase, it becomes possible to gain an in-depth understanding of feedforward mechanisms, such as early and anticipatory postural adjustments, and assess the dynamic adaptability of the neuro-motor system (Sousa et al., 2015). Additionally, as a task that reflects real-world functional demands, it offers significant clinical relevance for evaluating and addressing PC impairments in rehabilitation settings (Khanmohammadi et al., 2016; Yiou et al., 2017).

In this study, no restrictions were imposed on which lower limb-initiated GI, as the aim was to evaluate the natural strategies employed by the CNS during the postural phase of GI. Motor variability reflects the CNS's ability to explore and adapt movement

strategies, a critical aspect of functional capacity (Harbourne & Stergiou, 2009). Allowing participants to initiate GI with either limb ensured the preservation of natural variability, which is essential for assessing complexity in realistic contexts (Stergiou, 2016). Imposing constraints could interfere with the natural adaptations of the CNS, particularly in individuals' post-stroke, who often rely on compensatory strategies to manage motor deficits (Delafontaine et al., 2019). Such restrictions would reduce the ecological validity of the findings, as spontaneous limb choice better represents real-world functionality and highlights the CNS's capacity to resolve movement degrees of freedom under motor constraints (Caballero et al., 2014; Caballero et al., 2019; Latash, 2012; Sternad, 2018).

Collecting data across 10 repetitions ensures sufficient trials to enhance reliability while accounting for inter-trial variability (Fernandes et al., 2017). This approach provides a robust dataset suitable for both linear and non-linear analyses, ensuring methodological rigour. To ensure accuracy and precision in measurements, a single investigator was responsible for the preparation and meticulous placement of the markers (Schroeder et al., 2022). Additionally, a pilot study was conducted to familiarise participants with the experimental protocol and to refine the experimental setup, enhancing data robustness and alignment with the latest technological advancements (Couto et al., 2024).

Thus, this methodological approach aligns with the principles of non-linear dynamics, which emphasize the role of variability and complexity in understanding motor control during dynamic tasks such as GI.

Motion Capture and Force Platforms: High-resolution kinematic and kinetic data systems enable comprehensive insights into CoP dynamics and joint kinematics. These tools ensure precision and reliability in capturing the nuanced neurobiomechanical behaviours essential for this analysis (Matthew et al., 2019). The camera system and force platforms operated at 100 Hz (Sousa et al., 2015). Based on the findings of Koltermann et al. (2023), a sampling frequency of 100 Hz is sufficient for capturing PC variables, including CoP dynamics (Koltermann et al., 2023).

Variables: The selection of multiple linear variables, including position (POS), total displacement (TDISP), mean displacement (MDISP), amplitude (AMPL) and mean velocity (MVEL) for both the CoP and joint kinematics, was guided by the need to

provide a comprehensive characterisation of postural and movement dynamics (Federolf, 2016). Each variable serves a distinct purpose: POS indicates the instantaneous position, offering a snapshot of spatial orientation and capturing immediate shifts in postural alignment (Freyler et al., 2015). TDISP reflects the overall range of motion, highlighting the extent of displacements that occur during postural adjustments (Haid & Federolf, 2018). MDISP, on the other hand, represents the average movement across the task, providing insight into the central tendency of adjustments and general movement patterns (Rast et al., 2017). AMPL highlights the peak magnitude of excursions, revealing extremes in joint or CoP corrections and the boundaries of postural stability (Ueta et al., 2015). MVEL captures the mean speed of movement throughout the task, reflecting how quickly postural or segmental adjustments are performed, and offering insight into the reactivity and responsiveness of the motor system (Quijoux et al., 2021).

For the non-linear analysis, position (POS) and displacement (DISPL) were included as they allow for the continuous tracking of temporal variations, which is essential for accurately assessing the system's complexity and stability. These measures capture dynamic behaviours in postural and joint regulation by reflecting changes over time (Karimi et al., 2021).

Non-linear measures: The choice of MSE and the LyE was guided by their unique capabilities to address the specific objectives of this study (Kedziorek & Blazkiewicz, 2020). These metrics were selected to complement linear measures, providing deeper insights into the dynamic behaviour of PC, particularly during the feedforward phase of GI (Vonesch et al., 2023). MSE was chosen for its ability to quantify complexity across multiple temporal scales, capturing both short- and medium-term dynamics (Siciliano et al., 2019). This is particularly relevant for analysing the adaptive capacity of the PC system, which requires the integration of feedback and feedforward mechanisms over time (Busa & van Emmerik, 2016). Compared to other entropy-based measures, such as Approximate Entropy or Sample Entropy, MSE offers a more robust framework for assessing complexity, as it accounts for variations across different temporal resolutions. This capability aligns with the study's focus on dynamic adaptability (Harezlak & Kasprowski, 2020). LyE is particularly suited for evaluating PC, as it captures both chaotic behaviours and the ability to maintain stability—characteristics often disrupted

in stroke survivors (Dabrowski et al., 2020). This measure offers critical information about the system's sensitivity to initial conditions, reflecting its stability and flexibility under perturbations (Jinzhong et al., 2019). Other measures of stability, such as Floquet Multipliers, are less commonly applied to transient tasks like GI, making LyE a more appropriate choice (Liu et al., 2015). These measures were prioritised over other non-linear metrics due to their alignment with the study's goals and their established validity in the context of neurobiomechanical analyses of postural dynamics (Siciliano et al., 2019).

The full details are provided in the subsequent chapter of this thesis.

CHAPTER III: ORIGINAL STUDIES

Study I

Biomechanical Assessment Methods Used in Chronic Stroke: A Scoping Review of Non-Linear Approaches

Marta Freitas ^{1,2,3,4}, Francisco Pinho ^{1,2}, Liliana Pinho ^{1,2,3,4}, Sandra Silva ^{1,2,5,6}, Vânia Figueira ^{1,2,4}, João Paulo Vilas-Boas ^{6,7} and Augusta Silva ^{3,8}

¹ Escola Superior de Saúde do Vale do Ave, Cooperativa de Ensino Superior Politécnico e Universitário, Rua José António Vidal, 81, 4760-409 Vila Nova de Famalicão, Portugal;

² H2M—Health and Human Movement Unit, Polytechnic University of Health, Cooperativa de Ensino Superior Politécnico e Universitário, CRL, 4760-409 Vila Nova de Famalicão, Portugal

³ Center for Rehabilitation Research (CIR), R. Dr. António Bernardino de Almeida 400, 4200-072 Porto, Portugal

⁴ Porto Biomechanics Laboratory (LABIOMEPE), 4200-450 Porto, Portugal

⁵ Department of Medical Sciences, University of Aveiro, 3810-193 Aveiro, Portugal

⁶ School of Health Sciences, University of Aveiro, 3810-193 Aveiro, Portugal

⁷ Centre for Research, Training, Innovation, and Intervention in Sport (CIFI2D), Faculty of Sport, University of Porto, 4200-450 Porto, Portugal

⁸ Department of Physiotherapy, School of Health, Polytechnic

<https://doi.org/10.3390/s24072338>

Abstract

Non-linear and dynamic systems analysis of human movement has recently become increasingly widespread with the intention of better reflecting how complexity affects the adaptability of motor systems, especially after a stroke. The main objective of this scoping review was to summarize the non-linear measures used in the analysis of kinetic, kinematic, and EMG data of human movement after stroke. PRISMA-ScR guidelines were followed, establishing the eligibility criteria, the population, the concept, and the contextual framework. The examined studies were published between 1 January 2013 and 12 April 2023, in English or Portuguese, and were indexed in the databases selected for this research: PubMed®, Web of Science®, Institute of Electrical and Electronics Engineers®, Science Direct® and Google Scholar®. In total, 14 of the 763 articles met the inclusion criteria. The non-linear measures identified included entropy ($n = 11$), fractal analysis ($n = 1$), the short-term local divergence exponent ($n = 1$), the maximum Floquet multiplier ($n = 1$), and the Lyapunov exponent ($n = 1$). These studies focused on different motor tasks: reaching to grasp ($n = 2$), reaching to point ($n = 1$), arm tracking ($n = 2$), elbow flexion ($n = 5$), elbow extension ($n = 1$), wrist and finger extension upward (lifting) ($n = 1$), knee extension ($n = 1$), and walking ($n = 4$). When studying the complexity of human movement in chronic post-stroke adults, entropy measures, particularly sample entropy, were preferred. Kinematic assessment was mainly performed using motion capture systems, with a focus on joint angles of the upper limbs.

Keywords: chronic stroke; assessment; non-linear; kinetic; kinematic; EMG

1. Introduction

The integrated concept of the human movement system (HMS) results from a broad physiological network comprising interactions between the neurological, musculoskeletal, cardiovascular, respiratory, tegumentary, and metabolic systems in order to move the body or parts of it (Saladin & Voight, 2017). This interaction fluctuates in a continuous, complex, and non-linear manner (Cavanaugh et al., 2017; Ihlen et al., 2018), acting on different time scales in response to different contextual conditions to adapt and maintain harmonious movement based on its characteristic variability (Ihlen et al., 2018).

Motor variability is an inherent feature of HMS, enabling a variety of solutions and strategies during one task (Stergiou & Decker, 2011), and providing flexibility to the response depending on context or unexpected environmental changes (Cavanaugh et al., 2017). Thus, human movement is also endowed with complexity, consisting of the ability to perform a specific task with different strategies over a period and the regularity of the inherent variability pattern (Bisi & Stagni, 2018). These properties should allow movements without rigid patterns (Stergiou & Decker, 2011) to respond to small perturbations and task demands (da Costa et al., 2013). Thus, all functional movements ideally have variability and complexity, translating into a state between high variability with multiple movement options and complete repeatability (Harbourne & Stergiou, 2009). This needs to be described and studied objectively for better understanding.

Linear measures are limited in explaining the variability of human movement and cannot fully describe its characteristics (Barela & Duarte, 2011), which are predominantly non-linear (van Emmerik et al., 2016). The use of non-linear measures allows the description of small and subtle changes that depend on time and the environment, which, according to a linear approach, could be diluted by the averaging of global data, making them imperceptible, despite their existence (Gorniak, 2019).

Both approaches, linear and non-linear, are complementary and should be considered in the analysis of human movement, as both are sensitive to small perturbations that occur and affect performance and motor capacity (da Costa et al., 2013). According to a linear perspective, any typical movement without deviations that could be considered as errors

represents human movement with optimal variability (Cavanaugh et al., 2017). This contrasts with the perspective of the non-linear approach, where movement with ideal variability is actually fundamental for individuals to perform a range of variations to adapt to small perturbations induced by the environment (Cavanaugh et al., 2017; Stergiou, 2016). A non-linear approach appears to be more consistent with dynamic human systems, as suggested by Montesinos et al. (Montesinos et al., 2018), and with the way interventions should be advocated for in this domain (Cavanaugh et al., 2017; Harbourne & Stergiou, 2009; Kędziorek & Błażkiewicz, 2020).

Among neuromotor disorders, stroke is the second leading cause of death and the third leading cause of disability worldwide (Feigin et al., 2021). It is commonly characterized by impairments in movement complexity and variability, resulting in functional task difficulties and reduced patient autonomy due to limitations in motor and postural control (Adegoke et al., 2012; Hartman-Maeir et al., 2007). Linear approaches may provide limited information about the motor control system's response to change and may not include inherent aspects of the complex movement system (Stergiou & Decker, 2011; Strongman & Morrison, 2020). Recognizing that variability analysis can enhance our understanding of adaptive strategies and the overall behaviour of dynamic systems in post-stroke recovery, the investigation of non-linear measurements has emerged as a novel approach for the better interpretation of the neuromotor expression of this condition (Stergiou & Decker, 2011).

To our knowledge, there has not been a comprehensive review of the non-linear methods used to study sensorimotor recovery after stroke, despite emerging studies utilizing non-linear analysis to study stroke populations (Dugan & Combs-Miller, 2019; Kim et al., 2020; Liu et al., 2016). Understanding sensorimotor recovery is crucial for neurorehabilitation, particularly post-stroke recovery. Identifying measures and methods can aid in compiling data, interpreting the mechanisms underlying motor recovery, and guiding more effective intervention strategies (Kwakkel et al., 2017).

Thus, the main objective of this scoping review was to summarize the non-linear measures used in the analysis of kinetic, kinematic, and electromyographic (EMG) data of human movement after stroke. The secondary aim was to summarize the

methodological considerations, namely participant characteristics, studied tasks, measurement instruments and kinetic, kinematic, and EMG variables.

Review questions

The main review question was “What non-linear measures are used in the processing of kinematic, kinetic, and EMG data in the assessment of human movement after chronic stroke?”

The review sub-questions are listed as follows:

1. What tasks were performed in the identified studies?
2. What laboratory instruments were used to collect kinematic, kinetic, and EMG data in the identified studies?
3. Which kinematic, kinetic, and EMG variables were included in the identified studies?

2. Materials and Methods

Our scoping review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analysis extension for Scoping Reviews (PRISMA-ScR) (Tricco et al., 2018). The Supplementary Material protocol was registered on the Open Science Framework, in which the review questions and the methodology were specified, <https://osf.io/r3pe9> (accessed 28 July 2023). The following supporting information can be downloaded from <https://doi.org/10.17605/OSF.IO/R3PE9> (accessed on 7 July 2022).

2.1. Eligibility Criteria

Eligibility criteria were defined a priori using the acronym PCC (population, concept, and context) according to the methodology of the Joanna Briggs Institute (JBI) (Peters et al., 2020) (Table 1).

Table 1. Eligibility criteria according to PCC.

Criteria	
Population	Chronic (Bernhardt et al., 2017) poststroke adults (>19 years old)
Concept	Non-linear measures in kinetic, kinematic, or EMG data processing of human movement analysis
Context	Open

Experimental and epidemiological study designs published in English or Portuguese were eligible for inclusion. Systematic, narrative, or scoping reviews (to avoid duplication of data), letters, editorials, and qualitative methodological designs were excluded.

2.2. Search Strategy

Relevant studies were identified by searching through the PubMed®, Web of Science®, Institute of Electrical and Electronics Engineers® (IEEE) and Science Direct® databases. In addition to these databases, the scholarly literature web search engine, Google Scholar®, was also used. To identify other eligible studies, the reference lists of the original research articles and reviews on the topic were manually reviewed. Studies published from 1st January 2013 to 12 April 2023 were included.

The search strategy for PubMed® was as follows: stroke AND (measure OR measurement OR evaluation OR analysis OR assessment) AND (non-linear OR nonlinear OR entropy OR Lyapunov OR “nonlinear variables” OR tools OR dynamic OR variability) AND (“human movement” OR motion) NOT (EEG OR cardiac). Two reviewers independently carried out the search.

2.3. Selection of Evidence Sources

The selection of evidence sources considered the PCC acronym, purpose, and research questions. Both investigators (MF and LP) performed the search simultaneously in the same databases using the defined strategies. No discrepancies were found during the data extraction process, which was imported into Endnote® where duplicates were removed. To facilitate the screening process and confirm the presence of any duplicates not identified by the software, all extracted articles were imported into Microsoft Excel. Two independent reviewers analysed the same 25 abstracts that met the eligibility criteria in a pilot test (the first 25 titles/abstracts of the PubMed database) (Aromataris & Munn, 2020). The screening process did not begin until a consensus of at least 75% was reached (Aromataris & Munn, 2020).

Two reviewers screened the titles and abstracts and categorized studies as either ‘included’ or ‘excluded’. This stage allowed for the identification of articles for full-text screening. Two independent reviewers (MF and LP) extracted the data, and any disagreements were resolved by a third reviewer (SS).

2.4. Data Extraction

Two authors (MF and LP) independently extracted the relevant data using a draft charting table adapted from the original JBI template. Data were extracted according to the following categories: authors, year of publication, study design, participant characteristics (n, sex, age, side lesion, stroke type, time post-stroke), tasks studied, assessment instruments, kinetic, kinematic and EMG variables used to obtain the non-linear measures, and non-linear measures. Disagreements were resolved by a third author.

2.5. Data Presentation

To summarize the extracted data, a narrative report was produced on the following outcomes: tasks, assessment instruments, kinetic, kinematic and EMG variables, non-linear measures, and non-linear parameters. The results were expressed in relation to the main question of the study, complemented by a tabular form summarizing the main findings.

3. Results

A total of 763 articles were identified - 761 records via a database search and 2 additional articles via a manual search of the reference lists. After removing 2 duplicates, 761 records remained. The screening of titles and abstracts resulted in the removal of 714 articles, while 2 articles were not retrieved, leaving 45 for full-text analysis. Of these, 33 were excluded after full-text analysis because they did not meet the inclusion criteria, namely the population ($n = 9$) and concept ($n = 24$). The remaining 14 articles were included in this review. The results of the search were presented in a PRISMA-ScR flowchart, as shown in Figure 1.

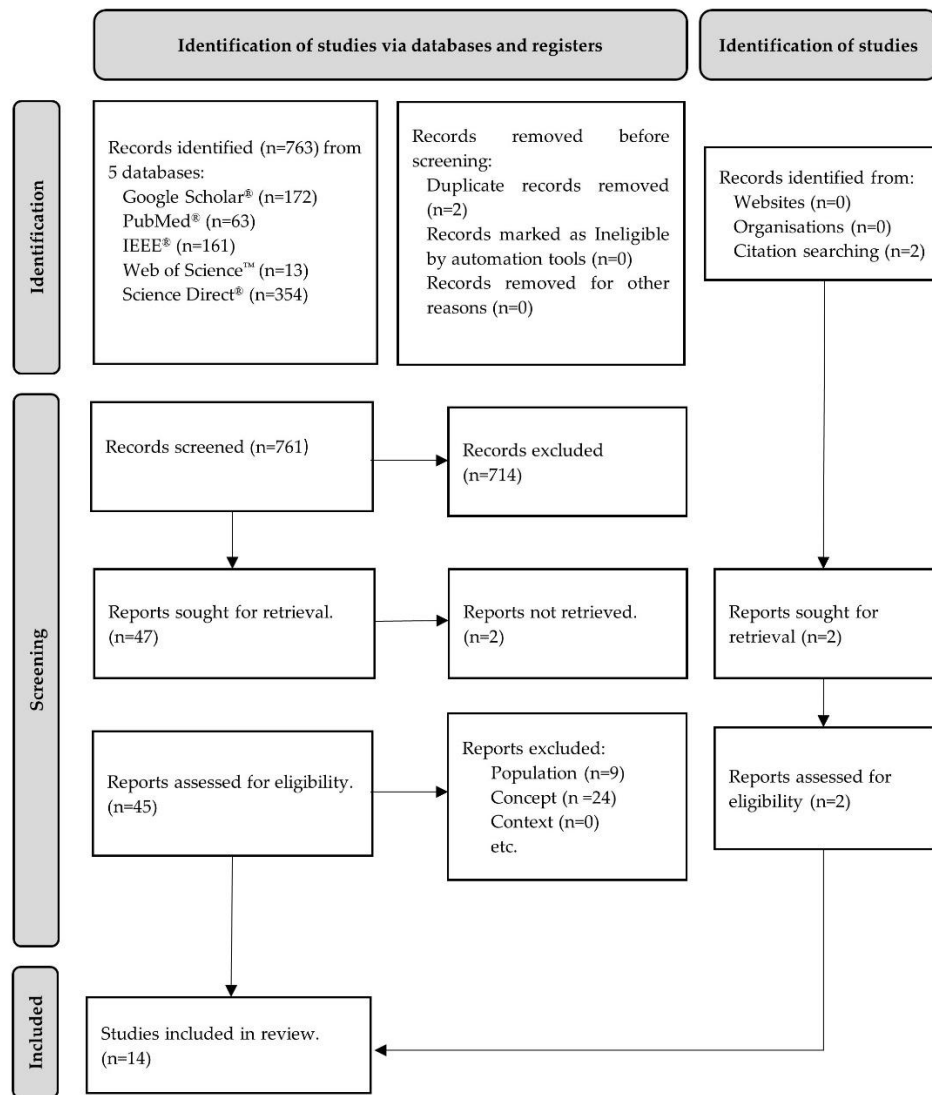


Figure 1. Flow diagram for the scoping review process adapted from the PRISMA-ScR statement (Page et al., 2021).

Tables 2 and 3 summarize the details of the reviewed articles, including participant characteristics, tasks, assessment instruments, kinetic, kinematic and EMG variables, non-linear measures, and non-linear parameters.

Table 2. Characteristics of the participants, study design, and tasks.

Author, Year	Study Design	Participants	Task
Sethi et al., 2013 (Sethi, Patterson, et al., 2013)	Observational, analytical study (with healthy control group)	n=16 (11M/5F) 67.60 ± 8.1 years old 6 CLR / 10 CLL 16 Isch 71.31 ± 48.84 months poststroke UE_FM 37.27 ± 9.27	Performed 3 valid reaching trials to grasp a soda can (56 mm diameter; 208 mm circumference) placed at 80% arm's length on a table in front of each shoulder with the paretic UL. All participants wore dark sleeveless shirts and sat on an adjustable backless bench with knees bent at 90° and feet flat on the floor. Their hands were placed palms down on a table in front of them and supported at 90° elbow flexion by armrests positioned flush with the table. They were instructed to reach for the can, lift it off the table, place it back on the table and return to the starting position as quickly as possible.
Sethi et al., 2013 (Sethi, Davis, et al., 2013)	Quasi-experimental	n=6 (2M/4F) 67.00 ± 10.69 years old 2 CLR / 4 CLL 6 Isch 41.83 ± 35.01 months poststroke UE_FM 32 ± 6.9 MAS <2 MAL ≤3	Performed 3 valid reaching trials to grasp a soda can (56 mm diameter; 208 mm circumference) placed at 80% arm's length on a table in front of each shoulder with the paretic UL. All participants wore dark sleeveless shirts and sat on an adjustable backless bench with knees bent at 90° and feet flat on the floor. Their hands were placed palms down on a table in front of them and supported at 90° elbow flexion by armrests positioned flush with the table. They were instructed to reach for the can, lift it off the table, place it back on the table and return to the starting position as quickly as possible.
Chow and Stokic, 2014 (Chow & Stokic, 2014)	Randomized Controlled Trial (with healthy control group)	n=23 (13M/10F) 64.90 ± 13.6 years old 9 CLR / 14 CLL 16.6 ± 22.7 months poststroke LE_FM 26.0 ± 6.7 MAS <2 RMI 13.4 ± 6.7	Performed 2 trials of maximum isometric knee extension (10s) of both legs, in random order, at different levels (10%, 20%, 30% or 50% of MVC), as accurately and consistently as possible, in a seated position, with 60 s of rest in between. Subjects were asked to extend the knee and match the displayed torque signal (a horizontal line) to a specified target force, marked on the monitor and placed according to individual preference, usually 40-50 cm in front of the head.
Sun et al., 2014 (Sun et al., 2014)	Quasi-experimental	n=8 (7M/1F) 50.13 ± 9.13 years old 3 CLR / 5 CLL 4 Hemo / 4 Isch 132.00 ± 101.76 months poststroke	Two tasks were carried out: 1. Performance of the MIVE and the MIVF on the affected elbow at 90° of flexion, 3 times for 5 s each. 2. Performing 3 repetitive arm tracking trials, starting with the elbow at 90°. Two points were displayed in real time on a computer screen in front of the subjects. Subjects attempted to control their elbow movement to track and match the target pointer. During the elbow extension, the robotic system

Kao et al., 2014 (Kao et al., 2014)	Observational, analytical study (with healthy control group)	n=9 (5M/4F) 60.8 ± 9.0 years old 40.8 ± 39.6 months poststroke LE_FM 27 ± 4	continuously generated an assistive torque to support the elbow movement. Walking on a treadmill at 60%, 80% and 100% of the preferred walking speed (determined from 5 trials of walking 10 m on the ground) and the fastest achievable speed (determined as the fastest speed the subjects could maintain for 1 min). Each speed was tested 3 times for 1 minute.
Ao et al., 2015 (Ao et al., 2015)	Observational, analytical study (with healthy control group)	n=11 (9M/2F) 47.00 ± 10.86 years old 4 CLR / 7 CLL 4 Hemo / 7 Isch 53.30 ± 50.9 months poststroke MAS ≤3	Performed 18 trials (36 s each) of elbow flexion, divided into 3 blocks (at 6 different speed levels), in a sinusoidal trajectory tracking task ranging from 30° to 90°, with 5 min of rest between each block and 30 s of rest between each trial. Subjects were seated at a table with the elbow at 30° of flexion and the shoulder at almost 90° of abduction, with the forearms attached to a lightweight aluminium manipulandum. Target and elbow angles were provided by real-time feedback on a computer screen placed in front of the subjects.
Sethi et. al., 2017 (Sethi et al., 2017)	Observational, analytical study	n=10 (9M/1F) 67.00 ± 8.90 years old 4 CLR / 6 CLL 10 Isch (3 RMCA, 2 LMCA, 1 PVWM, 1 LLI, 1 LPI, 1 RCS, 1 RSI) 53.30 ± 50.9 months poststroke UE_FM 36.9 ± 7.9	Performed 3 trials of reach-to-point movements (drawn at 80% arm length) in three conditions, without randomization: - Voluntary reaching at preferred speed (PREFERRED). - Reaching as fast as possible (FAST). - Reaching with rhythmic auditory cues generated by a metronome (RHYTHM). Participants were seated on an adjustable backless bench with no trunk restraint, knees bent at 90° and feet flat on the floor. Their hands were placed palms down on a table in front of them and supported at 90° elbow flexion by arm rests level with the table. Post-stroke participants reached the target with a more impaired UL.
Zhang et al., 2017 (Zhang et al., 2017)	Observational, analytical study	n=10 (7M/3F) 62.40 ± 12.34 years old 5 CLR / 5 CLL 49.20 ± 26.47 months poststroke MAS <2	Performance of 2 MVC trials of submaximal isometric elbow flexion for 10 s each at different torque targets (10% to 80%), with the impaired and non-impaired arm separately. The target values were displayed as visual targets on the computer screen in a random order. During the period of isometric muscle contraction, which lasted from 2 s to 8 s, the subjects were verbally instructed to match the visual target and to maintain it as accurately as possible for all trials. Subjects were seated comfortably in a height-adjusted chair with the arm to be tested firmly attached to a custom-made device with the shoulder flexed approximately 30° and abducted 45°, the elbow flexed 90°, and the forearm in

			a neutral position. The other arm was placed next to the body.
Kempski et al., 2018 (Kempski et al., 2018)	Observational, analytical study	n=7 (5M/2F) 62.57 ± 5.86 years old 4 CLR / 3 CLL 42.30 ± 49.03 months poststroke LE_FM 25.71 ± 5.22	Walking in sports shoes for 2 minutes on an instrumented split-belt treadmill at an individual's self-selected speed (determined by a 10 m walk test) and long-distance walking speed (determined by a 6 min walk test).
Tang et. al., 2018 (Tang et al., 2018)	Observational, analytical study (with healthy control group)	n=11 (7M/4F) 61.55 ± 12.05 years old 6 CLR / 5 CLL 46.00 ± 27.00 months poststroke UE_FM 43.14 ± 11.68 MAS <2	Performed 3 trials of elbow flexion with isometric graded increasing force levels corresponding to 10%, 30%, 50%, 70%, submaximal (90%) and almost 100% of MVC for at least 3 seconds each. Sufficient rest was allowed between 2 consecutive trials to avoid mental or muscular fatigue. Subjects were seated comfortably in a mobile chair or wheelchair next to a height-adjustable desk, with the tested elbow flexed at 90 degrees on the paretic and contralateral side in a randomized order.
Dugan et. Al., 2020 (Dugan & Combs-Miller, 2019)	Observational, analytical study (with healthy control group)	n=11 (8M/3F) 57.91 ± 14.7 years old 177.34 ± 7.2 cm LE_FM 25.00 ± 2.93	Walking for 2 minutes at their preferred speed around a level, tiled 60 m indoor walking track, without any aids or LL orthoses.
Kim et al., 2020 (Kim et al., 2020)	Observational, analytical study	n=14 (7M/7F) 63.80 ± 15.9 years old 4 CLR / 10 CLL 2 Hemo / 12 Isch 38.7 ± 45.2 months poststroke Hand Function (%) in SIS (3.0) 52.9 ± 31.7 MMSE >23	Performance of 2 isometric force control tasks in 3 different randomized conditions: unimanual paretic, unimanual non-paretic and bimanual. - 2 Submaximal force control task of 3 MVC trials (5s) with a rest interval of 60s - 2 Maximal sustained force production task of 3 MVC trials (8s) with a rest interval of 60s. For both tasks, participants performed either isometric unimanual or bimanual wrist and finger extension upwards (lifting) towards the padded platforms. Participants sat 78 cm away from a 43.2 cm LCD monitor and placed their forearms on the table in a stable position, maintaining 15-20° of shoulder flexion and 20-40° of elbow flexion. They were instructed to place either unilateral or bilateral hands under the specially padded platforms and to adjust the height of the platform.
Tian et al., 2021 (Tian et al., 2021)	Observational, analytical study (with healthy control group)	n=3 (2M/1F) 52.33 ± 24.19 years old 1 CLR / 2 CLL 2 Hemo / 1 Isch 12.67 ± 5.03 months poststroke UE_FM 33.42 ± 19.70	Two tracking tasks of elbow flexion and extension were performed in which the activation of the agonist muscle increased from 0 to 15% MVC in 0-5 s, then gradually relaxed within 5-10 s and returned to 0. Each round movement was performed at a constant speed (15%MVC/5 s) from the origin to the target point, and these included pointing (0 to 15% of amplitude) under elbow flexion and pointing (15% to 0 of amplitude) under elbow extension. The

		MAS <2 MMSE >23	above procedure was repeated 3 times as a trial. Subjects randomly performed 10 trials (5 flexion trials and 5 extension trials) and rested for 30 s after each trial. During performance, they were instructed to sit in a height-adjusted chair and place their impaired arm on the horizontal armrest with the elbow flexed at 90° and the shoulders abducted at 90°. They were asked to grasp the handle attached to the armrest.
Xu et al., 2022 (Xu et al., 2022)	Observational, analytical study (with healthy control group)	n=10 (8M/2F) 48.3 ± 12.8 years old	Performed 3 trials of walking on a treadmill at a comfortable speed for 3 minutes, with 5 minutes of rest in between, using special experimental shoes.

M: male; F: female; CLR: contralesional right; CCL: contralesional left; Isch: ischemic; Hemo: hemorrhagic; UE_FM: Fugl–Meyer Assessment Upper Extremity; LE_FM: Fugl–Meyer Assessment Lower Extremity; MAS: Modified Ashworth Scale; MAL: Motor Activity Log; RMI: Rivermead Mobility Index; SIS: Stroke Impact Scale; MMSE: Mini Mental State Examination; MVC: maximal voluntary contraction; MIVE: maximum isometric voluntary extension. MIVF: maximum isometric voluntary flexion; UL: upper limb; LL: lower limb.

Table 3. Assessment instruments, kinematic, kinetic and EMG variables, non-linear measures and their parameters.

Author, Year	Assessment Instrument	Kinematic, Kinetic and EMG Variables	Non-linear measure	Non-linear Measures Parameters
Sethi et al., 2013 (Sethi, Patterson, et al., 2013)	Kinematics: 12-camera VICON™ motion capture system (Vicon 612; Oxford Metrics Inc., Oxford, UK) 67 reflective markers in UB were placed using a marker set described by the VICON Plug-In-UE.	Joint Kinematics: Shoulder, elbow, wrist, and PIP index finger (°)	ApEn	- Kinematic data not filtered and surrogation with Theiler's first algorithm (20 surrogate time series of each trial) - Each joint angle time series was analyzed from the start of the reach through the entire length of the respective time series including the pauses between the 3 trials. 4 time series were obtained (one for each joint) - lag =1, m = 2, and r = 0.2 times the

				SD of the time series
				▪ ApEn values of each participant's was normalized to the length of their time series
Sethi et al., 2013 (Sethi, Davis, et al., 2013)	Kinematics: ▪ 12-camera VICON™ motion capture system (Vicon 612; Oxford Metrics Inc., Oxford, UK) ▪ 67 reflective markers in UB were placed using a marker set described by the VICON Plug-In-UE.	Joint Kinematics: ▪ Shoulder, elbow, and wrist (°)	▪ ApEn	▪ Kinematic data not filtered and surrogation with Theiler's first algorithm (20 surrogate time series of each trial) ▪ Each joint angle time series was analyzed from the start of the reach through the entire length of the respective time series including the pauses between the three trials. ▪ 4 time series were obtained (one for each joint) ▪ lag =1, m = 2, and r = 0.2 times the SD of the time series ▪ ApEn values of each participant's was normalized to the length of their time series
Chow and Stokic, 2014 (Chow & Stokic, 2014)	Kinetics: ▪ Biodex System 3 isokinetic dynamometer (Biodex Medical Systems, Inc., New York, NY, USA) and a custom-built amplifier connected directly to the torque sensor of the dynamometer (overall sensitivity 57.5 mV/Nm)	Torque Measurement: ▪ MVC torque of quadriceps (Nm) ▪ MVC Power of quadriceps (Nm2)	▪ SampEn	▪ Torques were filtered using a second-order Butterworth low-pass filter with 30-Hz cutoff ▪ Only the middle 8 s of each 10 s trial were analyzed. Out of 2 trials collected at each force level, the one with a lower CV was used for statistical analysis. ▪ N=800, m=3, and r=0.2 SD of the time series
Sun et al.,	Kinetics:	Torque Measurement:	fApEn	▪ The EMG data were not filtered

2014 (Sun et al., 2014)	- Robot-aided developed dynamometer electromyography: - sEMG recording system (Noraxon, Scottsdale, AZ, USA)	- MIVE torque of TRI (Nm) - MIVF torque of BIC (Nm) Electromyographic activity: - Raw EMG data of TRI and BIC	- N=1000, m=2, and r=0.2 SD of the time series Torque Measurement: - A segment of 1000 samples (500 samples before and after the maximum value) were selected for calculating fApEn Electromyographic activity: fApEn values were calculated with a 1000 ms sliding window and a 10 ms window increment in consideration of the computation power of the computer
Kao et al., 2014 (Kao et al., 2014)	Kinematics: 8-camera video system (Motion Analysis Corporation, Santa Rosa, CA, USA) 46 reflective markers attached on the LB, trunk and over the C7 vertebra	Spatiotemporal parameters: Vertical, anteroposterior and mediolateral of C7 velocities (m/s)	- Short-term LDE - maxFM Delay embedded state spaces were reconstructed independently from the 3 velocities of non-filtered C7 vertebral marker data - Data of 30 continuous strides were extracted for each trial Short-term LDE: - Data were resampled to 3000 total data points, approximately 100 data points per stride maxFM: - The state spaces were first divided for individual strides and then each stride was time normalized to 101 samples
Ao et al., 2015 (Ao et al., 2015)	Kinematics: Motion capture system (OptiTrack®, NaturalPoint, USA)	Joint Kinematics: Elbow (°)	- fApEn - ApEn - SampEn The EMG signals were band-pass filtered through a 4th-order, zero-phase Butterworth digital filter with a

	▪ 2 reflective markers attached on the elbow joint and at the end of the handle Electromyography: • Tele-EMG system (MyoSystem2400T, Noraxon, USA) ▪ 2 Ag/AgCl bipolar surface electrodes (Noraxon, USA)	Electromyographic activity: ▪ EMG Amplitude (mv) TRI and BIC	frequency band from 5 to 400 Hz and a 50 Hz digital notch filter ▪ The performances of the 3 entropies were compared using both simulated signals MIX(p) and real EMG signals. Three simulated signals, MIX(0.1), MIX(0.5) and MIX(0.9) were generated and each one had 5000 samples ▪ The 100-point segments were selected randomly from each of the 5000-sample simulated MIX(0.1), MIX(0.5), and MIX(0.9) signals, respectively ▪ $m=2$ ▪ N and r were carried out to find a suitable complexity measurement with optimal N and r
Sethi et. al., 2017 (Sethi et al., 2017)	Kinematics: ▪ 12-camera VICON™ motion capture system cameras (Vicon 612/T40; Oxford Metrics, Oxford, England) ▪ 67 reflective markers in UB were placed using a marker set described by the VICON Plug-In-UE	Joint Kinematics: ▪ Shoulder, elbow, wrist, and PIP index finger (°) Kinematics Spaciotemporal Parameters: ▪ Index finger velocity (m/s) ▪ PV (m/s)	▪ ApEn ▪ Kinematic data not filtered and surrogation with Theiler's first algorithm (20 surrogate time series of each trial) ▪ Each joint angle time series was analyzed from the start of the reach through the entire length of the respective time series including the pauses between the three trials. ▪ 4 time series were obtained (one for each joint) ▪ lag =1, m = 2, and r = 0.2 times the SD of the time series

				▪ ApEn values of each participant's was normalized to the length of their time series
Zhang et al., 2017 (Zhang et al., 2017)	Kinetic: ▪ 1 torque sensor (Model TRS 500, Transducers Techniques, CA) on BIC Electromyography: ▪ Porti sEMG system (TMS International, The Netherlands)	Torque Measurement: ▪ MVC torque of elbow flexion (Nm) Electromyographic activity: ▪ Root mean square (V) BIC	▪ SampEn	▪ The EMG signals were filtered using a zero-lag band-pass (20–450 Hz) fourth-order Butterworth filter ▪ The torque signal was filtered using a zero-lag low-pass second-order Butterworth filter ▪ Both surface EMG and torque data correspond to the same 2 s time window selected for data analysis. ▪ N=4000, m = 2, and r = 0.25 times the SD of the time series
Kempski et al., 2018 (Kempski et al., 2018)	Kinematics: ▪ 8-camera motion capture system (Motion Analysis Corporation) ▪ 25 single reflective markers and 19 markers on shells placed on the bony landmarks and tracking segments	Joint Kinematics: ▪ Hip, knee and ankle (°) Kinematics Spaciotemporal Parameters: ▪ Gait velocity (m/s)	▪ MLyE (Wolf's algorithm)	▪ Not specified
Tang et. al., 2018 (Tang et al., 2018)	Electromyography: ▪ Home-made multi-channel sEMG recording system ▪ 1 large round reference electrode (Dermatode; American Imex, Irvine, CA) was placed on arm fossa cubitalis	Electromyography activity: ▪ EMG Integral (V) of BIC	▪ SampEn	▪ The EMG signal was filtered with a fourth-order zero-lag non-causal Butterworth band-pass filter set at 20–500 Hz. Then, a set of second-order notch filters were used to remove the 50 Hz power line interference and its harmonics. ▪ N: the EMG signal was divided into several non-overlapping epochs, each with a time length of 1 s (equivalent to 1000 sample points)

				▪ $m = 2$ and $r = 0.25$ times of the SD of the time series
Dugan et al., 2020 (Dugan & Combs-Miller, 2019)	Kinematics: ▪ Wireless Inertial Measurement Units (IMUs) (InterSense Inertia Cube BT) attached to each LL segment and pelvis	Joint Kinematics: ▪ Hip, knee and ankle ($^{\circ}$)	▪ mMSE	▪ The tri-axial accelerometer data from each IMU dataset were unfiltered ▪ N: the last 6000 data points, corresponding to the last 100 seconds of the walking trials were used for analysis. ▪ $m = 2$ and $r = 0.2$
Kim et al., 2020 (Kim et al., 2020)	Kinetics: ▪ Force transducers (MLP-75, Transducer Techniques, $4.16 \times 1.27 \times 1.90$ cm, range = 75 lbs., 0.1% sensitivity) attached to the padded platforms	Force Measurement: ▪ MVC torque of wrist and fingers extension (N)	▪ SampEn	▪ The force data were filtered using a bidirectional fourth-order Butterworth filter with a cutoff frequency = 30 Hz ▪ N: for the submaximal force control tasks, the middle 16 s of the force signals were used ▪ N: For the maximal sustained force production tasks, the middle 5 s of the force data were analyzed ▪ $m = 2$, and $r = 0.2$ SD of the force signals
Tian et al., 2021 (Tian et al., 2021)	Electromyography: ▪ sEMG system (DAQ USB- 6341, National Instruments, USA)	Electromyography activity: ▪ Raw EMG data (V) BIC and TRI	▪ C-FuzzyEn ▪ i-FuzzyEn ▪ iC-FuzzyEn	The raw EMG signals were bandpass filtered using a 4th-order Butterworth filter at 20-300 Hz and a 50 Hz notch filter C-FuzzyEn and iC-FuzzyEn: ▪ $N = 500$ (0,5 s), $m = 2$, and $r = 0.2$ SD of the EMG signal i-FuzzyEn: ▪ $N = 500$, $m = 2$, and $r = 0.15$ SD of the EMG signal

Xu et. al., 2022 (Xu et al., 2022)	Kinematics: ▪ 6-camera motion capture system (OptiTrack®, NaturalPoint, USA) ▪ Ten 12mm reflective markers bilaterally in LL placed on the second and third metatarsal space, the lateral malleolus, the midleg, the lateral knee, and the mid-thigh	Joint Kinematics: ▪ Knee (°) ▪ Ankle (°)	▪ MFDFA	▪ Proper polynomial order = 2 ▪ The short-scale exponent was computed within the segment size ranging $20 < n < 100$ sample. Meanwhile, the long-scale exponent was evaluated in the range of $170 < n < 1000$ sample
---	---	---	---	--

UB: upper body; UE: upper extremity; LL: lower limb; sEMG: surface electromyography; PIP: proximal interphalangeal; PV: peak velocity; MVC: maximal voluntary contraction; MIVE: maximum isometric voluntary extension. MIVF: maximum isometric voluntary flexion; BIC: biceps brachii; TRI: triceps; SD: standard deviation; V: volts.

3.1. Participant's Characteristics

Of the 14 included studies, 6 only included post-stroke subjects (Kempski et al., 2018; Kim et al., 2020; Sethi, Davis, et al., 2013; Sethi et al., 2017; Sun et al., 2014; Zhang et al., 2017), and 8 also included healthy subjects (Ao et al., 2015; Chow & Stokic, 2014; Dugan & Combs-Miller, 2019; Kao et al., 2014; Sethi, Patterson, et al., 2013; Tang et al., 2018; Tian et al., 2021; Xu et al., 2022). The sample size of chronic post-stroke participants ranged from 3 (Tian et al., 2021) to 23 (Chow & Stokic, 2014).

A total of 150 chronic post-stroke subjects, 102 men and 51 women, with a mean age of 52.33 years, were included in the studies. All the subjects were at a chronic stage, ranging from 12.67 (Tian et al., 2021) to 177.34 (Dugan & Combs-Miller, 2019) months after stroke, and presented with a single and unilateral (Dugan & Combs-Miller, 2019; Kempinski et al., 2018; Kim et al., 2020; Sethi, Davis, et al., 2013; Sethi, Patterson, et al., 2013; Sethi et al., 2017; Sun et al., 2014; Tian et al., 2021; Xu et al., 2022) or multiple and unilateral strokes (Chow & Stokic, 2014). Two studies did not report lesion characteristics (Amirpourabasi et al., 2022; Ao et al., 2015).

The side of the body most affected was reported in 11 studies (Ao et al., 2015; Chow & Stokic, 2014; Kempinski et al., 2018; Kim et al., 2020; Sethi, Davis, et al., 2013; Sethi, Patterson, et al., 2013; Sethi et al., 2017; Sun et al., 2014; Tang et al., 2018; Tian et al., 2021; Zhang et al., 2017), with a total of 48 right-sided and 71 left-sided strokes. According to the type of stroke, four trials included both ischemic and haemorrhagic stroke (Ao et al., 2015; Kim et al., 2020; Sun et al., 2014; Tian et al., 2021) and three trials analysed only ischemic stroke (Sethi, Davis, et al., 2013; Sethi, Patterson, et al., 2013; Sethi et al., 2017). Overall, seven trials did not report the type of stroke (Chow & Stokic, 2014; Dugan & Combs-Miller, 2019; Kao et al., 2014; Kempinski et al., 2018; Tang et al., 2018; Xu et al., 2022; Zhang et al., 2017). Only one study reported the location of the stroke (Kim et al., 2020; Sethi et al., 2017).

The Mini Mental State Examination (MMSE) was used in two trials to ensure an understanding of the instructions in the required tasks (Kim et al., 2020; Tian et al., 2021). To assess sensorimotor impairment, the Fugl–Meyer Upper Extremity (UE_FM) was used in five studies (Sethi, Davis, et al., 2013; Sethi, Patterson, et al., 2013; Sethi et al., 2017; Tang et al., 2018; Tian et al., 2021), while the Fugl–Meyer Lower Extremity

(LE_FM) was used in four studies (Chow & Stokic, 2014; Dugan & Combs-Miller, 2019; Kao et al., 2014; Kempinski et al., 2018). Other clinical measures were included in three trials, namely the Motor Activity Log (Sethi, Davis, et al., 2013), the Rivermead Mobility Index (RMI) (Chow & Stokic, 2014), and the Stroke Impact Scale (SIS)—Hand Function (Kim et al., 2020). The Modified Ashworth Scale (MAS) was used to quantify spasticity in six studies (Ao et al., 2015; Chow & Stokic, 2014; Sethi, Patterson, et al., 2013; Tang et al., 2018; Tian et al., 2021; Zhang et al., 2017). Only two studies did not identify a clinical measure to meet inclusion criteria or sample characterization (Sun et al., 2014; Xu et al., 2022).

3.2. Tasks

Considering the tasks (described in Table 2), nine studies focused on UL and four on LL assessment (Figure 2). Regarding UL tasks, two studies analysed reaching to grasp (Sethi, Davis, et al., 2013; Sethi, Patterson, et al., 2013) and one analysed reaching to point (Sethi et al., 2017). Arm tracking movement was assessed by two studies (Ao et al., 2015; Sun et al., 2014). Five studies focused on elbow flexion (Ao et al., 2015; Sun et al., 2014; Tang et al., 2018; Tian et al., 2021; Zhang et al., 2017), one on extension (Tian et al., 2021), and one on wrist and finger extension upward (lifting) (Kim et al., 2020). The remaining studies analysed knee extension (Chow & Stokic, 2014) and walking (Dugan & Combs-Miller, 2019; Kao et al., 2014; Kempinski et al., 2018; Xu et al., 2022).

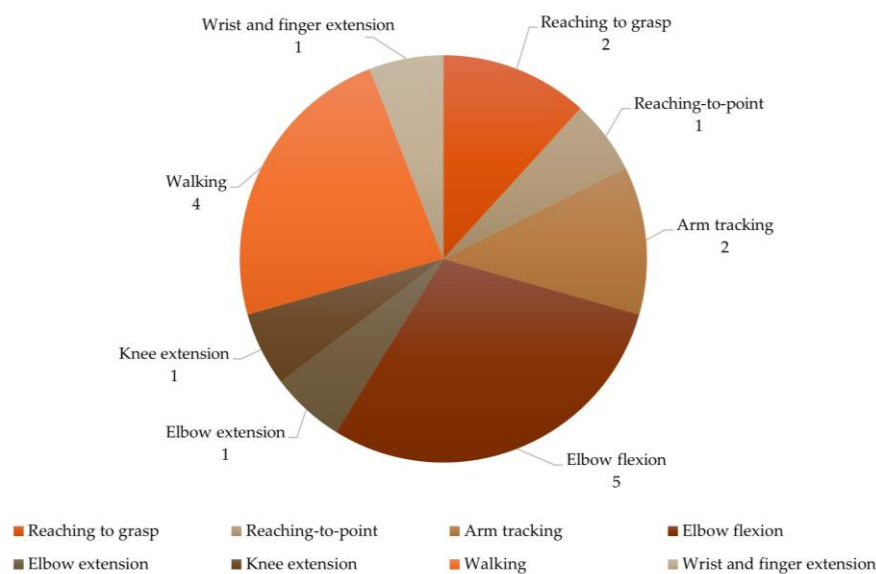


Figure 2. Characterization of the tasks.

3.3. Assessment Instruments

Table 3 shows the instruments used to explore kinematic, kinetic, and EMG variables in the 14 studies. Kinetic data were collected in four studies (Chow & Stokic, 2014; Kim et al., 2020; Sun et al., 2014; Zhang et al., 2017), kinematic data were collected in eight studies (Ao et al., 2015; Dugan & Combs-Miller, 2019; Kao et al., 2014; Kempinski et al., 2018; Sethi, Davis, et al., 2013; Sethi, Patterson, et al., 2013; Sethi et al., 2017; Xu et al., 2022), and sEMG data were collected in five studies (Ao et al., 2015; Sun et al., 2014; Tang et al., 2018; Tian et al., 2021; Zhang et al., 2017) (Figure 3).

Force transducers (Kim et al., 2020), isokinetic dynamometers (Chow & Stokic, 2014; Sun et al., 2014), and a torque sensor (Zhang et al., 2017) were used to evaluate the kinetic data. The muscular activity was assessed using a sEMG system (Ao et al., 2015; Sun et al., 2014; Tang et al., 2018; Tian et al., 2021; Zhang et al., 2017). Three different motion capture systems were used for kinematic data: VICON™ (Sethi, Davis, et al., 2013; Sethi, Patterson, et al., 2013; Sethi et al., 2017), Motion Analysis Corporation (Kao et al., 2014; Kempinski et al., 2018), and OptiTrack® (Ao et al., 2015; Xu et al., 2022), with several cameras, ranging from 6 (Xu et al., 2022) to 12 (Sethi, Davis, et al., 2013; Sethi, Patterson, et al., 2013; Sethi et al., 2017) in number. One study did not report the number of cameras (Ao et al., 2015). The number of reflective markers ranged from 2 (Ao et al., 2015) to 67 (Sethi, Davis, et al., 2013; Sethi, Patterson, et al., 2013; Sethi et al., 2017), as different anatomical references were considered within each identified segment according to each author (see Table 3). One study (Dugan & Combs-Miller, 2019) used wireless inertial units (IMUs) in lower limb segments and the pelvis to collect kinematic data.

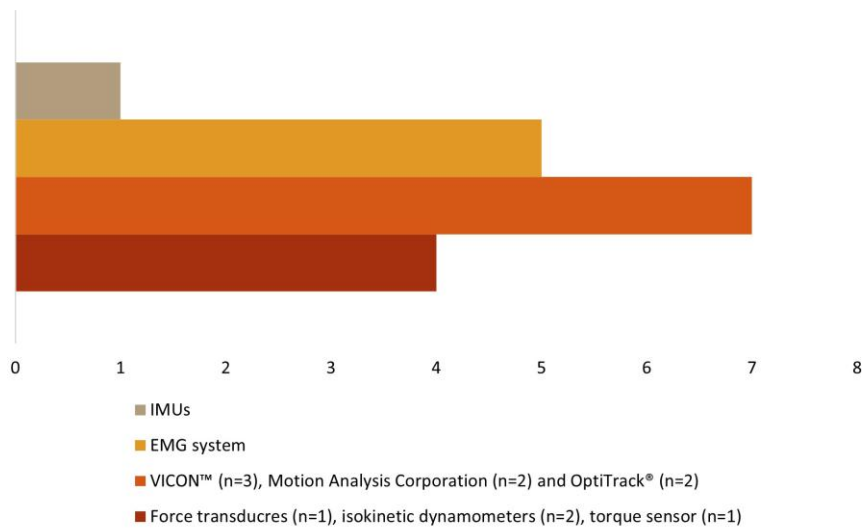


Figure 3. Types of assessment instruments.

3.4. Kinetic, Kinematic and EMG Variables

To analyse the human movement data, different instruments were used to collect several variables (Table 3). For kinetic data (Figure 4), three studies quantified the maximal voluntary contraction (MVC) torque and power of the quadriceps (Chow & Stokic, 2014), elbow flexion (Zhang et al., 2017), and wrist and finger extension (Kim et al., 2020); one study used the maximum isometric voluntary extension (MIVE) torque of the elbow (Sun et al., 2014); and another used the maximum isometric voluntary flexion (MIVF) torque of the elbow (Sun et al., 2014). Regarding sEMG data (Figure 5), one study each measured muscle activity using the root mean square (RMS) of the biceps (BIC) (Zhang et al., 2017), the EMG amplitude of the BIC and triceps (TRI) (Ao et al., 2015), the EMG integral of the BIC (Tang et al., 2018); the remaining two studies used raw sEMG data of the BIC and TRI (Sun et al., 2014; Tian et al., 2021).

To analyse the kinematic data (Figure 6), four studies considered the range of motion (ROM) of the upper limb, namely the shoulder (Sethi, Davis, et al., 2013; Sethi, Patterson, et al., 2013; Sethi et al., 2017), elbow (Ao et al., 2015; Sethi, Davis, et al., 2013; Sethi, Patterson, et al., 2013; Sethi et al., 2017), wrist (Sethi, Davis, et al., 2013; Sethi, Patterson, et al., 2013; Sethi et al., 2017) and proximal interphalangeal (PIP) index finger (Sethi, Patterson, et al., 2013; Sethi et al., 2017). The range of motion of the lower limb was considered in three studies, specifically the hip (Dugan & Combs-Miller, 2019; Kempfski et al., 2018), knee (Dugan & Combs-Miller, 2019; Kempfski et

al., 2018; Xu et al., 2022), and ankle (Dugan & Combs-Miller, 2019; Kempski et al., 2018; Xu et al., 2022). Only three studies included spatial-temporal kinematic parameters such as index finger velocity and peak velocity (Sethi et al., 2017), C7 velocity (Kao et al., 2014), and gait velocity (Kempski et al., 2018).

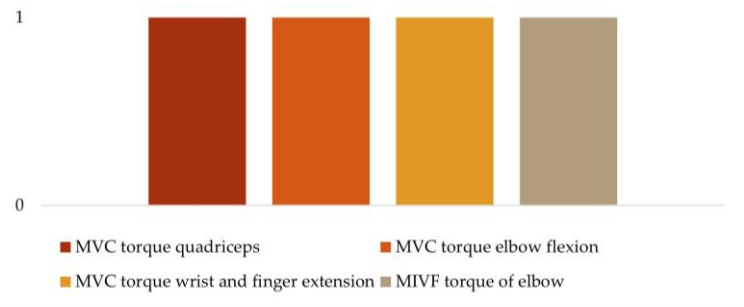


Figure 4. Kinetic variables.

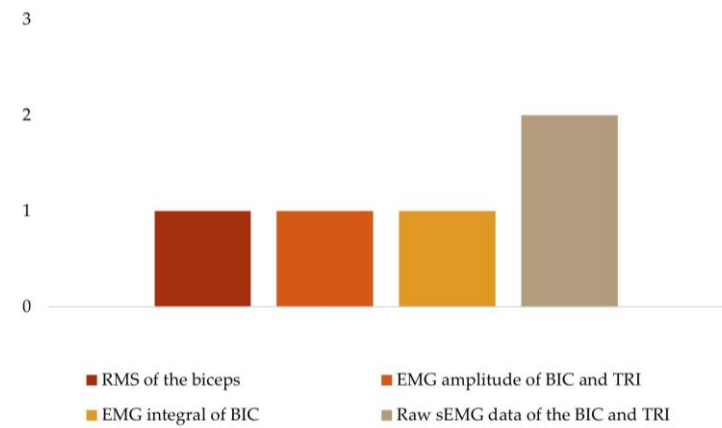


Figure 5. EMG variables.

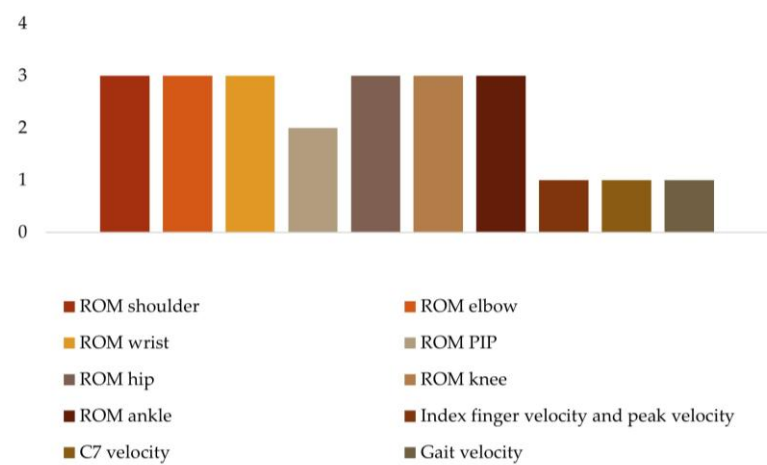


Figure 6. Kinematic variables.

3.5. Non-Linear Measures

Considering the units included in this review, 11 studies used entropy measures (Table 3). Approximate entropy (ApEn) was used in four studies (Ao et al., 2015; Sethi, Davis, et al., 2013; Sethi, Patterson, et al., 2013; Sethi et al., 2017); sample entropy (SampEn) was in five studies (Ao et al., 2015; Chow & Stokic, 2014; Kim et al., 2020; Tang et al., 2018; Zhang et al., 2017); fuzzy approximate entropy (fApEn) was used in two studies (Ao et al., 2015; Sun et al., 2014), and multivariate multiscale entropy (mMSE) was used in one study (Dugan & Combs-Miller, 2019). One study (Tian et al., 2021) considered the instantaneous fuzzy entropy (i-FuzzyEn), the cross-fuzzy entropy (C-FuzzyEn), and the instantaneous cross-fuzzy entropy (iC-FuzzyEn). The three remaining studies utilized the short-term local divergence exponent (LDE) and the maximum Floquet multiplier (maxFM) (Kao et al., 2014), the maximum Lyapunov exponent (MLyE) (Kempski et al., 2018), and the multifractal detrended fluctuation analysis (MFDFA) (Xu et al., 2022). Figure 7 summarizes the non-linear measures utilized in the studies included.

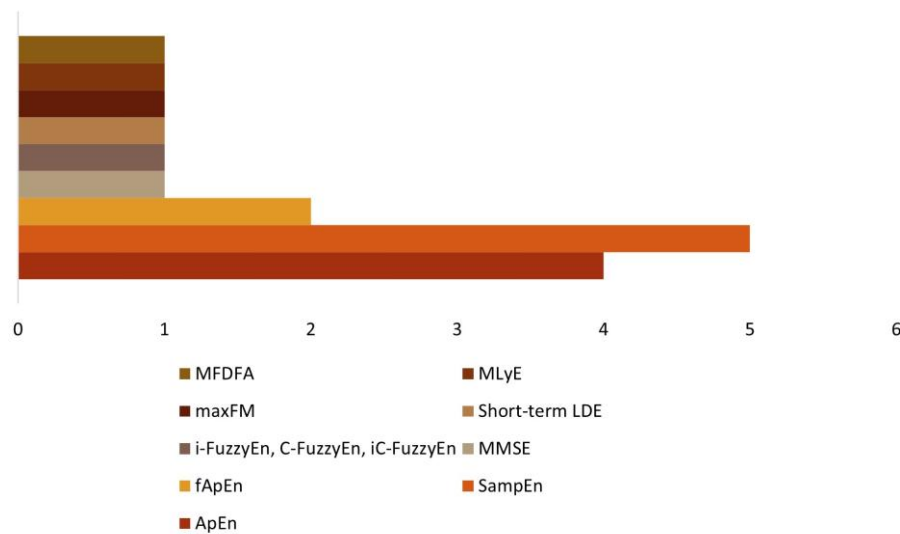


Figure 7. Non-linear measures.

3.6. Non-Linear Measures Parameters

For each of the non-linear measures, the included authors generally described their parameters in detail. Specifically, seven studies mentioned the dataset length (N) (Chow & Stokic, 2014; Dugan & Combs-Miller, 2019; Kao et al., 2014; Kim et al., 2020; Sun et al., 2014; Tang et al., 2018; Zhang et al., 2017), eleven studies described the specific

pattern length (m) (Ao et al., 2015; Chow & Stokic, 2014; Dugan & Combs-Miller, 2019; Kim et al., 2020; Sethi, Davis, et al., 2013; Sethi, Patterson, et al., 2013; Sethi et al., 2017; Sun et al., 2014; Tang et al., 2018; Tian et al., 2021; Zhang et al., 2017), and ten studies specified the criterion of similarity (r) (Chow & Stokic, 2014; Dugan & Combs-Miller, 2019; Kim et al., 2020; Sethi, Davis, et al., 2013; Sethi, Patterson, et al., 2013; Sethi et al., 2017; Sun et al., 2014; Tang et al., 2018; Tian et al., 2021; Zhang et al., 2017). Time series were reduced to N points by analysing between 20 (Xu et al., 2022) and 5000 points (Ao et al., 2015). The time delay between related series of observations (lag) was described in three studies (Sethi, Davis, et al., 2013; Sethi, Patterson, et al., 2013; Sethi et al., 2017). Furthermore, there is variation in the length of m, ranging from 2 (n = 10) (Ao et al., 2015; Dugan & Combs-Miller, 2019; Kim et al., 2020; Sethi, Davis, et al., 2013; Sethi, Patterson, et al., 2013; Sethi et al., 2017; Sun et al., 2014; Tang et al., 2018; Tian et al., 2021; Zhang et al., 2017) to 3 (n = 1) (Chow & Stokic, 2014), and r ranging from 0.2 (Chow & Stokic, 2014; Dugan & Combs-Miller, 2019; Kim et al., 2020; Sethi, Davis, et al., 2013; Sethi, Patterson, et al., 2013; Sethi et al., 2017; Sun et al., 2014; Tian et al., 2021) to 0.25 (Tang et al., 2018; Zhang et al., 2017). In the studies that included lag (n = 3), the value remained constant at 1 (Sethi, Davis, et al., 2013; Sethi, Patterson, et al., 2013; Sethi et al., 2017). Additionally, the studies had varying numbers of trials and lengths, ranging from 2 (Chow & Stokic, 2014) to 18 trials/condition (Ao et al., 2015), and from 3 s (Tang et al., 2018) to 3 min (Xu et al., 2022), respectively. Only nine studies described the number of attempts/times analysed in non-linear analyses (Chow & Stokic, 2014; Dugan & Combs-Miller, 2019; Kao et al., 2014; Kim et al., 2020; Sethi, Davis, et al., 2013; Sethi, Patterson, et al., 2013; Sethi et al., 2017; Tang et al., 2018; Zhang et al., 2017).

4. Discussion

This scoping review aimed to summarize information on the current published research related to the non-linear measures used in the kinetic, kinematic, and EMG data analysis of human movement after stroke.

Considering that everyday functional tasks involve the continuous adaptation of movement patterns to meet their dynamic demands, the study of variability in everyday tasks is a key point in human movement analysis due to its non-linear behavior. This information can provide a greater opportunity to better understand the mechanisms

underlying an impaired sensorimotor system and may suggest better interventions to improve movement adaptability while encouraging reflection on key findings to be considered in future research. Therefore, this discussion is divided into different aspects: (1) sample characterization; (2) tasks, non-linear measures, and non-linear parameters; (3) assessment instruments; and (4) kinematic, kinetic, and EMG variables.

4.1. Sample Characterization

In the included studies, the characteristics of sex, age, affected side, time after injury, and motor function were found to be the most common and frequently reported anthropometric variables. However, other important features such as stroke location, severity, ethnicity, pre-existing comorbid conditions (diabetes, cognitive impairment, or depression) (Kwakkel et al., 2017), and pre-stroke lifestyle factors (social engagement and exercise) were not consistently considered (Pongmoragot et al., 2016). Also, body function, structure, activity limitations, and participation restriction should be assessed using appropriate and adequate clinical measures. Indeed, although the Fugl–Meyer Assessment (FM) was commonly used in the present findings, it was not included in all studies, which may affect our understanding of participants' behaviour (Kwakkel et al., 2017).

It is important to note that limited or varied demographic and stroke-related data may hinder our understanding of stroke recovery trajectories (Bernhardt et al., 2015). Therefore, it is crucial to follow the core recommendations for stroke trials, which state that pre-stroke clinical, demographic, and stroke-related data are core measures that should be collected to improve the clinical prediction of recovery and characterization of patient cohorts. For instance, active hand movements and walking assessment are recommended, especially in studies with chronic stroke, when the NIHSS could not be collected at stroke onset (Kwakkel et al., 2017).

Another important consideration is the presence or absence of non-disabled matched individuals, which facilitates comparisons. Comparing an individual's motor task performance with a reference population of non-disabled matched individuals has been shown to be advantageous for better understanding disabled performance (Kwakkel et al., 2017). Despite this assumption, this was only considered in about half of the present studies.

4.2. Tasks and Non-Linear Measures

The intrinsic variability of human movement can be assessed by considering two parameters: stability and complexity (Stergiou et al., 2006; van Emmerik et al., 2016). Both parameters can be measured using several non-linear measures, such as the MLYE, the maxFM, and fractal measures like MFDFA for stability assessment. In addition, entropy measures are used to quantify the irregularity that is associated with movement complexity (Bruijn et al., 2013; Harbourne & Stergiou, 2009; van Emmerik et al., 2016).

Although entropy measures provide valuable insights into one aspect of variability, they do not capture the structural abundance and widespread component characterization of a complex system operating across multiple spatial and temporal scales (Yentes & Raffalt, 2021). Therefore, it is recommended to combine them with other non-linear measures for a more comprehensive assessment (Harbourne & Stergiou, 2009). Entropy was the most used measure for processing kinetic, kinematic, and EMG data in the reviewed studies. It is worth noting that none of the studies combined entropy with other non-linear measures, and only two studies combined different entropy measures (Ao et al., 2015; Tian et al., 2021). ApEn is a metric commonly used in the biomechanics literature to assess complexity (van Emmerik et al., 2016; Yentes et al., 2013). However, SampEn was the most frequently reported measure in the studies reviewed, followed by ApEn. Despite its frequent use, ApEn may lead to inconsistent results due to its sensitivity to the length of the time series (van Emmerik et al., 2016). It should be noted that the studies included in this review used ApEn to quantify the temporal structure of variability during three trials of reaching-to-grasp (Sethi, Davis, et al., 2013; Sethi, Patterson, et al., 2013) and reaching-to-point (Sethi et al., 2017) tasks. Although the authors normalized the ApEn values to the length of their time series (Sethi, Davis, et al., 2013; Sethi, Patterson, et al., 2013; Sethi et al., 2017), the number of trials and time series length may not be sufficient for consistent results.

SampEn is generally considered a better option for analyzing time series due to its greater relative consistency and lesser dependence on the length of the dataset (Liu et al., 2016). It has been widely used as a complexity measure in various fields of research to evaluate the impact of age, illness (Delgado-Bonal & Marshak, 2019), and performance (Lubetzky et al., 2018). In clinical contexts, this measure can help identify

motor coordination disorders (Harrison & Stergiou, 2015). In this review, five of the studies used SampEn, with short-length tasks, to quantify the complexity of the sEMG signal during knee extension (Chow & Stokic, 2014) and elbow flexion (Ao et al., 2015; Zhang et al., 2017); Tang et al. (Tang et al., 2018) used it as an indicator of the complexity and randomness of the sEMG signal during elbow flexion; and it was used as an indicator of the temporal structure of variability (force regularity) during wrist or finger extension (Kim et al., 2020). Additionally, SampEn can differentiate specific characteristics of distinct populations (Montesinos et al., 2018).

Although SampEn demonstrates relative consistency and less dependence on data length, its similar definition of vectors is based on the Heaviside function, as in ApEn (Richman & Moorman, 2000). However, the use of the Heaviside function has inherent flaws, which can lead to problems in the validity of the entropy definition, particularly when small parameters are involved (Chen et al., 2009). In this review, two studies used fApEn (Ao et al., 2015; Sun et al., 2014) to measure the time series regularity and complexity of sEMG signals of BIC and TRI during an arm tracking task. This measure was developed resulting from a combination of the concept of “fuzzy sets” and ApEn (Chen et al., 2007), showing better relative consistency and robustness to noisy physiological signals with short data length (Hornero et al., 2009; Xie et al., 2010).

Because neuromuscular activities are inherently non-linear (Jin et al., 2010), cross-entropy-based measures are used to characterize pattern synchronization and quantify inter-muscular coupling (Tian et al., 2021). Xie et al. (Xie et al., 2010) introduced the C-FuzzyEn, based on FuzzyEn. This method appears to be better suited to short time series and is more robust to noise, allowing the observation of the global intermuscular coupling between two separated but interconnected sEMG signals (Xie et al., 2010). C-FuzzyEn was used in a study included in this review to characterize the global intermuscular coupling during a tracking task of elbow flexion and extension (Tian et al., 2021). The iC-FuzzyEn and i-FuzzyEn are proposed by the authors to characterize the instantaneous intermuscular coupling and the dynamic complexity, respectively, in order to gain a better understanding of the neuromuscular mechanisms after a stroke (Tian et al., 2021).

Van Emmerik and colleagues (van Emmerik et al., 2016) demonstrated that ApEn, SampEn, and their variants are limited in their ability to provide a detailed analysis of

physiological signals because they only assess entropy on a temporal scale. As physiological systems exhibit structures across multiple time scales (Ahmed & Mandic, 2011), mMSE was developed to quantify the intrinsic complexity of the system at small and large scales (Ahmed & Mandic, 2011; Busa & van Emmerik, 2016; Costa et al., 2005). Nevertheless, only one of the studies included in this review used it to analyse the complexity of gait after stroke (Dugan & Combs-Miller, 2019). This may suggest an emerging interest in using measures that can better reflect the impact of complexity on the adaptability of the motor system after stroke.

According to the abovementioned studies, using different entropy measures shows a variety of approaches to the analysis of the data. The term complexity seems to have acquired synonyms such as ‘randomness’, ‘temporal structure of variability’, ‘predictability’, or ‘regularity’, depending on the research question of the studies. Therefore, the variety of entropy measures used in the studies analysed in our review suggests an increasing interest in measures that can more accurately capture the complexity of movement.

Despite the growth of entropy measures, some authors question their validity in assessing the complexity of motion (Stergiou et al., 2006). With our review, MFDFA (Xu et al., 2022), MLyE (Kempski et al., 2018), short-term LDE (Kao et al., 2014) and MaxFM (Kao et al., 2014) were identified as non-linear measures to assess stability during a treadmill (TM) walking task. These are commonly used to assess the local (MLyE and short-term LDE) and orbital (MaxFM) stability of the neuromuscular system, as in the ability to attenuate small perturbations (Bruijn et al., 2013).

Xu et al. (Xu et al., 2022) considered MFDFA to assess gait variability. This measure allows one to capture the multifractal scaling elements in a nonstationary time series (Kantelhardt et al., 2002). Fractal patterns are frequently observed in healthy and well-controlled movements, indicating a certain level of adaptability and flexibility in motor control (Marmelat et al., 2014), and providing information about the underlying control processes involved in movement (Rhea et al., 2014). As human gait is a cyclic and repetitive set of movements, fractal analysis can be a valuable tool in assessing gait adaptability and flexibility, identifying gait disorders, and predicting fall risk due to central nervous system dysfunction (Amirpourabasi et al., 2022; Marmelat et al., 2014; Phinyomark et al., 2020). Concerning the quantification of the local dynamic stability of

complex non-linear systems, MLyE using Wolf's algorithm (Kempski et al., 2018) and short-term LDE (Kao et al., 2014) were the measures applied. MLyE quantifies the rate of trajectory convergence or divergence in an n-dimensional state phase and how sensitive the system is to initial conditions (Liu et al., 2015; Mehdizadeh, 2018; Stergiou, 2016). Short-term LDE, on the other hand, is a measure of the local divergence or convergence of trajectories over a short period of time (Stergiou, 2016). It focuses on how trajectories behave in the immediate neighborhood of a given point in phase space (Stergiou, 2016). Hence, both concepts are related to the sensitivity of a dynamic system to initial conditions (Toebe et al., 2012). However, MLyE is typically concerned with long-term behavior, while short-term LyE focuses on local behavior over shorter time intervals, which is consistent with the included studies (Kao et al., 2014; Kempski et al., 2018). In the present review, it was identified that Wolf's method was used to calculate MLyE (Kempski et al., 2018). Nevertheless, the algorithm developed by Rosenstein is the most widely used in biomechanical studies (Mehdizadeh & Sanjari, 2017). Considering the length of the data in Kempski et al.'s (Kempski et al., 2018) study, Wolf's algorithm appears to be more appropriate for small gait datasets (Cignetti et al., 2012). The authors of this study considered, based on Moraiti et al. (Moraiti et al., 2010), that assessing two minutes of walking is sufficient for accurately calculating the LyE.

The MaxFM method, which quantifies the convergence/divergence of continuous gait variables towards a limit cycle (Bruijn et al., 2013), seems to be particularly relevant for analyzing long-distance walking or walking with many steps (Ahn & Hogan, 2014). However, this condition was not observed in the study that used this measure (Kempski et al., 2018). In this case, the authors needed to adjust the protocol because the population included (post-stroke) was unable to walk long distances.

These measures address different aspects of stability and can complement each other, revealing underlying patterns, attractor states, and dynamical properties that are not evident through traditional linear methods.

Although non-linear measures can be helpful in interpreting variability dynamics, it is important not to underestimate the importance of appropriate parameter selection (Caballero et al., 2014). Inadequate selection of non-linear analysis parameters can impact the measurement of system complexity, leading to inconsistent outcomes

(Müller et al., 2017). Time series data from biological systems are typically non-stationary and noisy, containing extreme values (Wijnants et al., 2009). Noise can have an impact on both the magnitude and structure of variability, potentially obscuring patterns and leading to inaccurate results (Costa et al., 2007). To reduce noise and facilitate the accurate identification and analysis of non-linear features (Rhea et al., 2014), filters were employed in eleven of the studies included, with frequencies that preserve relevant physiological information (Ao et al., 2015; Chow & Stokic, 2014; Dugan & Combs-Miller, 2019; Kao et al., 2014; Kim et al., 2020; Sethi, Davis, et al., 2013; Sethi, Patterson, et al., 2013; Sethi et al., 2017; Tang et al., 2018; Tian et al., 2021; Zhang et al., 2017). An important methodological consideration is the length of the data time series, as almost all non-linear measures are affected by this feature (Caballero et al., 2014). Regarding the specific parameters m , r , N , and lag, most of the included studies did not explain why they were chosen, and no article described all of them at the same time. Lag was described in only three studies written by the same study group (Sethi, Davis, et al., 2013; Sethi, Patterson, et al., 2013; Sethi et al., 2017). It is important to note that all authors included the data collection time/number of trials in their evaluation protocol. However, two authors did not specify which data were included in the non-linear analysis (Tian et al., 2021; Xu et al., 2022). To improve clarity, it is recommended to define the specific data used in the analysis.

Among the tasks analysed, it is important to highlight that three studies were related to reaching (Sethi, Davis, et al., 2013; Sethi, Patterson, et al., 2013; Sethi et al., 2017) and four to walking (Dugan & Combs-Miller, 2019; Kao et al., 2014; Kempinski et al., 2018; Xu et al., 2022), with both being considered functional daily tasks. The remaining protocols studied focused on isolated components of task execution, such as muscular strength (Chow & Stokic, 2014; Kim et al., 2020; Sun et al., 2014; Tang et al., 2018; Zhang et al., 2017), muscle activity (Ao et al., 2015; Sun et al., 2014; Tang et al., 2018; Tian et al., 2021; Zhang et al., 2017), or range of motion (Ao et al., 2015). However, research in movement sciences suggests that understanding integrated measures of task execution, such as coordination and adaptability, can provide the necessary information for the mechanisms underlying human movement (Kwakkel et al., 2023). Therefore, an incomplete assessment limited to the execution of isolated components diminishes the understanding of movement dysfunction (Kwakkel et al., 2023). The study of SMH

should involve analysing various motor tasks (Ozturk et al., 2016). Although the reviewed studies analysed several tasks (reaching and walking), it is important to also consider other core tasks such as sitting, standing, transitioning from sitting to standing, transitioning from standing to sitting and climbing or descending a step (Hedman et al., 2018). These tasks can be used as a starting point for different clinical situations and can help to identify critical aspects of movement (Hedman et al., 2018; Quinn et al., 2021). This may lead to the development of a standardized approach for analysing human movement (Hedman et al., 2018; Quinn et al., 2021).

Considering the walking tasks, variability has been assessed in both overground (OG) (Dugan & Combs-Miller, 2019) and TM walking (Kao et al., 2014; Kempinski et al., 2018; Xu et al., 2022). The use of TM walking emphasizes the need for a significant amount of continuous data to calculate all non-linear dynamic measures, particularly LyE (Kyvelidou et al., 2008). However, when using a TM, the constant speed imposes constraints on the gait, reducing the amount of movement variability. It appears to make the temporal structure of gait variability unrealistically regular compared to OG walking (Hollman et al., 2016; Terrier & Dériaz, 2011). Sloot et al. (Sloot et al., 2011) suggested that multiple episodes of shorter data can also be used to increase statistical precision. Therefore, OG walking appears to be a more accurate reflection of gait variability outcomes.

Another aspect to emphasize is that around nine of the included studies focused on the assessment of UL, rather than LL. It has been reported in the literature that the LL recovers more rapidly than the UL (Hamzat et al., 2014; Kong & Lee, 2013; Paci et al., 2016; Rand & Eng, 2012; Skurvydas et al., 2018), and that about 40–50% of stroke survivors have UL dysfunction (Broeks et al., 1999). Considering this review in a chronic stroke population, the results obtained may reflect these assumptions. Also, the lower number of results with protocols involving LL tasks seems to reduce the fact that LL and gait may not express the higher CNS control centers. Thus, walking in humans is mainly produced by the combined roles of the reflex circuit, which produces motor patterns triggered by sensory feedback, and the central pattern generators (CPGs), (Minassian et al., 2017; Ryu & Kuo, 2021). The CPGs mainly innervate the muscles of the lower limb (Klarner & Zehr, 2018), and they may not be affected following a stroke (Kathe et al., 2022). Consequently, rhythmic pattern movement such as stepping during

walking can be generated even in the absence of control of the higher CNS areas (Ryu & Kuo, 2021). However, further investigation and analysis are needed to validate this hypothesis and understand the complex mechanisms underlying motor control in the lower limbs.

Incorporating the principles of variability and chaotic variation, together with non-linear tools, can provide additional insights to guide practice and assess human movement dysfunction. It is important to note that non-linear analysis complements traditional linear methods in the understanding of neuromotor control following central nervous system dysfunction.

4.3. Assessment Instruments and Kinematic, Kinetic and EMG Variables

In terms of kinematic data analysis instruments, three motion capture systems were used, namely VICON™ (Sethi, Davis, et al., 2013; Sethi, Patterson, et al., 2013; Sethi et al., 2017), Motion Analysis Corporation (Kao et al., 2014; Kempinski et al., 2018), and OptiTrack® (Ao et al., 2015; Xu et al., 2022), mostly for upper limb tasks. These systems feature high-precision optoelectronic cameras that are considered highly accurate measurement tools for kinematic analysis in the study of human movement (Corazza et al., 2010). In one of the included studies (Dugan & Combs-Miller, 2019), inertial measurement units (IMUs) were used to evaluate kinematic data during walking. Despite the high accuracy and precision of motion capture systems, they are relatively costly and time-consuming and only allow data to be evaluated in a laboratory context (Hamacher et al., 2011). IMUs can collect data outside the laboratory environment (Usmani et al., 2021) to assess human movement in an easier, low-cost, valid, and reliable way (Chen et al., 2016; Drapeaux & Carlson, 2020). Thus, in the context of research or clinical practice, they could be a viable alternative to motion capture systems. They allow evaluation in a simulated context, as described in the articles included in this review, but also over extended periods in real-world environments (Kwakkel et al., 2023). IMUs could contribute to the improvement of motor variability assessment by providing essential data required for the interpretation of real-world readiness for participation (Kwakkel et al., 2023).

The accuracy of motion capture systems depends on the relative positions of the cameras, the position, the type and number of markers, and their movement within the

capture volume (Maletsky et al., 2007). The number of cameras in the included studies ranged from 6 (Xu et al., 2022) to 12 (Sethi, Davis, et al., 2013; Sethi, Patterson, et al., 2013; Sethi et al., 2017). The use of a larger number of cameras can be seen as an advantage, knowing that more cameras allow for better visual coverage (van der Kruk & Reijne, 2018), help to avoid marker occlusion by body parts, and allow for better reconstruction of motion in the observed time frame (Stancic et al., 2013).

The optoelectronic systems mentioned in the included studies (Ao et al., 2015; Kao et al., 2014; Kempinski et al., 2018; Sethi, Davis, et al., 2013; Sethi, Patterson, et al., 2013; Sethi et al., 2017; Xu et al., 2022), used passive marker systems that reflect light back to the sensor. Although the active marker systems may provide more robust measurements, they require additional cables and batteries, limiting freedom of movement (Stancic et al., 2013). The passive marker systems appear to be less invasive and can provide highly accurate information and simultaneous 3D kinematic measurements during different tasks.

Different motion capture protocols have been found, with varying marker sets, positions, and numbers. The well-documented and consistent use of a set of 67 reflective markers for upper limb joint kinematics is found in only three studies (Sethi, Davis, et al., 2013; Sethi, Patterson, et al., 2013; Sethi et al., 2017). Kinematic results are highly sensitive to anatomical markers (Della Croce et al., 2005; Kainz et al., 2016). The use of different marker sets can be a source of variability that can have a significant impact on the kinematic data generated (Mantovani & Lamontagne, 2017). The only study that used IMUs placed on the LL and pelvis did not specify the number and exact placement of the sensors. Sensor specifications, such as differences in sensor range, sampling rate, and placement, may be the reasons for variability in the reporting of non-linear measurements (Preatoni et al., 2022).

Furthermore, the lack of a standardized procedure for kinematic analysis may lead to discrepancies between studies. Data collection, processing, and analysis should be standardized and properly reported to facilitate comparisons between studies and the establishment of reference values for the field. The actual accuracy and precision achieved in practice may vary depending on the setup, user expertise, and environmental conditions (Colyer et al., 2018). Therefore, appropriate models for the specific research purpose, a single investigator to accurately place the markers (Della

Croce et al., 2005) or sensors, prior testing of the experimental protocol, and improvement of the most accurate setups could be important factors in increasing the reliability of the data.

A wide variety of kinematic results were observed, with the most pronounced being those related to the joint kinematics of the upper (Ao et al., 2015; Sethi, Davis, et al., 2013; Sethi, Patterson, et al., 2013; Sethi et al., 2017) and lower limbs (Kempski et al., 2018; Xu et al., 2022). Kinematic assessment is a reliable and objective method and provides quantitative measures of movement control, including motor performance and movement quality (Collins et al., 2018; Colyer et al., 2018). Only two authors suggested combining joint kinematics with spatial–temporal parameters (Kempski et al., 2018; Sethi et al., 2017). This approach integrates the complexity of joint motion and overall movement patterns in space and time, promoting objectivity and practicality by ensuring that assessments are directly related to real-world activities and functional tasks (Roggio et al., 2021).

Regarding the kinetic data, the analyzed articles assessed the torque of several muscles. The UL torque muscle was the most assessed, using an isokinetic dynamometer (Sun et al., 2014), a torque sensor (Zhang et al., 2017), or a force transducer (Kim et al., 2020). An isokinetic dynamometer is frequently used in scientific research to assess muscle strength due to its simplicity and accuracy (Rabelo et al., 2016). It is a reference in the comparison of measurements obtained with other instruments, with excellent levels of validity (Ekstrand et al., 2015; Kwong et al., 2017) and reliability of muscle strength assessment in UL and LL in chronic post-stroke patients (Abdollahi et al., 2015; Karthikbabu & Chakrapani, 2017; Rabelo & Fachin-Martins, 2018; Rabelo et al., 2016).

The use of sEMG systems has been prevalent in assessing muscle activity during UL-isolated components of task execution (Ao et al., 2015; Sun et al., 2014; Tang et al., 2018; Tian et al., 2021; Zhang et al., 2017). Clinically, sEMG provides a non-invasive method to observe neuromotor activity and to assess the individual's neurological status and nervous system reorganization (Merletti et al., 2023).

However, neuromuscular signals have limitations in providing insights into movement quality, which is often assessed via movement function tests or biomechanical performance (Belfatto et al., 2018). Additionally, a broader range of assessment

methods and metrics that integrate the benefits of biomechanical (kinematic and kinetic) and neuromuscular (sEMG) measures have been highlighted (Belfatto et al., 2018; Fang et al., 2020; Pierella et al., 2020). Although one study combined kinematic and sEMG data (Ao et al., 2015) and two studies combined kinetic and sEMG data (Sun et al., 2014; Zhang et al., 2017), none of the others attempted this. Combining data from different domains can provide comprehensive insights by enabling the understanding of the origin of neuromuscular activity through the expression of biomechanical variables. The complexity of human movement's neuromotor behaviour justifies a combined approach. Particularly in cases of neurological injury, kinematic and kinetic changes occur due to an altered ability to influence neural circuits, whose function is intrinsically linked to muscle activity (Hallett et al., 2021). Such changes can be more accurately documented using sEMG (Maura et al., 2023).

Some limitations need to be acknowledged. Firstly, the search was restricted to five databases, which means that it is possible that we may have overlooked some of the literature. Secondly, we intentionally developed a broad search strategy to prevent the possibility of missing important studies. Nevertheless, this scoping review and its findings seem to be indicative of the advances made in this field. The study of non-linear dynamics will allow us to understand the complexity of human movement and evaluate their biological adaptivity.

5. Conclusions

This scoping review provides a comprehensive overview of the current research landscape on non-linear measures in the analysis of human movement post-stroke. Entropy measures, particularly sample entropy, have been the preferred measures when investigating the complexity of human movement. The focus has been on UL tasks such as reaching and components of task execution, such as elbow flexion and extension. Regarding the analysed variables, the joint kinematics and muscle torque and activity were the most prominent during the UL tasks. Assessment instruments employing motion capture systems and sEMG were the most used tools for kinematic and muscle activity analysis, respectively.

6. References

- Abdollahi, I., Taghizadeh, A., Shakeri, H., Eivazi, M., & Jaberzadeh, S. (2015). The relationship between isokinetic muscle strength and spasticity in the lower limbs of stroke patients. *J Bodyw Mov Ther*, 19(2), 284-290. <https://doi.org/10.1016/j.jbmt.2014.07.002>
- Adegoke, B. O., Olaniyi, O., & Akosile, C. O. (2012). Weight bearing asymmetry and functional ambulation performance in stroke survivors. *Glob J Health Sci*, 4(2), 87-94. <https://doi.org/10.5539/gjhs.v4n2p87>
- Ahmed, M. U., & Mandic, D. P. (2011). Multivariate multiscale entropy: a tool for complexity analysis of multichannel data. *Phys Rev E Stat Nonlin Soft Matter Phys*, 84(6 Pt 1), 061918. <https://doi.org/10.1103/PhysRevE.84.061918>
- Ahn, J., & Hogan, N. (2014, 25-27 April 2014). Is estimation of Floquet multipliers of human walking valid? 2014 40th Annual Northeast Bioengineering Conference (NEBEC),
- Amirpourabasi, A., Lamb, S. E., Chow, J. Y., & Williams, G. K. R. (2022). Nonlinear Dynamic Measures of Walking in Healthy Older Adults: A Systematic Scoping Review. *Sensors*, 22(12). <https://doi.org/10.3390/s22124408>
- Ao, D., Sun, R., Tong, K. Y., & Song, R. (2015). Characterization of stroke- and aging-related changes in the complexity of EMG signals during tracking tasks. *Ann Biomed Eng*, 43(4), 990-1002. <https://doi.org/10.1007/s10439-014-1150-1>
- Aromataris, E., & Munn, Z. (2020). Furthering the science of evidence synthesis with a mix of methods. *JBIM Manual Evid Synth*, 18, 2106-2107. <https://doi.org/10.46658/JBIMES-20-02>
- Barela, A. M. F., & Duarte, M. (2011). Use of force plate for acquisition of kinetic data during human gait. *Braz. J. Mot. Behav*, 6(1), 56-61. <https://doi.org/10.20338/bjmb.v6i1.32>
- Belfatto, A., Scano, A., Chiavenna, A., Mastropietro, A., Mrakic-Sposta, S., Pittaccio, S., Molinari Tosatti, L., Molteni, F., & Rizzo, G. (2018). A Multiparameter Approach to Evaluate Post-Stroke Patients: An Application on Robotic Rehabilitation. *Appl. Sci*, 8(11), 2248. <https://www.mdpi.com/2076-3417/8/11/2248>

- Bernhardt, J., Hayward, K. S., Kwakkel, G., Ward, N. S., Wolf, S. L., Borschmann, K., Krakauer, J. W., Boyd, L. A., Carmichael, S. T., Corbett, D., & Cramer, S. C. (2017). Agreed Definitions and a Shared Vision for New Standards in Stroke Recovery Research: The Stroke Recovery and Rehabilitation Roundtable Taskforce. *Neurorehabil Neural Repair*, 31(9), 793-799. <https://doi.org/10.1177/1545968317732668>
- Bernhardt, J., Raffelt, A., Churilov, L., Lindley, R. I., Speare, S., Ancliffe, J., Katijjahbe, M. A., Hameed, S., Lennon, S., McRae, A., Tan, D., Quiney, J., Williamson, H. C., Collier, J., Dewey, H. M., Donnan, G. A., Langhorne, P., & Thrift, A. G. (2015). Exploring threats to generalisability in a large international rehabilitation trial (AVERT). *BMJ Open*, 5(8), e008378. <https://doi.org/10.1136/bmjopen-2015-008378>
- Bisi, M. C., & Stagni, R. (2018). Changes of human movement complexity during maturation: quantitative assessment using multiscale entropy. *Comput Methods Biomech Biomed Engin*, 21(4), 325-331. <https://doi.org/10.1080/10255842.2018.1448392>
- Broeks, J., Lankhorst, G., Rumping, K., & Prevo, A. (1999). The long-term outcome of arm function after stroke: Results of a follow-up study. *Disabil. Rehabil*, 21, 357-364. <https://doi.org/10.1080/096382899297459>
- Bruijn, S. M., Meijer, O. G., Beek, P. J., & van Dieën, J. H. (2013). Assessing the stability of human locomotion: a review of current measures. *J R Soc Interface*, 10(83), 20120999. <https://doi.org/10.1098/rsif.2012.0999>
- Busa, M. A., & van Emmerik, R. E. A. (2016). Multiscale entropy: A tool for understanding the complexity of postural control. *J Sport Health Sci*, 5(1), 44-51. <https://doi.org/10.1016/j.jshs.2016.01.018>
- Caballero, C., Barbado, D., & Moreno, F. (2014). Non-linear tools and methodological concerns measuring human movement variability: an overview. *Eur J Hum Mov*, 32, 61-81.
- Cavanaugh, J. T., Kelty-Stephen, D. G., & Stergiou, N. (2017). Multifractality, Interactivity, and the Adaptive Capacity of the Human Movement System: A Perspective for Advancing the Conceptual Basis of Neurologic Physical Therapy. *J Neurol Phys Ther*, 41(4), 245-251. <https://doi.org/10.1097/npt.0000000000000199>

- Chen, S., Lach, J., Lo, B., & Yang, G. Z. (2016). Toward Pervasive Gait Analysis With Wearable Sensors: A Systematic Review. *IEEE J Biomed Health Inform*, 20(6), 1521-1537. <https://doi.org/10.1109/jbhi.2016.2608720>
- Chen, W., Wang, Z., Xie, H., & Yu, W. (2007). Characterization of surface EMG signal based on fuzzy entropy. *IEEE Trans Neural Syst Rehabil Eng*, 15(2), 266-272. <https://doi.org/10.1109/tnsre.2007.897025>
- Chen, W., Zhuang, J., Yu, W., & Wang, Z. (2009). Measuring complexity using FuzzyEn, ApEn, and SampEn. *Med Eng Phys*, 31(1), 61-68. <https://doi.org/10.1016/j.medengphy.2008.04.005>
- Chow, J. W., & Stokic, D. S. (2014). Variability, frequency composition, and complexity of submaximal isometric knee extension force from subacute to chronic stroke. *Neuroscience*, 273, 189-198. <https://doi.org/10.1016/j.neuroscience.2014.05.018>
- Cignetti, F., Decker, L. M., & Stergiou, N. (2012). Sensitivity of the Wolf's and Rosenstein's algorithms to evaluate local dynamic stability from small gait data sets. *Ann Biomed Eng*, 40(5), 1122-1130. <https://doi.org/10.1007/s10439-011-0474-3>
- Collins, K. C., Kennedy, N. C., Clark, A., & Pomeroy, V. M. (2018). Kinematic Components of the Reach-to-Target Movement After Stroke for Focused Rehabilitation Interventions: Systematic Review and Meta-Analysis. *Front Neurol*, 9, 472. <https://doi.org/10.3389/fneur.2018.00472>
- Colyer, S. L., Evans, M., Cosker, D. P., & Salo, A. I. T. (2018). A Review of the Evolution of Vision-Based Motion Analysis and the Integration of Advanced Computer Vision Methods Towards Developing a Markerless System. *Sports Med Open*, 4(1), 24. <https://doi.org/10.1186/s40798-018-0139-y>
- Corazza, S., Mündermann, L., Gambaretto, E., Ferrigno, G., & Andriacchi, T. (2010). Markerless Motion Capture through Visual Hull, Articulated ICP and Subject Specific Model Generation. *Int J Comput Vis*, 87, 156-169. <https://doi.org/10.1007/s11263-009-0284-3>
- Costa, M., Goldberger, A. L., & Peng, C. K. (2005). Multiscale entropy analysis of biological signals. *Phys Rev E Stat Nonlin Soft Matter Phys*, 71(2 Pt 1), 021906. <https://doi.org/10.1103/PhysRevE.71.021906>
- Costa, M., Priplata, A. A., Lipsitz, L. A., Wu, Z., Huang, N. E., Goldberger, A. L., & Peng, C. K. (2007). Noise and poise: Enhancement of postural complexity in the

- elderly with a stochastic-resonance-based therapy. *Europhys Lett*, 77, 68008.
<https://doi.org/10.1209/0295-5075/77/68008>
- da Costa, C. S., Batistão, M. V., & Rocha, N. A. (2013). Quality and structure of variability in children during motor development: a systematic review. *Res Dev Disabil*, 34(9), 2810-2830. <https://doi.org/10.1016/j.ridd.2013.05.031>
- Delgado-Bonal, A., & Marshak, A. (2019). Approximate Entropy and Sample Entropy: A Comprehensive Tutorial. *Entropy*, 21(6). <https://doi.org/10.3390/e21060541>
- Della Croce, U., Leardini, A., Chiari, L., & Cappozzo, A. (2005). Human movement analysis using stereophotogrammetry. Part 4: assessment of anatomical landmark misplacement and its effects on joint kinematics. *Gait Posture*, 21(2), 226-237. <https://doi.org/10.1016/j.gaitpost.2004.05.003>
- Drapeaux, A., & Carlson, K. (2020). A comparison of inertial motion capture systems: DorsaVi and Xsens. *International Journal of Kinesiology & Sports Science*, 8(3), 24-27. <https://doi.org/10.7575/aiac.ijkss.v.8n.3p.24>
- Dugan, E. L., & Combs-Miller, S. A. (2019). Physiological complexity of gait is decreased in individuals with chronic stroke. *Comput Methods Biomech Biomed Engin*, 22(6), 658-663. <https://doi.org/10.1080/10255842.2019.1578961>
- Ekstrand, E., Lexell, J., & Brogårdh, C. (2015). Isometric and isokinetic muscle strength in the upper extremity can be reliably measured in persons with chronic stroke. *J Rehabil Med*, 47(8), 706-713. <https://doi.org/10.2340/16501977-1990>
- Fang, C., He, B., Wang, Y., Cao, J., & Gao, S. (2020). EMG-Centered Multisensory Based Technologies for Pattern Recognition in Rehabilitation: State of the Art and Challenges. *Biosensors*, 10(8). <https://doi.org/10.3390/bios10080085>
- Feigin, V. L., Stark, B. A., Johnson, C. O., Roth, G. A., Bisignano, C., Abady, G. G., Abbasifard, M., Abbasi-Kangevari, M., Abd-Allah, F., Abedi, V., Abualhasan, A., Abu-Rmeileh, N. M. E., Abushouk, A. I., Adebayo, O. M., Agarwal, G., Agasthi, P., Ahinkorah, B. O., Ahmad, S., Ahmadi, S., . . . Murray, C. J. L. (2021). Global, regional, and national burden of stroke and its risk factors, 1990–2019: a systematic analysis for the Global Burden of Disease Study 2019. *The Lancet Neurology*, 20(10), 795-820. [https://doi.org/10.1016/S1474-4422\(21\)00252-0](https://doi.org/10.1016/S1474-4422(21)00252-0)

- Gorniak, S. L. (2019). The relationship between task difficulty and motor performance complexity. *Atten Percept Psychophys*, 81(1), 12-19. <https://doi.org/10.3758/s13414-018-1634-4>
- Hallett, M., DelRosso, L. M., Elble, R., Ferri, R., Horak, F. B., Lehericy, S., Mancini, M., Matsushashi, M., Matsumoto, R., Muthuraman, M., Raethjen, J., & Shibasaki, H. (2021). Evaluation of movement and brain activity. *Clin Neurophysiol*, 132(10), 2608-2638. <https://doi.org/https://doi.org/10.1016/j.clinph.2021.04.023>
- Hamacher, D., Singh, N. B., Van Dieën, J. H., Heller, M. O., & Taylor, W. R. (2011). Kinematic measures for assessing gait stability in elderly individuals: a systematic review. *J R Soc Interface*, 8(65), 1682-1698. <https://doi.org/10.1098/rsif.2011.0416>
- Hamzat, T. K., Owolabi, M. O., & Vincent-Onabajo, G. O. (2014). Trajectory of Motor Performance Over Twelve Months in Nigerian Stroke Survivors. *Brain Impairment*, 15(1), 43-50. <https://doi.org/10.1017/BrImp.2014.3>
- Harbourne, R. T., & Stergiou, N. (2009). Movement variability and the use of nonlinear tools: principles to guide physical therapist practice. *Phys Ther*, 89(3), 267-282. <https://doi.org/10.2522/ptj.20080130>
- Harrison, S. J., & Stergiou, N. (2015). Complex Adaptive Behavior and Dexterous Action. *Nonlinear Dynamics Psychol Life Sci*, 19(4), 345-394.
- Hartman-Maeir, A., Soroker, N., Ring, H., Avni, N., & Katz, N. (2007). Activities, participation and satisfaction one-year post stroke. *Disabil Rehabil*, 29(7), 559-566. <https://doi.org/10.1080/09638280600924996>
- Hedman, L. D., Quinn, L., Gill-Body, K., Brown, D. A., Quiben, M., Riley, N., & Scheets, P. L. (2018). White Paper: Movement System Diagnoses in Neurologic Physical Therapy. *J Neurol Phys Ther*, 42(2), 110-117. <https://doi.org/10.1097/npt.0000000000000215>
- Hollman, J. H., Watkins, M. K., Imhoff, A. C., Braun, C. E., Akervik, K. A., & Ness, D. K. (2016). Complexity, fractal dynamics and determinism in treadmill ambulation: Implications for clinical biomechanists. *Clin Biomech*, 37, 91-97. <https://doi.org/10.1016/j.clinbiomech.2016.06.007>
- Hornero, R., Abásolo, D., Escudero, J., & Gómez, C. (2009). Nonlinear analysis of electroencephalogram and magnetoencephalogram recordings in patients with

- Alzheimer's disease. *Philos Trans A Math Phys Eng Sci*, 367(1887), 317-336.
<https://doi.org/10.1098/rsta.2008.0197>
- Ihlen, E. A. F., van Schooten, K. S., Bruijn, S. M., van Dieën, J. H., Vereijken, B., Helbostad, J. L., & Pijnappels, M. (2018). Improved Prediction of Falls in Community-Dwelling Older Adults Through Phase-Dependent Entropy of Daily-Life Walking. *Front Aging Neurosci*, 10, 44.
<https://doi.org/10.3389/fnagi.2018.00044>
- Jin, S. H., Lin, P., & Hallett, M. (2010). Linear and nonlinear information flow based on time-delayed mutual information method and its application to corticomuscular interaction. *Clin Neurophysiol*, 121(3), 392-401.
<https://doi.org/10.1016/j.clinph.2009.09.033>
- Kainz, H., Modenese, L., Lloyd, D. G., Maine, S., Walsh, H. P. J., & Carty, C. P. (2016). Joint kinematic calculation based on clinical direct kinematic versus inverse kinematic gait models. *J Biomech*, 49(9), 1658-1669.
<https://doi.org/https://doi.org/10.1016/j.jbiomech.2016.03.052>
- Kantelhardt, J. W., Zschiegner, S. A., Koscielny-Bunde, E., Havlin, S., Bunde, A., & Stanley, H. E. (2002). Multifractal detrended fluctuation analysis of nonstationary time series. *Physica A: Statistical Mechanics and its Applications*, 316(1), 87-114. [https://doi.org/https://doi.org/10.1016/S0378-4371\(02\)01383-3](https://doi.org/https://doi.org/10.1016/S0378-4371(02)01383-3)
- Kao, P. C., Dingwell, J. B., Higginson, J. S., & Binder-Macleod, S. (2014). Dynamic instability during post-stroke hemiparetic walking. *Gait Posture*, 40(3), 457-463.
<https://doi.org/10.1016/j.gaitpost.2014.05.014>
- Karthikbabu, S., & Chakrapani, M. (2017). Hand-Held Dynamometer is a Reliable Tool to Measure Trunk Muscle Strength in Chronic Stroke. *J Clin Diagn Res*, 11(9), Yc09-yc12. <https://doi.org/10.7860/jcdr/2017/28105.10672>
- Kathe, C., Skinnider, M. A., Hutson, T. H., Regazzi, N., Gautier, M., Demesmaeker, R., Komi, S., Ceto, S., James, N. D., Cho, N., Baud, L., Galan, K., Matson, K. J. E., Rowald, A., Kim, K., Wang, R., Minassian, K., Prior, J. O., Asboth, L., . . . Courtine, G. (2022). The neurons that restore walking after paralysis. *Nature*, 611(7936), 540-547. <https://doi.org/10.1038/s41586-022-05385-7>
- Kędziorek, J., & Błażkiewicz, M. (2020). Nonlinear Measures to Evaluate Upright Postural Stability: A Systematic Review. *Entropy (Basel)*, 22(12).
<https://doi.org/10.3390/e22121357>

- Kempski, K., Awad, L. N., Buchanan, T. S., Higginson, J. S., & Knarr, B. A. (2018). Dynamic structure of lower limb joint angles during walking post-stroke. *J Biomech*, 68, 1-5. <https://doi.org/10.1016/j.jbiomech.2017.12.019>
- Kim, H. J., Kang, N., & Cauraugh, J. H. (2020). Transient changes in paretic and non-paretic isometric force control during bimanual submaximal and maximal contractions. *J Neuroeng Rehabil*, 17(1), 64. <https://doi.org/10.1186/s12984-020-00693-3>
- Klarner, T., & Zehr, E. P. (2018). Sherlock Holmes and the curious case of the human locomotor central pattern generator. *J Neurophysiol*, 120(1), 53-77. <https://doi.org/10.1152/jn.00554.2017>
- Kong, K. H., & Lee, J. (2013). Temporal recovery and predictors of upper limb dexterity in the first year of stroke: a prospective study of patients admitted to a rehabilitation centre. *NeuroRehabilitation*, 32(2), 345-350. <https://doi.org/10.3233/nre-130854>
- Kwakkel, G., Lannin, N. A., Borschmann, K., English, C., Ali, M., Churilov, L., Saposnik, G., Winstein, C., van Wegen, E. E., Wolf, S. L., Krakauer, J. W., & Bernhardt, J. (2017). Standardized measurement of sensorimotor recovery in stroke trials: Consensus-based core recommendations from the Stroke Recovery and Rehabilitation Roundtable. *Int J Stroke*, 12(5), 451-461. <https://doi.org/10.1177/1747493017711813>
- Kwakkel, G., Stinear, C., Essers, B., Munoz-Novoa, M., Branscheidt, M., Cabanas-Valdés, R., Lakičević, S., Lampropoulou, S., Luft, A. R., Marque, P., Moore, S. A., Solomon, J. M., Swinnen, E., Turolla, A., Alt Murphy, M., & Verheyden, G. (2023). Motor rehabilitation after stroke: European Stroke Organisation (ESO) consensus-based definition and guiding framework. *Eur Stroke J*, 8(4), 880-894. <https://doi.org/10.1177/23969873231191304>
- Kwong, P. W. H., Ng, S. S. M., Chung, R. C. K., & Ng, G. Y. F. (2017). A structural equation model of the relationship between muscle strength, balance performance, walking endurance and community integration in stroke survivors. *PLoS One*, 12(10), e0185807. <https://doi.org/10.1371/journal.pone.0185807>
- Kyvelidou, A., Kurz, M. J., Ehlers, J. L., & Stergiou, N. (2008). Aging and partial body weight support affects gait variability. *J Neuroeng Rehabil*, 5, 22. <https://doi.org/10.1186/1743-0003-5-22>

- Liu, K., Wang, H., Xiao, J., & Taha, Z. (2015). Analysis of human standing balance by largest lyapunov exponent. *Comput Intell Neurosci*, 2015, 158478. <https://doi.org/10.1155/2015/158478>
- Liu, X., Jiang, A., Xu, N., & Xue, J. (2016). Increment Entropy as a Measure of Complexity for Time Series. *Entropy*, 18(1), 22. <https://www.mdpi.com/1099-4300/18/1/22>
- Lubetzky, A. V., Harel, D., & Lubetzky, E. (2018). On the effects of signal processing on sample entropy for postural control. *PLoS One*, 13(3), e0193460. <https://doi.org/10.1371/journal.pone.0193460>
- Maletsky, L. P., Sun, J., & Morton, N. A. (2007). Accuracy of an optical active-marker system to track the relative motion of rigid bodies. *J Biomech*, 40(3), 682-685. <https://doi.org/10.1016/j.jbiomech.2006.01.017>
- Mantovani, G., & Lamontagne, M. (2017). How Different Marker Sets Affect Joint Angles in Inverse Kinematics Framework. *J Biomech Eng*, 139(4). <https://doi.org/10.1115/1.4034708>
- Marmelat, V., Torre, K., Beek, P. J., & Daffertshofer, A. (2014). Persistent fluctuations in stride intervals under fractal auditory stimulation. *PLoS One*, 9(3), e91949. <https://doi.org/10.1371/journal.pone.0091949>
- Maura, R. M., Rueda Parra, S., Stevens, R. E., Weeks, D. L., Wolbrecht, E. T., & Perry, J. C. (2023). Literature review of stroke assessment for upper-extremity physical function via EEG, EMG, kinematic, and kinetic measurements and their reliability. *J. Neuroeng. Rehabilitation.*, 20(1), 21. <https://doi.org/10.1186/s12984-023-01142-7>
- Mehdizadeh, S. (2018). The largest Lyapunov exponent of gait in young and elderly individuals: A systematic review. *Gait Posture*, 60, 241-250. <https://doi.org/10.1016/j.gaitpost.2017.12.016>
- Mehdizadeh, S., & Sanjari, M. A. (2017). Effect of noise and filtering on largest Lyapunov exponent of time series associated with human walking. *J Biomech*, 64, 236-239. <https://doi.org/10.1016/j.jbiomech.2017.09.009>
- Merletti, R., Temporiti, F., Gatti, R., Gupta, S., Sandrini, G., & Serrao, M. (2023). Translation of surface electromyography to clinical and motor rehabilitation applications: The need for new clinical figures. *Transl Neurosci*, 14(1), 20220279. <https://doi.org/10.1515/tnsci-2022-0279>

- Minassian, K., Hofstoetter, U. S., Dzeladini, F., Guertin, P. A., & Ijspeert, A. (2017). The Human Central Pattern Generator for Locomotion: Does It Exist and Contribute to Walking? *Neuroscientist*, 23(6), 649-663. <https://doi.org/10.1177/1073858417699790>
- Montesinos, L., Castaldo, R., & Pecchia, L. (2018). On the use of approximate entropy and sample entropy with centre of pressure time-series. *J Neuroeng Rehabil*, 15(1), 116. <https://doi.org/10.1186/s12984-018-0465-9>
- Moraiti, C. O., Stergiou, N., Vasiliadis, H. S., Motsis, E., & Georgoulis, A. (2010). Anterior cruciate ligament reconstruction results in alterations in gait variability. *Gait & Posture*, 32(2), 169-175. <https://doi.org/https://doi.org/10.1016/j.gaitpost.2010.04.008>
- Müller, W., Jung, A., & Ahammer, H. (2017). Advantages and problems of nonlinear methods applied to analyze physiological time signals: human balance control as an example. *Sci Rep*, 7(1), 2464. <https://doi.org/10.1038/s41598-017-02665-5>
- Ozturk, A., Tartar, A., Ersoz Huseyinsinoglu, B., & Ertas, A. H. (2016). A clinically feasible kinematic assessment method of upper extremity motor function impairment after stroke. *Measurement*, 80, 207-216. <https://doi.org/https://doi.org/10.1016/j.measurement.2015.11.026>
- Paci, M., Nannetti, L., Casavola, D., & Lombardi, B. (2016). Differences in motor recovery between upper and lower limbs: does stroke subtype make the difference? *Int J Rehabil Res*, 39(2), 185-187. <https://doi.org/10.1097/mrr.0000000000000172>
- Page, M. J., Moher, D., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., . . . McKenzie, J. E. (2021). PRISMA 2020 explanation and elaboration: updated guidance and exemplars for reporting systematic reviews. *Bmj*, 372, n160. <https://doi.org/10.1136/bmj.n160>
- Peters, M. D. J., Marnie, C., Tricco, A. C., Pollock, D., Munn, Z., Alexander, L., McInerney, P., Godfrey, C. M., & Khalil, H. (2020). Updated methodological guidance for the conduct of scoping reviews. *JBIM Evid Synth*, 18(10), 2119-2126. <https://doi.org/10.11124/jbies-20-00167>

- Phinyomark, A., Larracy, R., & Scheme, E. (2020). Fractal Analysis of Human Gait Variability via Stride Interval Time Series. *Front Physiol*, 11, 333. <https://doi.org/10.3389/fphys.2020.00333>
- Pierella, C., Pirondini, E., Kinany, N., Coscia, M., Giang, C., Miehlbradt, J., Magnin, C., Nicolo, P., Dalise, S., Sgherri, G., Chisari, C., Van De Ville, D., Guggisberg, A., & Micera, S. (2020). A multimodal approach to capture post-stroke temporal dynamics of recovery. *J Neural Eng*, 17(4), 045002. <https://doi.org/10.1088/1741-2552/ab9ada>
- Pongmoragot, J., Lee, D. S., Park, T. H., Fang, J., Austin, P. C., & Saposnik, G. (2016). Stroke and Heart Failure: Clinical Features, Access to Care, and Outcomes. *J Stroke Cerebrovasc Dis*, 25(5), 1048-1056. <https://doi.org/10.1016/j.jstrokecerebrovasdis.2016.01.013>
- Preatoni, E., Bergamini, E., Fantozzi, S., Giraud, L. I., Orejel Bustos, A. S., Vannozzi, G., & Camomilla, V. (2022). The Use of Wearable Sensors for Preventing, Assessing, and Informing Recovery from Sport-Related Musculoskeletal Injuries: A Systematic Scoping Review. *Sensors (Basel)*, 22(9). <https://doi.org/10.3390/s22093225>
- Quinn, L., Riley, N., Tyrell, C. M., Judd, D. L., Gill-Body, K. M., Hedman, L. D., Packel, A., Brown, D. A., Nabar, N., & Scheets, P. (2021). A Framework for Movement Analysis of Tasks: Recommendations From the Academy of Neurologic Physical Therapy's Movement System Task Force. *Phys Ther*, 101(9). <https://doi.org/10.1093/ptj/pzab154>
- Rabelo, M., & Fachin-Martins, E. (2018). Inter-rater and test/retest reliabilities of the isokinetic measurements: assessing strength and endurance of the trunk muscles in two different protocols for able-bodied and post-stroke hemiparesis. *Top Stroke Rehabil*, 25(6), 424-431. <https://doi.org/10.1080/10749357.2018.1481568>
- Rabelo, M., Nunes, G. S., da Costa Amante, N. M., de Noronha, M., & Fachin-Martins, E. (2016). Reliability of muscle strength assessment in chronic post-stroke hemiparesis: a systematic review and meta-analysis. *Top Stroke Rehabil*, 23(1), 26-36. <https://doi.org/10.1179/1945511915y.0000000008>
- Rand, D., & Eng, J. J. (2012). Disparity between functional recovery and daily use of the upper and lower extremities during subacute stroke rehabilitation.

- Neurorehabil Neural Repair, 26(1), 76-84.
<https://doi.org/10.1177/1545968311408918>
- Rhea, C. K., Kiefer, A. W., Wittstein, M. W., Leonard, K. B., MacPherson, R. P., Wright, W. G., & Haran, F. J. (2014). Fractal gait patterns are retained after entrainment to a fractal stimulus. *PLoS One*, 9(9), e106755.
<https://doi.org/10.1371/journal.pone.0106755>
- Richman, J. S., & Moorman, J. R. (2000). Physiological time-series analysis using approximate entropy and sample entropy. *Am J Physiol Heart Circ Physiol*, 278(6), H2039-2049. <https://doi.org/10.1152/ajpheart.2000.278.6.H2039>
- Roggio, F., Ravalli, S., Maugeri, G., Bianco, A., Palma, A., Di Rosa, M., & Musumeci, G. (2021). Technological advancements in the analysis of human motion and posture management through digital devices. *World J Orthop*, 12(7), 467-484.
<https://doi.org/10.5312/wjo.v12.i7.467>
- Ryu, H. X., & Kuo, A. D. (2021). An optimality principle for locomotor central pattern generators. *Sci Rep*, 11(1), 13140. <https://doi.org/10.1038/s41598-021-91714-1>
- Saladin, L., & Voight, M. (2017). Introduction to the movement system as the foundation for physical therapist practice education and research. *Int J Sports Phys Ther*, 12(6), 858-861.
- Sethi, A., Davis, S., McGuirk, T., Patterson, T. S., & Richards, L. G. (2013). Effect of intense functional task training upon temporal structure of variability of upper extremity post stroke. *J Hand Ther*, 26(2), 132-137; quiz 138.
<https://doi.org/10.1016/j.jht.2012.09.001>
- Sethi, A., Patterson, T., McGuirk, T., Patten, C., Richards, L. G., & Stergiou, N. (2013). Temporal structure of variability decreases in upper extremity movements post stroke. *Clin Biomech*, 28(2), 134-139.
<https://doi.org/10.1016/j.clinbiomech.2012.11.006>
- Sethi, A., Stergiou, N., Patterson, T. S., Patten, C., & Richards, L. G. (2017). Speed and Rhythm Affect Temporal Structure of Variability in Reaching Poststroke: A Pilot Study. *J Mot Behav*, 49(1), 35-45.
<https://doi.org/10.1080/00222895.2016.1219304>
- Skurvydas, A., Juodzbaliene, V., Darbutas, T., & Brazaitis, M. (2018). One year after ischemic stroke: Changes in leg movement path stability in a speed-accuracy

- task but no major effects on the hands. *Hum Mov Sci*, 57, 50-58.
<https://doi.org/10.1016/j.humov.2017.11.005>
- Sloot, L. H., van Schooten, K. S., Bruijn, S. M., Kingma, H., Pijnappels, M., & van Dieën, J. H. (2011). Sensitivity of local dynamic stability of over-ground walking to balance impairment due to galvanic vestibular stimulation. *Ann Biomed Eng*, 39(5), 1563-1569. <https://doi.org/10.1007/s10439-010-0240-y>
- Stancic, I., Supuk, T., & Panjkota, A. (2013). Design, development and evaluation of optical motion-tracking system based on active white light markers. *IET Sci. Meas*, 7, 206-214. <https://doi.org/10.1049/iet-smt.2012.0157>
- Stergiou, N. (2016). *Nonlinear Analysis for Human Movement Variability*. CRC Press.
<https://doi.org/10.1201/9781315370651>
- Stergiou, N., & Decker, L. M. (2011). Human movement variability, nonlinear dynamics, and pathology: is there a connection? *Hum Mov Sci*, 30(5), 869-888.
<https://doi.org/10.1016/j.humov.2011.06.002>
- Stergiou, N., Harbourne, R., & Cavanaugh, J. (2006). Optimal movement variability: a new theoretical perspective for neurologic physical therapy. *J Neurol Phys Ther*, 30(3), 120-129. <https://doi.org/10.1097/01.npt.0000281949.48193.d9>
- Strongman, C., & Morrison, A. (2020). A scoping review of non-linear analysis approaches measuring variability in gait due to lower body injury or dysfunction. *Human Movement Science*, 69, 102562.
<https://doi.org/https://doi.org/10.1016/j.humov.2019.102562>
- Sun, R., Song, R., & Tong, K. Y. (2014). Complexity analysis of EMG signals for patients after stroke during robot-aided rehabilitation training using fuzzy approximate entropy. *IEEE Trans Neural Syst Rehabil Eng*, 22(5), 1013-1019.
<https://doi.org/10.1109/tnsre.2013.2290017>
- Tang, X., Zhang, X., Gao, X., Chen, X., & Zhou, P. (2018). A Novel Interpretation of Sample Entropy in Surface Electromyographic Examination of Complex Neuromuscular Alternations in Subacute and Chronic Stroke. *IEEE Trans Neural Syst Rehabil Eng*, 26(9), 1878-1888. <https://doi.org/10.1109/tnsre.2018.2864317>
- Terrier, P., & Dériaz, O. (2011). Kinematic variability, fractal dynamics and local dynamic stability of treadmill walking. *J Neuroeng Rehabil*, 8, 12.
<https://doi.org/10.1186/1743-0003-8-12>

- Tian, N., Chen, Y., Sun, W., Liu, H., Wang, X., Yan, T., & Song, R. (2021). Investigating the Stroke- and Aging-Related Changes in Global and Instantaneous Intermuscular Coupling Using Cross-Fuzzy Entropy. *IEEE Trans Neural Syst Rehabil Eng*, 29, 1573-1582. <https://doi.org/10.1109/tnsre.2021.3101615>
- Toebes, M. J., Hoozemans, M. J., Furrer, R., Dekker, J., & van Dieën, J. H. (2012). Local dynamic stability and variability of gait are associated with fall history in elderly subjects. *Gait Posture*, 36(3), 527-531. <https://doi.org/10.1016/j.gaitpost.2012.05.016>
- Tricco, A. C., Lillie, E., Zarin, W., O'Brien, K. K., Colquhoun, H., Levac, D., Moher, D., Peters, M. D. J., Horsley, T., Weeks, L., Hempel, S., Akl, E. A., Chang, C., McGowan, J., Stewart, L., Hartling, L., Aldcroft, A., Wilson, M. G., Garritty, C., . . . Straus, S. E. (2018). PRISMA Extension for Scoping Reviews (PRISMA-ScR): Checklist and Explanation. *Ann Intern Med*, 169(7), 467-473. <https://doi.org/10.7326/m18-0850>
- Usmani, S., Saboor, A., Haris, M., Khan, M. A., & Park, H. (2021). Latest Research Trends in Fall Detection and Prevention Using Machine Learning: A Systematic Review. *Sensors*, 21(15), 5134. <https://www.mdpi.com/1424-8220/21/15/5134>
- van der Kruk, E., & Reijne, M. M. (2018). Accuracy of human motion capture systems for sport applications; state-of-the-art review. *Eur J Sport Sci*, 18(6), 806-819. <https://doi.org/10.1080/17461391.2018.1463397>
- van Emmerik, R. E. A., Ducharme, S. W., Amado, A. C., & Hamill, J. (2016). Comparing dynamical systems concepts and techniques for biomechanical analysis. *J Sport Health Sci*, 5(1), 3-13. <https://doi.org/10.1016/j.jshs.2016.01.013>
- Wijnants, M. L., Bosman, A. M., Hasselman, F., Cox, R. F., & Van Orden, G. C. (2009). 1/f scaling in movement time changes with practice in precision aiming. *Nonlinear Dynamics Psychol Life Sci*, 13(1), 79-98.
- Xie, H.-B., Zheng, Y.-P., Guo, J.-Y., & Chen, X. (2010). Cross-fuzzy entropy: A new method to test pattern synchrony of bivariate time series. *Information Sciences*, 180(9), 1715-1724. [https://doi.org/https://doi.org/10.1016/j.ins.2010.01.004](https://doi.org/10.1016/j.ins.2010.01.004)
- Xu, P., Yu, H., Wang, X., & Song, R. (2022). Characterizing stroke-induced changes in the variability of lower limb kinematics using multifractal detrended fluctuation analysis. *Front Neurol*, 13, 893999. <https://doi.org/10.3389/fneur.2022.893999>

- Yentes, J. M., Hunt, N., Schmid, K. K., Kaipust, J. P., McGrath, D., & Stergiou, N. (2013). The appropriate use of approximate entropy and sample entropy with short data sets. *Ann Biomed Eng*, 41(2), 349-365. <https://doi.org/10.1007/s10439-012-0668-3>
- Yentes, J. M., & Raffalt, P. C. (2021). Entropy Analysis in Gait Research: Methodological Considerations and Recommendations. *Ann Biomed Eng*, 49(3), 979-990. <https://doi.org/10.1007/s10439-020-02616-8>
- Zhang, X., Wang, D., Yu, Z., Chen, X., Li, S., & Zhou, P. (2017). EMG-Torque Relation in Chronic Stroke: A Novel EMG Complexity Representation With a Linear Electrode Array. *IEEE J Biomed Health Inform*, 21(6), 1562-1572. <https://doi.org/10.1109/jbhi.2016.2626399>

Study II

European Portuguese version of the Mini-BESTest: a cross-cultural adaptation and psychometric measurements in individuals with sensorimotor impairments

Marta Freitas^{a,b,c,d}, Francisco Pinho^{a,b}, Natália Cruz-Martins^{a,e,f}, Liliana Pinho^{a,b,c,d}, Sandra Silva^{a,b,g,h}, Vânia Figueira^{a,b,c,d}, João Paulo Vilas-Boas^{d,i} and Augusta Silva^{j,k}

^a Escola Superior de Saúde do Vale do Ave (ESSVA), Cooperativa de Ensino Superior Politécnico e Universitário (CESPU), Vila Nova de Famalicão, Portugal;

^b H2M—Health and Human Movement Unit, Polytechnic University of Health, Cooperativa de Ensino Superior Politécnico e Universitário, CRL, Vila Nova de Famalicão, Portugal;

^c Center for Rehabilitation Research (CIR), Porto, Portugal;

^d Porto Biomechanics Laboratory (LABIOME), Porto, Portugal;

^e Faculty of Medicine, University of Porto, Porto, Portugal;

^f Institute for Research and Innovation in Health (i3S), University of Porto, Porto, Portugal; ^g Department of Medical Sciences, University of Aveiro, Aveiro, Portugal;

^h School of Health Sciences, University of Aveiro, Aveiro, Portugal;

ⁱ Centre for Research, Training, Innovation, and Intervention in Sport (CIFI2D), Faculty of Sport, University of Porto, Porto, Portugal;

^j Área Científica de Fisioterapia, Centro de Investigação em Reabilitação, Centro de Estudos de Movimento e Atividade Humana, Escola Superior de Saúde do Porto, Instituto Politécnico do Porto, Porto, Portugal;

^k Department of Physiotherapy, School of Health, Polytechnic of Porto, Porto, Portugal

<https://doi.org/10.1080/09638288.2024.2402085>

Abstract

Purpose: This study aimed to translate and cross-culturally adapt the Mini-BESTest into European Portuguese and to evaluate its psychometric properties in individuals with sensorimotor impairments. **Material and Methods:** A cross-sectional cross-cultural adaptation and validation study was conducted according to the COSMIN guidelines and the STROBE statement. The study included 100 participants with sensorimotor impairments who were able to walk 6 m. Cronbach's alpha and item-total correlations were used to assess internal consistency. Interpretability was assessed by examining floor and ceiling effects and skewness. To investigate construct validity, Spearman correlation coefficients and Bland-Altman analysis were performed to compare the Berg Balance Scale, and the Mini-BESTest Inter- and intra-rater reliability were assessed by calculating the ICC, SEM and MDC based on video recordings of the participants during the Mini-BESTest assessments. **Results:** The European Portuguese Mini-BESTest showed good internal consistency (Cronbach's $\alpha = 0.892$) and no significant floor or ceiling effects. Excellent inter- and intra-rater reliability (ICC = 0.97) were also demonstrated, with MDC of 2.58 and 2.57, respectively. Furthermore, this instrument showed a significant correlation with the BBS ($r=0.902$). Bland-Altman analysis showed small absolute differences. **Conclusion:** The European Portuguese Mini-BESTest is comparable to the original English version in terms of validity and reliability and is therefore highly recommended for use by Portuguese-speaking professionals to assess postural control.

Keywords: Cross-cultural adaption, Mini-BESTest, Postural Control, Reliability, Validity

1. Introduction

According to the Human Movement System Concept, postural control (PC) is a complex sensorimotor behaviour mediated by the integration of multiple systems (Gill-Body et al., 2021), which enables the ability to control the body's position in space concerning gravity, support surfaces, the visual environment, and internal references (Horak et al., 2009; Shumway-Cook & Woollacott, 2017). This control is essential for maintaining verticality and stability, which are fundamental for predicting and adapting motor control to successfully perform most activities of daily living (ADLs) (Kandel et al., 2021; Le Mouel & Brette, 2017).

Changes in PC are increasingly recognized and are associated with a significant decline in quality of life and clinical status in patients (Horak et al., 2009), including those with Parkinson's disease (PD) (Kalia & Lang, 2015; Leddy et al., 2011; Pelicioni et al., 2019), stroke (Garland et al., 2009), multiple sclerosis (MS) (Comber et al., 2018; Coote et al., 2020), and older adults (Carmeli, 2017; Viveiro et al., 2019). Currently, it is possible to assess PC in terms of postural performance regardless of the population studied (healthy or pathological), the goal of the postural task, and the environmental conditions (Paillard & Noé, 2015). Performance-based outcome measures (PerFOMs) can provide quantifiable and objective data to support clinical reasoning and are an essential component of evidence-based practice (De Vet et al., 2011). They are useful for identifying specific difficulties (Franchignoni et al., 2010), allowing individualised adaptation of the intervention plan and monitoring the individual's progress towards achieving maximum functionality in ADLs (Mancini & Horak, 2010).

Among the many different PerFOMs, the Mini Balance Evaluation Systems Test (Mini-BESTest) is a highly recommended and comprehensive standardized balance measure for the assessment of impaired PC (Dos Santos et al., 2023; Sibley, Beauchamp, et al., 2015; Sibley, Howe, et al., 2015). In an expert review of the core outcome set recommendations for measuring standing balance in adults, 66 balance criteria systems were examined. However, consensus was only reached for the Mini-BESTest and the Berg Balance Scale (BBS) (Sibley, Howe, et al., 2015). The Mini-BESTest addresses eight components of the PC construct, including static stability, underlying motor systems, verticality, reactive PC, anticipatory PC, dynamic stability, sensory integration, and cognitive influences (Dos Santos et al., 2023; Sibley, Howe, et al., 2015). It is an

abbreviated version of the BESTest, based on the Systems Framework for PC theory (Franchignoni et al., 2010; Horak et al., 2009). The Mini-BESTest includes 14 items from the original version, selected by eliminating redundant and insensitive items using a Rasch analysis (Franchignoni et al., 2010). The short administration time of approximately 15 minutes (Franchignoni et al., 2010; Sibley, Beauchamp, et al., 2015) offers practical advantages over longer instruments, such as improved acceptability among study participants and increased feasibility for professionals administering the test (Rolstad et al., 2011).

The Mini-BESTest has been shown to have robust psychometric properties in a variety of populations. Many of its 14 items are drawn from well-established standardized PC assessments, supporting its content validity (Horak et al., 2009). This instrument shows strong internal consistency, ranging from good to high levels (Cronbach's $\alpha = 0.7\text{--}0.98$) (Dominguez-Olivan et al., 2020; Godi et al., 2013; Lemay et al., 2019; Niklas Löfgren et al., 2014), and exceptional inter-rater and test-retest (intraclass correlation coefficient [ICC] > 0.80) reliability when assessing individuals with chronic stroke, PD, and older adults (Alqahtani et al., 2022; Cramer et al., 2020; Lampropoulou et al., 2016; Lemay et al., 2019; Nakhostin-Ansari et al., 2022). Several studies have highlighted its effectiveness in predicting fall risk in different populations (Leddy et al., 2011; Tsang et al., 2013; Yingyongyudha et al., 2016). Compared with other dynamic balance assessment tools, the Mini-BESTest is one of the most responsive (Chinsongkram et al., 2016; Godi et al., 2013). It is suitable for assessing individuals with superior functional abilities (Potter & Brandfass, 2015), unlike the BBS, which may have a ceiling effect (Blum & Korner-Bitensky, 2008).

The validity and reliability of the Mini-BESTest have been verified in Portuguese populations with chronic obstructive pulmonary disease (Jácome et al., 2016), end-stage renal disease (Jácome et al., 2018), elderly people and in the community (Marques et al., 2016). However, considering that this instrument was developed in an English-speaking country, both linguistic translation and cultural adaptation are necessary to ensure content and face validity at the conceptual level across different cultures (D. Beaton et al., 2000). Although, to the authors knowledge, the Mini-BESTest has been translated into several languages (Alqahtani et al., 2022; Bergström et al., 2012; Cramer et al., 2020; Dogruoz Karatekin et al., 2023; Dominguez-Olivan et al., 2020;

Lampropoulou et al., 2016; Lemay et al., 2019; Maia et al., 2013), this instrument has not been formally translated into European Portuguese. Before its dissemination, it is necessary to analyse the validity and reliability of this useful tool for clinical practice in Portugal (Ramada-Rodilla et al., 2013). Therefore, the aim of this study was to translate and cross-culturally adapt the Mini-BESTest into European Portuguese and to evaluate its psychometric properties in individuals with sensorimotor impairments.

2. Methods

2.1 Study Design and Ethics

A cross-sectional, cross-cultural adaptation and validation study was conducted according to the criteria of the Consensus-based Standards for the Selection of Health Status Measurement Instruments (COSMIN) guidelines (Mokkink et al., 2010) and the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) statement (Elm et al., 2007). The study was carried out in two phases. The first phase involved the translation and cultural adaptation of the Mini-BESTest and the assessment of its content validity, while the second phase aimed to evaluate the psychometric properties of the European Portuguese Mini-BESTest (Mini-BESTest_EP). Ethical approval for this study was obtained from the Ethics Committee of the Instituto Politécnico de Saúde do Norte (IPSN) (13/04/2023, reference 8/CE-IPSN/2023). Written informed consent was obtained from all participants prior to data collection.

2.2 Participants

The sample size was selected according to the COSMIN guidelines to ensure a good and adequate assessment of the psychometric domains (Mokkink et al., 2010).

A convenience sample of 100 participants was recruited from two outpatient rehabilitation units between January and May 2023. An experienced physiotherapist recruited participants according to the following inclusion criteria: 18 years of age or older, Portuguese nationality, ability to walk 6 m (walking aids allowed) (Cramer et al., 2020), ability to perform tests without excessive fatigue (Dominguez-Olivan et al., 2020), and clinical condition of sensorimotor impairments affecting PC (musculoskeletal problems, stroke, MS, PD, traumatic brain injury, cerebellar or encephalic inflammation, hydrocephalus, or pendent foot) (Lampropoulou et al., 2016;

Lemay et al., 2019). Exclusion criteria included acute stages of any pathology, unstable health conditions, pregnant women (Lampropoulou et al., 2016) and individuals with a cognitive deficits on the Mini-Mental State Examination (MMSE), according to Portuguese normative data (Santana et al., 2016).

2.3 Data Collection Procedures

Sociodemographic (age, sex) and historical information about the participants was collected by completing an initial assessment form. Anthropometric measurements of body mass (in kg) and height (in m) were obtained using a Tanita® BC-601 scale (Tanita – Body Composition Monitor®, Tokyo, Japan).

2.4 Translation and cultural adaptation

The translation and cultural adaptation procedures followed the internationally recommended sequential methodology (D. Beaton et al., 2000; De Vet et al., 2011; Mokkink et al., 2010). This included six stages: translation, synthesis, back-translation, expert committee review, pre-testing, and final assessment, as shown in Figure 1.

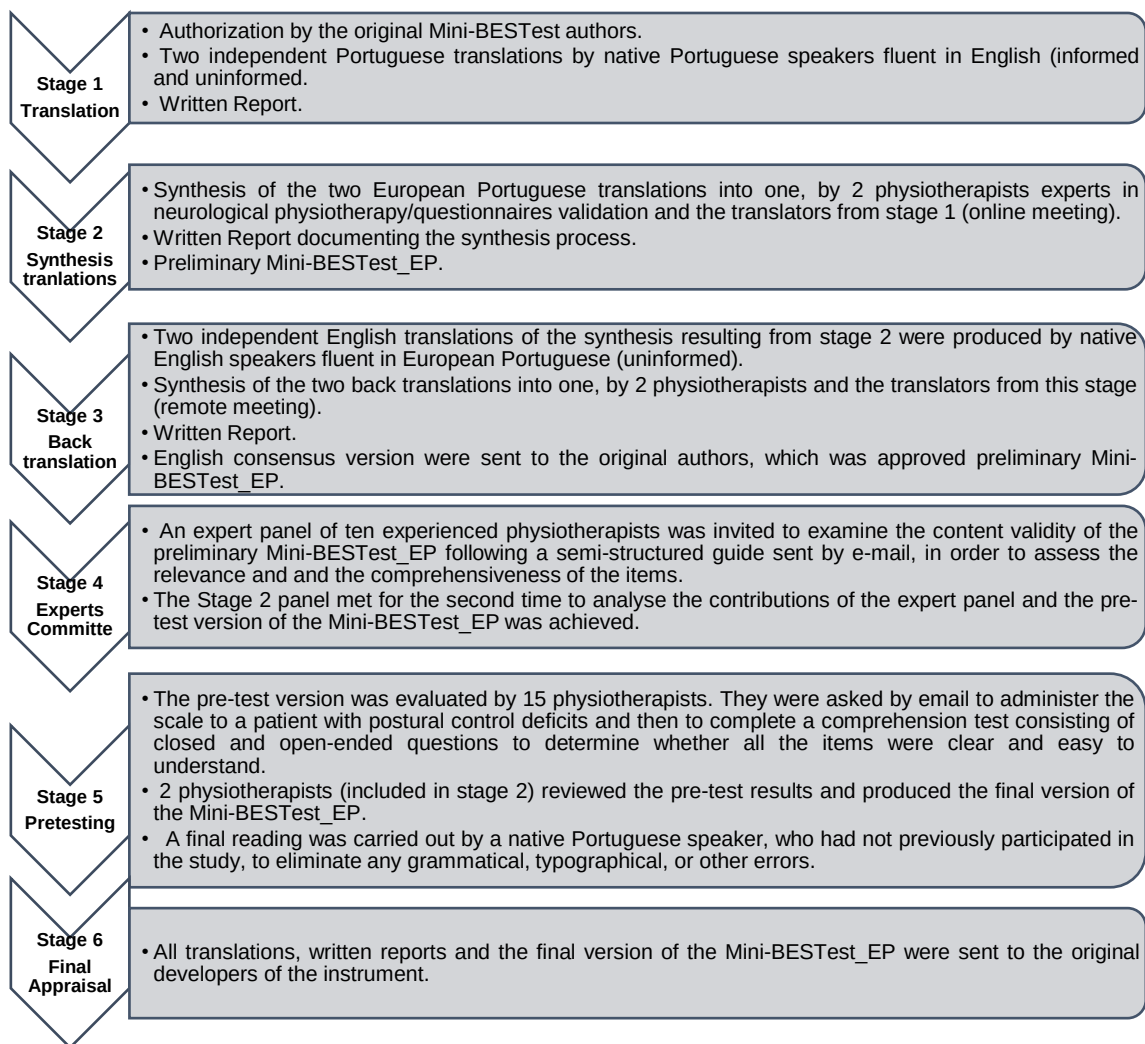


Figure 1. Stages of cross-cultural adaptation of the European Portuguese Mini-BESTest.

2.5 Psychometric Properties

Two experienced physiotherapists randomly assessed 100 participants, in two outpatient rehabilitation units. Prior to the study, both raters received two training sessions on the Mini-BESTest_EP and BBS items (Bergström et al., 2012; Nakhostin-Ansari et al., 2022). The training session included video demonstrations of the tests, scoring methods, and practice with administering the two balances scales on two patients (Nakhostin-Ansari et al., 2022). Any doubts were clarified by the study author at the end of the session. The clinical instruments were administered in a randomized order during the same session and in the same environment to prevent the results from being influenced by fatigue (Bergström et al., 2012; Cramer et al., 2020). All participants were

supervised during testing to ensure their safety and to prevent falls. A rest period was provided between the tests to prevent task-related fatigue (Bergström et al., 2012; Lampropoulou et al., 2016). Patients were instructed to wear comfortable clothes and flat shoes (Lampropoulou et al., 2016). For the inter- and intra-rater reliability study, a sub-sample of the last 30 participants were videotaped performing the Mini-BESTest_EP test items (Wong, 2014). The tests were administered by the same physiotherapist, and the participants' whole body was recorded using two stabilized iPhone 13 cameras from either the frontal or sagittal plane.

For inter- and intra-rater reliability, two physiotherapists, with more than 16 years or clinical experience, were asked to independently rate the performance of the 30 participants on the Mini-BESTest_EP using the video recordings (assessment 1). The same procedure was repeated 7 to 10 days after the initial assessment to assess intra-rater reliability, using the same videotape without the raters' knowledge (assessment 2). This was done to prevent raters from memorising information and learning from test to retest (Lemay et al., 2019).

2.6 Clinical Scales

Mini-BESTest

The Mini-BESTest is proposed to measure dynamic balance using 14 items, divided into four sections: anticipatory postural adjustments, reactive PC, sensory orientation, and dynamic gait (Franchignoni et al., 2010). Each item is scored on a three-point scale (ranging from 0 to 2), with a total score of 28 points, representing optimal balance performance. Both the right and left sides are assessed for two items, with only the lower score being included in the total score (King & Horak, 2013). In this study, if a participant chose not to perform one or more items, they were scored as 0. The assessment can be completed in approximately 10-15 min (King & Horak, 2013). The equipment required for the experiment includes a standard chair with armrests, a 10-cm-thick Tempur® foam, a stopwatch, an inclined surface (10°), and two shoe-boxes (Horak et al., 2009).

Berg Balance Scale

The Berg Balance Scale (BBS) is a well-known assessment tool used to evaluate functional balance by assessing the performance of 14 tasks of varying difficulty, including balance during sitting and standing activities. The balance test consists of 14 items that are scored on a five-point scale (0-4), with a maximum score of 56 indicating better balance performance. A score below 46 points indicates a high risk of falling. The BBS has been shown to have high interrater and test-retest reliability in patients with balance disorders (Godi et al., 2013). The test takes between 10 to 20 min to administer and requires a standard-height chair with armrests, a chair without armrests, a stopwatch, a ruler, appropriate footwear, and a 15-cm step (Berg et al., 1992).

2.7 Statistical Analysis

Data analysis was performed using IBM SPSS Statistics version 29.0 (IBM Corporation, Armonk, NY, USA). The significance level was set at 0.05. Normality tests, including the Kolmogorov-Smirnov and Shapiro-Wilk tests, were performed on continuous variables. Descriptive statistics were used to present the data, including mean $\pm$ standard deviation, or median and interquartile range, or minimum or maximum values, when applicable, for quantitative variables, and absolute and relative frequencies for qualitative data.

Interpretability was calculated based on the frequency of total scores for the Mini-BESTest_EP and BBS to determine the presence of floor and ceiling effects. A significant effect was present if $\geq 15\%$ of the highest or lowest possible score was achieved. The skewness of scores distribution, as a further estimator of ceiling and floor effects, was presented for total scores. A skewness value greater than 1 indicates a significant floor effect, while a value less than -1 indicates a significant ceiling effect.

Reliability was assessed using measures of internal consistency, inter-rater and intra-rater reliability, and measurement error (De Vet et al., 2011). Cronbach's alpha and Item-Total Correlation (ITC) were used to assess internal consistency. Items were scored according to the widely accepted guideline that Cronbach's alpha values should be between 0.70 and 0.95, and ITC values >0.30 (Terwee et al., 2007).

As recommended for reliability studies, relative inter- and intra-reliability were analysed using the intra-class correlation coefficient (ICC) with model 2,1 (two-way random effects or ICC2,1) and model 3,1 (two-way mixed effects or ICC3,1),

respectively, and the 95% confidence interval (CI). Inter-rater reliability was calculated using the scores obtained by the two raters at the first assessment, and inter-rater reliability was calculated using the scores obtained by the two raters at the first and second assessments. To estimate an ICC with a 95% confidence interval of 0.65-0.95 and an expected value of 0.80, 30 participants with 2 repeated measurements are required, according to simulation studies (Mokkink et al., 2022). The ICC was interpreted as excellent ($>.75$), moderate to good (0.5 to 0.75), or poor (<0.5) (Koo & Li, 2016). Bland-Altman plots and the Standard Error of Measurement (SEM) were used to assess absolute reliability (Moe-Nilssen et al., 2008).

The Bland-Altman approach is used to visually assess how well the measurements agreed between sessions. This method determines the degree of discrepancy between measurements by plotting the variations between two sets of values relative to their mean and the Limits of Agreement (LOA), which gives the mean difference between the two measures and its 95% CI (Francq & Govaerts, 2016).

The standard error of the mean (SEM) is a measure of the variability of a sample mean. It quantifies the amount of error in the sample mean and is expressed in the same units as the original measurement, making it more practical for clinical use (De Vet et al., 2011). The SEM was calculated based on the result of ICC from both inter-rater and intra-rater reliability, using the following equation:

$$(1) \text{ SEM} = \text{SD} \times \sqrt{(1-\text{ICC})}$$

where SD is the standard deviation of the scores obtained from all participants, ICC is the inter- or intra-rater reliability coefficient.

The MDC at the 95% confidence level (MDC_{95}) was calculated as follows:

$$(2) \text{ MDC}_{95} = \text{SEM} \times 1.96 \times \sqrt{2}$$

The MDC was also expressed as a percentage ($\text{MDC}_{\%}$), defined by the following equation:

$$(3) \text{ MDC}_{\%} = (\text{MDC}_{95}/\text{mean}) \times 100$$

where mean is the mean of the scores obtained in the two assessment sessions. The $\text{MDC}_{\%}$ is unit independent and allows comparison of random measurement error between different measures. An $\text{MDC}_{\%}$ of less than 30% is considered acceptable and less than 10% is considered excellent (Smidt et al., 2002).

Spearman's correlation coefficient (r_s) was used to assess the construct validity

(convergent validity) between the Mini-BESTest_EP and the BBS. The existence of a correlation ($r > 0,7$) between the two instruments was expected as they are both related to the construct they measure. According to COSMIN recommendations, construct validity is considered “positive” if the correlation coefficient is equal to or greater than 0.5 (Terwee et al., 2007). The strength of correlations was classified according to the British Medical Journal guidelines: very weak for correlation coefficients of 0-0.19, weak for 0.2-0.39, moderate for 0.4-0.59, strong for 0.6-0.79, and very strong for 0.8-1.0 (BMJ, 2021). The agreement between the total scores of the two instruments was assessed using Bland-Altman plot analysis (Francq & Govaerts, 2016).

3. Results

3.1 Participants

The study included 100 participants, consisting of 51 men and 49 women, with ages ranging from 19 to 93 years. The sub-sample of 30 participants selected for the inter- and intra-rater reliability study, comprising 16 men and 14 women, aged 20 to 93 years. Notably, a higher proportion of neurological conditions was observed in the sub-sample compared to the total sample (70% vs. 55%, respectively). Table 1 provides detailed demographic and clinical characteristics of all participants, along with their scores on the measurement instruments. No data were missing.

Table 1. Participant demographics and clinical characteristics.

Variable		
Sex, (n; %)	Male	51 (51%)
	Female	49 (49%)
Age (years) Md (Q1; Q3)	69 (53,25; 76,00)	
BMI M (SD)	25 (3,40)	
Clinical Condition (n; %)	Neurological	55 (55%)
	Musculoskeletal	45 (45%)
Sub-Clinical Condition (n; %)	AVC	20 (20%)
	Brain Vasculitis	12 (12%)
	Parkinson's disease	1 (1%)
	Cerebral Palsy	4 (4%)
	Traumatic Brain Injury	2 (2%)
	Multiple Sclerosis	2 (2%)
	Vestibular Syndrome	9 (9%)
	Polyneuropathy	4 (4%)
	Ataxy	2 (2%)
	Amyotrophic Lateral Sclerosis	8 (8%)
	Knee Ligamentoplasty	1 (1%)
	Total Hip Prosthesis	3 (3%)
	Rheumatoid Arthritis	4 (4%)
	Gonarthrosis	14 (14%)
	Meniscectomy	3 (3%)
	Lower Limb Fracture	6 (6%)
	Lower Limb Muscle Rupture	2 (2%)
	Ankle Sprain	2 (2%)
Walking Aids (n; %)	13 (13%)	
Mini-BESTest_EP Total Scores Md (Q1; Q3)	18 (13,00; 23,00)	
BBS Md (Q1; Q3)	46 (38,25; 51,00)	

BBS: Berg Balance Scale; BMI: Body mass index; Q1: Quartile; Q3: Quartile 3; M: Mean; Md: Median; Mini-BESTest_EP: European Portuguese Mini Balance Evaluation Systems Test; SD: Standard deviation.

3.2 Translation and cultural adaptation

The translation and back-translation of the Mini-BEST were analysed and all discrepancies, mostly related to synonymous grammatical and syntactical terms, were resolved by consensus. All units were converted to the international metric system (feet to m, inches to cm). The back-translated version of the Mini-BESTest was sent to the original authors (Horak, F.). Some changes were suggested, particularly in items 4 and 6, where the authors noted that 'what is being lost is going beyond your limits'. As a result, the phrases 'beyond your forward limits' and 'beyond your backward limits' were added to these two items, respectively. In item 10, it was suggested to change the instruction 'walk slowly' to 'walk very slowly'. It was also recommended that the

instruction descriptions for items 1, 3, 4, 5, 6, 8, and 12 be standardized and aligned with the terminology used in the item descriptions. These recommendations have been incorporated into the preliminary Mini-BESTest_EP.

The translation and back-translation panel analysed the qualitative approach of the expert panel and, after reaching consensus, made linguistic changes to the terms most used by Portuguese physiotherapists. Regarding the content validity analysis, the expert panel unanimously agreed with all items of this instrument to quantify PC impairments, with no suggestions for deleting or adding questions. The analysis of the pre-test data for the Mini-BESTest_EP showed that the items were clear, understandable, and relevant, and that their content was appropriate. The final version of the Mini-BESTest_EP was therefore produced (available at <https://www.bestest.us>).

3.3 Psychometric Properties

3.3.1 Interpretability

No floor or ceiling effects were found. The percentage of participants achieving the highest and lowest possible total scores was 3% and 2% on the Mini-BESTest_EP, and 2% and 5% on BBS, respectively. Slight negative skewness was found on the Mini-BESTest (-0.495) and the BBS (-0.719). The frequency distributions of the 14 item scores on the Mini-BESTest_EP are shown in Figure 2.

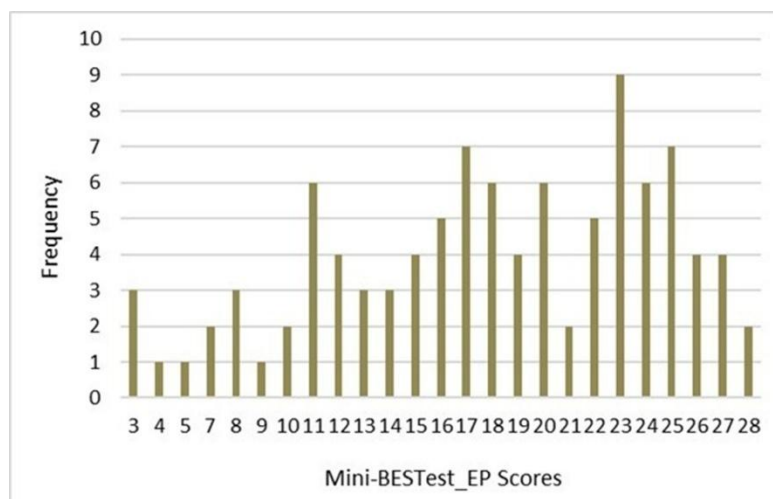


Figure 2. Distribution of sum scores on Mini-BESTest_EP.

3.3.2 Construct Validity

The correlation between the Mini-BESTest_EP and the BBS was significant, positive,

and very strong ($r=0,902$, $p<0,001$). The Bland-Altman analysis for the mean differences between the two instruments scores is shown in Figure 3, showing a good agreement between the scores of the two instruments. The mean difference of the Mini-BESTest_EP total score between the two raters was 26.3 ± 4.48 , representing a distribution of difference within the LOA.

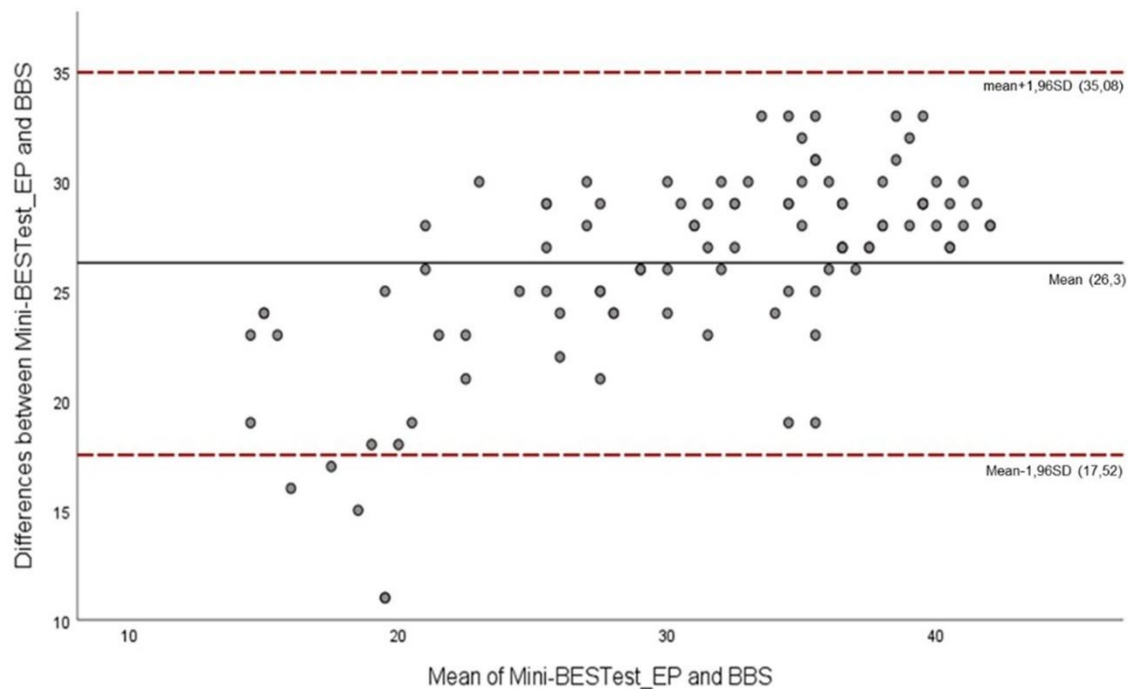


Figure 3. Bland–Altman analysis of differences between EP_Mini-BESTest and BBS. The solid line represents the mean difference between the two measures ($n=100$) and the dotted line two standard deviations (95% LOA).

3.3.3 Reliability

The Mini-BESTest_EP showed a good internal consistency, with a Cronbach alpha value of 0.892. For the ITC (Table 2), the correlations between the individual items ranged from 0.347 to 0.741, with most values above 0.5. The ITC scores for item 7 (standing position, feet together and eyes open, on a firm surface) and item 14 (Timed Up & Go test with dual task) were the lowest (0.35 and 0.45, respectively).

Table 2: Item-total correlation of Mini-BESTest_EP from n = 100.

Item	Item-Total Correlation	Cronbach's Alpha if Item Deleted
1	0.501	0.889
2	0.592	0.884
3	0.581	0.884
4	0.514	0.888
5	0.638	0.882
6	0.645	0.882
7	0.347	0.893
8	0.692	0.879
9	0.638	0.882
10	0.565	0.885
11	0.571	0.885
12	0.716	0.879
13	0.626	0.882
14	0.445	0.890

Table 3 shows excellent inter-rater reliability with an ICC of 0.97 (95% CI, 0.85–0.99) and intra-rater reliability with an ICC of 0.97 (95% CI 0.96–0.98) and an associated SEM value of 0.93. The MDC95 of the Mini-BESTest_EP was less than 3.

Table 3: Mean±SD and intra and inter-rater reliability of Mini-BESTest_EP from n = 30.

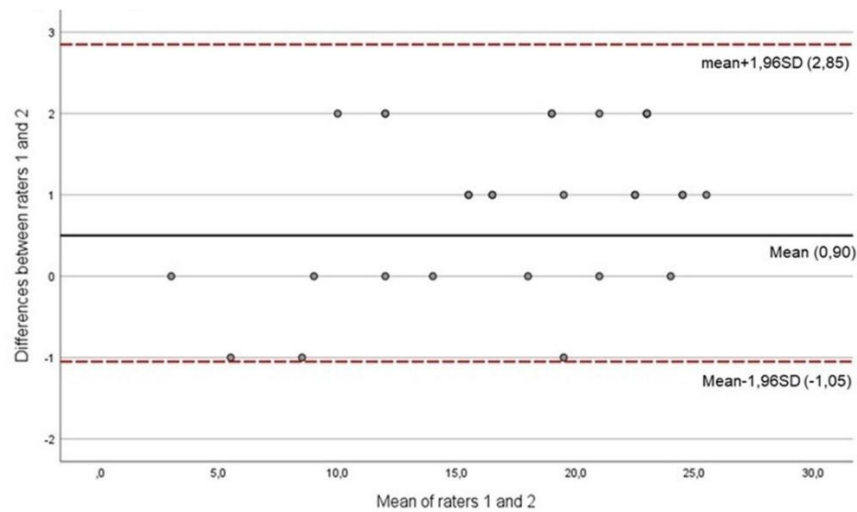
	Rater	Mini-BESTest_EP Median (Q1; Q3)	Inter-Rater Reliability ICC2,1 (95% CI) p-Value	Intra-Rater Reliability ICC3,1 (95% CI) p-Value
First assessment	1	19.5 (13.00; 24.00)	0.97 (0.85–0.99) p < 0.001	0.97 (0.96–0.98) p < 0.001
	2	18 (11.75; 22.00)		
Second assessment	1	18 (11.75; 22.25)	p < 0.001	p < 0.001
	2	18,5 (12.00; 22.00)		
SEM			0.93	0.93
MDC95			2.58	2.57
% MDC95			14.84%	14.91%

CI: Confidence interval; ICC: Intraclass correlation coefficient; ICC2,1: Two-way random effects; ICC3,1: Two-way mixed effect; MDC: Minimal detectable change; SD: Standard deviation; SEM: Standard error measurement.

According to Figure 4, the systematic errors were close to zero, and the 95% LOA were narrow, indicating good agreement of the measurements. Figure 3A) shows the total

score between the two raters. All data ($n = 30$) were within the LOA. The mean difference in the Mini-BESTest_EP total score between the two raters was 0.90 ± 0.995 , showing a distribution of difference within the LOA. Similar results were found for the graphical representation of the difference between two ratings (Figure 3B)). Almost all data ($n=28$) were within the LOA. The mean difference of the Mini-BESTest between the raters was -0.383 ± 0.795 , representing a distribution of the difference within the LOA.

A)



B)

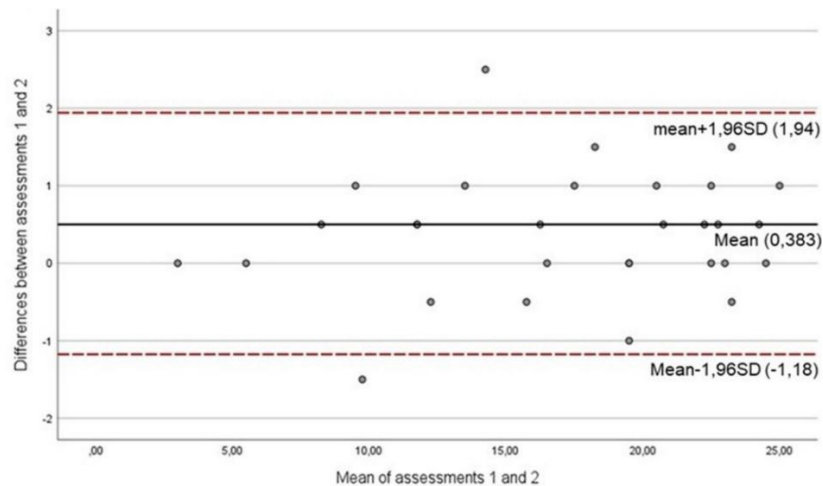


Figure 4. Bland & Altman graphs presenting the Mini-BESTest_EP for inter-rater A) and intra-rater B) reliability. A) The difference between rater A and B is plotted against the mean of rater A and B. B) The difference between assessments 1 and 2 is plotted against the mean of the two assessments (1 and 2). The solid line represents the mean difference between the two measures ($n=30$) and the dotted line two standard deviations (95% LOA).

4. Discussion

To the best of our knowledge, this study is the first to translate and culturally adapt the Mini-BESTest into European Portuguese and verify its psychometric properties in individuals with sensorimotor impairments affecting balance. The results indicate that the BESTest_EP is a valid and reliable tool for assessing dynamic balance, consistent with previous reports (Alqahtani et al., 2022; Bergström et al., 2012; Cramer et al., 2020; Dominguez-Olivan et al., 2020; Göktaş et al., 2020; Lampropoulou et al., 2016; Lemay et al., 2019).

When using the Mini-BESTest in a different context from its original development, factors such as culture, language, and geographical location must be considered (D. Beaton et al., 2000; De Vet et al., 2011). The cultural and linguistic adaptation of the Mini-BESTest to the European Portuguese followed international guidelines, similar to other cross-cultural adaptations (Alqahtani et al., 2022; Bergström et al., 2012; Cramer et al., 2020; Dominguez-Olivan et al., 2020; Göktaş et al., 2020; Lemay et al., 2019). These guidelines, originally developed for the transcultural adaptation and translation of self-report outcome measures, where instructions are directed to the person being assessed (D. Beaton et al., 2000). PerFOMs, such as the Mini-BESTest, are primarily designed for use by clinical professionals, who rely on standardized language to score performance. This reliance on precise terminology may have influenced the translation process, leading to adjustments based on feedback from physiotherapists involved in the expert panel and pre-test analysis. The Mini-BESTest_EP was well received by participants and physiotherapists for its clarity and comprehensibility, aligning with findings from other cross-cultural adaptation studies (Alqahtani et al., 2022; Bergström et al., 2012; Cramer et al., 2020; Lemay et al., 2019).

In a validation study, it is crucial that the study sample accurately represents the target population (De Vet et al., 2011). To ensure this, we included participants with diverse clinical conditions from two different rehabilitation centres, covering a heterogeneous population. The Mini-BESTest_EP scores ranged from 3 to 28 points, with participants presenting a variety of musculoskeletal and neurological conditions, some using walking aids and others walking independently. Consequently, the findings of this study are likely applicable to a broader population of individuals with sensorimotor impairments.

The presence of floor and ceiling effects can significantly impact the reproducibility and responsiveness of an instrument (Terwee et al., 2007). When more than 15% of the sample reaches the lowest or highest possible score, it indicates that a portion of individuals may not experience meaningful changes in their condition due to being at the extreme end of the scale (Mokkink et al., 2010). In the case of the Mini-BESTest_EP, no floor or ceiling effects were observed, consistent with previous studies (Dominguez-Olivan et al., 2020; Franchignoni et al., 2010; Lampropoulou et al., 2016; Lemay et al., 2019; Nakhostin-Ansari et al., 2022). Additionally, the Mini-BESTest_EP demonstrates less skewness compared to the BBS, aligning with findings for individuals with sensorimotor impairments (-0.595 to -0.612) (Lampropoulou et al., 2016; Lemay et al., 2019), and outperforming those reported for individuals with neurological disorders (-0.93 to -0.810) (King et al., 2012; Tsang et al., 2013). These results suggest that the Mini-BESTest_EP may be more effective than the BBS in distinguishing between different levels of balance performance. This advantage may be attributed to the inclusion of more challenging tasks and the comprehensive assessment of various aspects of PC in the Mini-BESTest_EP, which helps prevent score clustering at higher levels. In contrast, the BBS is more limited, lacking a thorough evaluation of anticipatory and reactive PC, sensory orientation, and dynamic gait, including dual-tasking (Franchignoni et al., 2010).

As hypothesised, the high correlation between the Mini-BESTest_EP and the BBS confirms its excellent construct validity, consistent with previous studies on the original (Di Carlo et al., 2016; Franchignoni et al., 2010) and cross-cultural adaptations (Bergström et al., 2012; Cramer et al., 2020; Lampropoulou et al., 2016; Lemay et al., 2019). However, it is important to note that high correlations do not necessarily imply agreement between PerFOMs. To further assess this, a Bland-Altman analysis (Giavarina, 2015) was conducted, which demonstrated strong agreement between the two instruments, as the lines of equality were within the LOA.

The Mini-BESTest_EP demonstrated excellent internal consistency with a Cronbach's alpha of 0.89, indicating that the measured variables consistently reflect the same construct (Mokkink et al., 2020). This is consistent with previous studies across different populations, where Cronbach's alpha ranging from 0.79–0.93 (Alqahtani et al., 2022; Cramer et al., 2020; Dogruoz Karatekin et al., 2023; Dominguez-Olivan et al.,

2020; Godi et al., 2013; Lampropoulou et al., 2016; Lemay et al., 2019). Additionally, it is comparable with other translated versions, such as the French (Cronbach's α range from 0,895 to 0,929) (Lemay et al., 2019), Greek (Cronbach's α of 0,883) (Lampropoulou et al., 2016), and German (Cronbach's α of 0,90) (Cramer et al., 2020) versions. According to ITC analysis, correlations between each Mini-BESTest_EP item and its score are generally greater than 0.6. Although items 7 and 14 had the lowest scores, removing them would result in a lower Cronbach's alpha. The variation in clarity may be attributed to the fact that item 7 is the easiest and item 14 is the most difficult. In this study, 89% of respondents rated item 7 the highest, compared to only 14% for item 14. The ITC values indicate that the patients were effectively discriminated based on the construct under investigation (De Vet et al., 2011).

The Mini-BESTest_EP also showed excellent inter- and intra-rater reliability (ICC = 0.97), consistent with findings in other populations, such as type 2 diabetic with peripheral neuropathy (ICC 0,93-0,95) (Phyu et al., 2022), MS (ICC 0.80–0.88) (Wallin et al., 2021), balance disorders (ICC 0,94-0,98) (Godi et al., 2013; Lemay et al., 2019), DP (ICC=0.91) (Godi et al., 2013; Leddy et al., 2011) and stroke (ICC 0.94-0.98) (Haakonsen, 2013; Tsang et al., 2013). It is important to note that ICC values tend to be higher when the sample includes a wide range of scores compared to a more limited range, so caution is advised when comparing results across different studies (Carter et al., 2011). Since no single statistical analysis provides a complete picture of reliability, high ICC values should be interpreted alongside absolute reliability measures (Moe-Nilssen et al., 2008). In this study, the SEM value of 0.93 indicates a low measurement error for the Mini-BESTest_EP, which is consistent with or slightly lower than previously reported SEMs ranging from 0.9 to 1.99 (Godi et al., 2013; Hamre et al., 2017; Lampropoulou et al., 2016; Lampropoulou et al., 2018; Niklas Löfgren et al., 2014; Roy et al., 2021; Tsang et al., 2013). A critical aspect of a clinical tool is its ability to accurately identify true changes in a patient's condition and differentiate between patients based on their level of functionality. Estimates of the MDC and LOA are crucial for defining the threshold for detecting changes beyond measurement error (De Vet et al., 2011). Based on our findings, a score difference of at least 3 points on the Mini-BESTest_EP can be considered a significant change with 95% confidence, which is similar to other studies (Dahl & Jørgensen, 2014; Dominguez-Olivan et al., 2020;

Nakhostin-Ansari et al., 2022; Phyu et al., 2022; Tsang et al., 2013). Some studies have reported higher MDC values, ranging from 3 to 4.4 (Godi et al., 2013; Jácome et al., 2018; N. Löfgren et al., 2014; Marques et al., 2016), which may be due to differences in methodology and population studied. It is also important to note that in these studies the Mini-BESTest was not scored by video raters. The MDCs identified in our study are useful (Smidt et al., 2002) for clinicians to detect real changes over time or in response to interventions in patients with sensorimotor impairments affecting balance. The absolute reliability of the Mini-BESTest_EP was further confirmed by Bland-Altman analysis, which showed good inter-rater and intra-rater agreement. These findings are consistent with previous studies on patients with PD, stroke or neurological disorders (Dahl & Jørgensen, 2014; Lampropoulou et al., 2018; Niklas Löfgren et al., 2014). Overall, these results demonstrate the stability, consistency, and reproducibility of the scale when measured by different raters and at different times under the same conditions.

Clinical Implications

This study provides the Portuguese clinical community with access to a reliable and valid balance assessment tool in their language. The Mini-BESTest may be a superior assessment tool compared to others because it can identify the specific postural control system that is impaired. In a clinical setting, this will aid in the development of appropriate intervention approaches, tailoring rehabilitation interventions to the specific needs of each patient.

Study limitations

This study used a convenience sample of participants from two outpatient clinics, providing a broad representation of the Portuguese population with balance problems. However, the lack of randomized sampling criteria could be considered a limitation of this study. Additionally, concerns may be raised about the inclusion of different balance conditions, as this might suggest a preference for a more homogeneous sample. However, the study deliberately selected a wide range of balance deficits to facilitate validation across a broader spectrum of clinical conditions.

Although identifying the MDC95% is clinically significant, this study did not provide a comprehensive investigation of the responsiveness of the EP_Mini-BESTest. Future

studies could benefit from employing a fully randomized sampling method, focusing on evaluating responsiveness, predictive validity, and specificity across different patient populations. Furthermore, determining sensitivity and the minimal clinically important difference (MCID) is crucial, not only to establish the tool's utility as a measure of postural control in individuals with sensorimotor impairments but also to facilitate the clinical interpretation of changes in the health status of these populations over time. It is recommended that future research assess the MCID by combining effect size with clinical anchors, conducting longitudinal studies involving physiotherapy interventions, and utilizing both distribution-based and anchor-based methods. Additionally, testing hypotheses across different groups is essential for establishing construct validity, ensuring the tool accurately measures what it intends to across varied clinical contexts. The reliability coefficients may have been strengthened by the assessments made by the two experienced physiotherapists. Additionally, a video-based scoring procedure was used to evaluate performance on the Mini-BESTest_EP. Therefore, this study did not account for various sources of variability, including those induced by protocol repetition or inherent biological variability, which may have contributed to an underestimation of the proposed measurement error. It is, consequently, important to use these values with caution in clinical practice, where assessments are often performed on multiple occasions compared to our protocol. To accurately estimate intra- and inter-rater reliability, a larger sample size and a methodological design with real-time observations would be required.

5. Conclusion

In conclusion, the study results suggest that the instructions and scoring descriptions of the Mini-BESTest_EP are equivalent to the original English version. This new adaption demonstrates excellent psychometric properties, including stability, reproducibility, and well-distributed score range, which is consistent with previous studies across different populations and languages. Based on these results, the Mini-BESTest_EP can be considered an effective tool for assessing dynamic balance within the scientific community. We, therefore, encourage rehabilitation professionals and researchers who speak European Portuguese to adopt this tool for evaluating postural control in individuals with sensorimotor impairments.

6. References

- Alqahtani, B. A., Alhowimel, A. S., Alshehri, M. M., Alqahtani, M. A., Almuhaysh, A. A., Alshakarah, A. O., Alanazi, A., Khoja, A. H., & Alenazi, A. M. (2022). Cross-Cultural Adaptation and Validation of the Arabic Version of the Mini-BESTest among Community-Dwelling Older Adults in Saudi Arabia. *Healthcare*, 10(10), 1903. <https://www.mdpi.com/2227-9032/10/10/1903>
- Beaton, D., Bombardier, C., Guillemin, F., & Ferraz, M. (2000). Guidelines for the process of cross-cultural adaptation of self-report measures. *Spine*, 25(24), 3186-3191.
- Berg, K. O., Wood-Dauphinee, S. L., Williams, J. I., & Maki, B. (1992). Measuring balance in the elderly: validation of an instrument. *Can J Public Health*, 83 Suppl 2, S7-11.
- Bergström, M., Lenholm, E., & Franzén, E. (2012). Translation and validation of the Swedish version of the mini-BESTest in subjects with Parkinson's disease or stroke: a pilot study. *Physiother Theory Pract*, 28(7), 509-514. <https://doi.org/10.3109/09593985.2011.653707>
- Blum, L., & Korner-Bitensky, N. (2008). Usefulness of the Berg Balance Scale in Stroke Rehabilitation: A Systematic Review. *Phys Ther*, 88(5), 559-566. <https://doi.org/10.2522/ptj.20070205>
- Carmeli, E. (2017). Physical Therapy for Neurological Conditions in Geriatric Populations [Mini Review]. *Frontiers in Public Health*, 5. <https://doi.org/10.3389/fpubh.2017.00333>
- Carter, R. E., Lubinsky, J., & Domholdt, E. (2011). *Rehabilitation Research: Principles and Applications*. Elsevier Saunders. <https://books.google.co.in/books?id=vN3ZRwAACAAJ>
- Chinsongkram, B., Chaikeeree, N., Saengsirisuwan, V., Horak, F. B., & Boonsinsukh, R. (2016). Responsiveness of the Balance Evaluation Systems Test (BESTest) in People With Subacute Stroke. *Physical Therapy*, 96(10), 1638-1647. <https://doi.org/10.2522/ptj.20150621>
- Comber, L., Sosnoff, J. J., Galvin, R., & Coote, S. (2018). Postural control deficits in people with Multiple Sclerosis: A systematic review and meta-analysis. *Gait Posture*, 61, 445-452. <https://doi.org/10.1016/j.gaitpost.2018.02.018>

- Coote, S., Comber, L., Quinn, G., Santoyo-Medina, C., Kalron, A., & Gunn, H. (2020). Falls in People with Multiple Sclerosis: Risk Identification, Intervention, and Future Directions. *International Journal of MS Care*, 22(6), 247-255. <https://doi.org/10.7224/1537-2073.2020-014>
- Cramer, E., Weber, F., Faro, G., Klein, M., Willeke, D., Hering, T., & Zietz, D. (2020). Cross-cultural adaption and validation of the German version of the Mini-BESTest in individuals after stroke: an observational study. *Neurol Res Pract*, 2(1), 27. <https://doi.org/10.1186/s42466-020-00078-w>
- Dahl, S. S. H., & Jørgensen, L. (2014). Intra- and Inter-Rater Reliability of the Mini-Balance Evaluation Systems Test in Individuals with Stroke. *Int J Ther Rehabil*, 2, 1-6.
- De Vet, H., Terwee, C., Mokkink, L., & Knol, D. (2011). *Measurement in Medicine: A Practical Guide*. <https://doi.org/10.1017/CBO9780511996214>
- Di Carlo, S., Bravini, E., Vercelli, S., Massazza, G., & Ferriero, G. (2016). The Mini-BESTest: a review of psychometric properties. *Int J Rehabil Res*, 39(2), 97-105. <https://doi.org/10.1097/mrr.0000000000000153>
- Dogruoz Karatekin, B., İcagasioglu, A., & Pasin, O. (2023). Validity, reliability and minimal detectable change of Mini-BESTest Turkish version in neurological disorders. *Acta Neurologica Belgica*, 123(4), 1519-1525. <https://doi.org/10.1007/s13760-023-02299-7>
- Dominguez-Olivan, P., Gasch-Gallen, A., Aguas-Garcia, E., & Bengoetxea, A. (2020). Validity and reliability testing of the Spanish version of the BESTest and mini-BESTest in healthy community-dwelling elderly. *BMC Geriatrics*, 20(1), 444. <https://doi.org/10.1186/s12877-020-01724-3>
- Dos Santos, R. B., Fiedler, A., Badwal, A., Legasto-Mulvale, J. M., Sibley, K. M., Olaleye, O. A., Diermayr, G., & Salbach, N. M. (2023). Standardized tools for assessing balance and mobility in stroke clinical practice guidelines worldwide: A scoping review. *Front Rehabil Sci*, 4, 1084085. <https://doi.org/10.3389/fresc.2023.1084085>
- Elm, E. v., Altman, D. G., Egger, M., Pocock, S. J., Gøtzsche, P. C., & Vandenbroucke, J. P. (2007). Strengthening the reporting of observational studies in epidemiology (STROBE) statement: guidelines for reporting observational

- studies. *Bmj*, 335(7624), 806-808.
<https://doi.org/10.1136/bmj.39335.541782.AD>
- Franchignoni, F., Horak, F., Godi, M., Nardone, A., & Giordano, A. (2010). Using psychometric techniques to improve the Balance Evaluation Systems Test: the mini-BESTest. *J Rehabil Med*, 42(4), 323-331.
<https://doi.org/10.2340/16501977-0537>
- Francq, B. G., & Govaerts, B. (2016). How to regress and predict in a Bland-Altman plot? Review and contribution based on tolerance intervals and correlated-errors-in-variables models. *Stat Med*, 35(14), 2328-2358.
<https://doi.org/10.1002/sim.6872>
- Garland, S. J., Gray, V. L., & Knorr, S. (2009). Muscle activation patterns and postural control following stroke. *Motor Control*, 13(4), 387-411.
<https://doi.org/10.1123/mcj.13.4.387>
- Giavarina, D. (2015). Understanding Bland Altman analysis. *Biochem Med (Zagreb)*, 25(2), 141-151. <https://doi.org/10.11613/bm.2015.015>
- Gill-Body, K. M., Hedman, L. D., Plummer, L., Wolf, L., Hanke, T., Quinn, L., Riley, N., Kaufman, R., Verma, A., Quiben, M., & Scheets, P. (2021). Movement System Diagnoses for Balance Dysfunction: Recommendations From the Academy of Neurologic Physical Therapy's Movement System Task Force. *Phys Ther*, 101(9). <https://doi.org/10.1093/ptj/pzab153>
- Godi, M., Franchignoni, F., Caligari, M., Giordano, A., Turcato, A. M., & Nardone, A. (2013). Comparison of Reliability, Validity, and Responsiveness of the Mini-BESTest and Berg Balance Scale in Patients With Balance Disorders. *Phys Ther*, 93(2), 158-167. <https://doi.org/10.2522/ptj.20120171>
- Göktaş, A., Çolak, F., Kar, I., & Ekici, G. (2020). Reliability and Validity of the Turkish Version of the Mini-BESTest Balance Scale in Patients with Stroke. *Turkish Journal Of Neurology*, 26, 303-310. <https://doi.org/10.4274/tnd.2020.36043>
- Haakonsen, S. (2013). Intra- and Inter-Rater Reliability of the Mini-Balance Evaluation Systems Test in Individuals with Stroke. *International Journal of Physical Medicine & Rehabilitation*, 02. <https://doi.org/10.4172/2329-9096.1000177>
- Hamre, C., Botolfson, P., Tangen, G. G., & Helbostad, J. L. (2017). Interrater and test-retest reliability and validity of the Norwegian version of the BESTest and mini-

- BESTest in people with increased risk of falling. *BMC Geriatrics*, 17(1), 92. <https://doi.org/10.1186/s12877-017-0480-x>
- Horak, F. B., Wrisley, D. M., & Frank, J. (2009). The Balance Evaluation Systems Test (BESTest) to differentiate balance deficits. *Phys Ther*, 89(5), 484-498. <https://doi.org/10.2522/ptj.20080071>
- Jácome, C., Cruz, J., Oliveira, A., & Marques, A. (2016). Validity, Reliability, and Ability to Identify Fall Status of the Berg Balance Scale, BESTest, Mini-BESTest, and Brief-BESTest in Patients With COPD. *Phys Ther*, 96(11), 1807-1815. <https://doi.org/10.2522/ptj.20150391>
- Jácome, C., Flores, I., Martins, F., Castro, C., McPhee, C. C., Shepherd, E., Demain, S., Figueiredo, D., & Marques, A. (2018). Validity, reliability and minimal detectable change of the balance evaluation systems test (BESTest), mini-BESTest and brief-BESTest in patients with end-stage renal disease. *Disability and rehabilitation*, 40(26), 3171-3176. <https://doi.org/10.1080/09638288.2017.1375034>
- Kalia, L. V., & Lang, A. E. (2015). Parkinson's disease. *Lancet*, 386(9996), 896-912. [https://doi.org/10.1016/s0140-6736\(14\)61393-3](https://doi.org/10.1016/s0140-6736(14)61393-3)
- Kandel, E. R., Koester, J. D., Mack, S. H., & Siegelbaum, S. A. (2021). In *Principles of Neural Science*, 6e. McGraw Hill. accessbiomedicalsscience.mhmedical.com/content.aspx?aid=1180370208
- King, L., & Horak, F. (2013). On the mini-BESTest: scoring and the reporting of total scores. *Phys Ther*, 93(4), 571-575. <https://doi.org/10.2522/ptj.2013.93.4.571>
- King, L. A., Priest, K. C., Salarian, A., Pierce, D., & Horak, F. B. (2012). Comparing the Mini-BESTest with the Berg Balance Scale to Evaluate Balance Disorders in Parkinson's Disease. *Parkinson's Disease*, 2012, 375419. <https://doi.org/10.1155/2012/375419>
- Koo, T. K., & Li, M. Y. (2016). A Guideline of Selecting and Reporting Intraclass Correlation Coefficients for Reliability Research. *J Chiropr Med*, 15(2), 155-163. <https://doi.org/10.1016/j.jcm.2016.02.012>
- Lampropoulou, S., Gedikoglou, I., Michailidou, C., & Billis, E. (2016). *World Journal of Research & Review*, 3, 61-67.

- Lampropoulou, S. I., Billis, E., Gedikoglou, I. A., Michailidou, C., Nowicky, A. V., Skrinou, D., Michailidi, F., Chandrinou, D., & Meligkoni, M. (2018). Reliability, validity and minimal detectable change of the Mini-BESTest in Greek participants with chronic stroke. *Physiother Theory Pract*, 35(2), 171-182. <https://doi.org/10.1080/09593985.2018.1441931>
- Le Mouel, C., & Brette, R. (2017). Mobility as the Purpose of Postural Control [Hypothesis and Theory]. *Front Comput Neurosci*, 11, 67. <https://doi.org/10.3389/fncom.2017.00067>
- Leddy, A. L., Crowner, B. E., & Earhart, G. M. (2011). Functional gait assessment and balance evaluation system test: reliability, validity, sensitivity, and specificity for identifying individuals with Parkinson disease who fall. *Phys Ther*, 91(1), 102-113. <https://doi.org/10.2522/ptj.20100113>
- Lemay, J.-F., Roy, A., Nadeau, S., & Gagnon, D. H. (2019). French version of the Mini BESTest: A translation and transcultural adaptation study incorporating a reliability analysis for individuals with sensorimotor impairments undergoing functional rehabilitation. *Ann Phys Rehabil Med*, 62(3), 149-154. <https://doi.org/https://doi.org/10.1016/j.rehab.2018.12.001>
- Löfgren, N., Lenholm, E., Conradsson, D., Ståhle, A., & Franzén, E. (2014). The Mini-BESTest--a clinically reproducible tool for balance evaluations in mild to moderate Parkinson's disease? *BMC Neurol*, 14, 235. <https://doi.org/10.1186/s12883-014-0235-7>
- Löfgren, N., Lenholm, E., Conradsson, D., Ståhle, A., & Franzén, E. (2014). The Mini-BESTest - a clinically reproducible tool for balance evaluations in mild to moderate Parkinson's disease? *BMC Neurology*, 14(1), 235. <https://doi.org/10.1186/s12883-014-0235-7>
- Maia, A., Rodrigues-de-Paula, F., Magalhaes, L., & Teixeira, R. (2013). Cross-cultural adaptation and analysis of the psychometric properties of the Balance Evaluation Systems Test and MiniBESTest in the elderly and individuals with Parkinson's disease: application of the Rasch model. *Brazilian journal of physical therapy*, 17, 195-217. <https://doi.org/10.1590/S1413-35552012005000085>
- Mancini, M., & Horak, F. B. (2010). The relevance of clinical balance assessment tools to differentiate balance deficits. *Eur J Phys Rehabil Med*, 46(2), 239-248.

- Marques, A., Almeida, S., Carvalho, J., Cruz, J., Oliveira, A., & Jácome, C. (2016). Reliability, Validity, and Ability to Identify Fall Status of the Balance Evaluation Systems Test, Mini-Balance Evaluation Systems Test, and Brief-Balance Evaluation Systems Test in Older People Living in the Community. *Archives of Physical Medicine and Rehabilitation*, 97(12), 2166-2173.e2161. <https://doi.org/https://doi.org/10.1016/j.apmr.2016.07.011>
- Moe-Nilssen, R., Nordin, E., & Lundin-Olsson, L. (2008). Criteria for evaluation of measurement properties of clinical balance measures for use in fall prevention studies. *J Eval Clin Pract*, 14(2), 236-240. <https://doi.org/10.1111/j.1365-2753.2007.00839.x>
- Mokkink, L., Vet, H., Diemeer, S., & Eekhout, I. (2022). Sample size recommendations for studies on reliability and measurement error: an online application based on simulation studies. *Health Services and Outcomes Research Methodology*, 23. <https://doi.org/10.1007/s10742-022-00293-9>
- Mokkink, L. B., Boers, M., van der Vleuten, C. P. M., Bouter, L. M., Alonso, J., Patrick, D. L., de Vet, H. C. W., & Terwee, C. B. (2020). COSMIN Risk of Bias tool to assess the quality of studies on reliability or measurement error of outcome measurement instruments: a Delphi study. *BMC Medical Research Methodology*, 20(1), 293. <https://doi.org/10.1186/s12874-020-01179-5>
- Mokkink, L. B., Terwee, C. B., Patrick, D. L., Alonso, J., Stratford, P. W., Knol, D. L., Bouter, L. M., & de Vet, H. C. W. (2010). The COSMIN checklist for assessing the methodological quality of studies on measurement properties of health status measurement instruments: an international Delphi study. *Qual Life Res*, 19(4), 539-549. <https://doi.org/10.1007/s11136-010-9606-8>
- Nakhostin-Ansari, A., Nakhostin Ansari, N., Mellat-Ardakani, M., Nematizad, M., Naghdi, S., Babaki, M., Farhangian, M., Habibi, A. H., Tafakhori, A., & Hasson, S. (2022). Reliability and validity of Persian versions of Mini-BESTest and Brief-BESTest in persons with Parkinson's disease. *Physiother Theory Pract*, 38(9), 1264-1272. <https://doi.org/10.1080/09593985.2020.1822967>
- Paillard, T., & Noé, F. (2015). Techniques and Methods for Testing the Postural Function in Healthy and Pathological Subjects. *Biomed Res Int*, 2015, 891390. <https://doi.org/10.1155/2015/891390>

- Pelicioni, P. H. S., Menant, J. C., Latt, M. D., & Lord, S. R. (2019). Falls in Parkinson's Disease Subtypes: Risk Factors, Locations and Circumstances. *International Journal of Environmental Research and Public Health*, 16(12), 2216. <https://www.mdpi.com/1660-4601/16/12/2216>
- Phyu, S. N., Peungsuwan, P., Puntumetakul, R., & Chatchawan, U. (2022). Reliability and Validity of Mini-Balance Evaluation System Test in Type 2 Diabetic Patients with Peripheral Neuropathy. *Int J Environ Res Public Health*, 19(11). <https://doi.org/10.3390/ijerph19116944>
- Potter, K., & Brandfass, K. (2015). The Mini-Balance Evaluation Systems Test (Mini-BESTest). *J Physiother*, 61(4), 225. <https://doi.org/10.1016/j.jphys.2015.04.002>
- Ramada-Rodilla, J. M., Serra-Pujadas, C., & Delclós-Clanchet, G. L. (2013). [Cross-cultural adaptation and health questionnaires validation: revision and methodological recommendations]. *Salud Publica Mex*, 55(1), 57-66. <https://doi.org/10.1590/s0036-36342013000100009> (Adaptación cultural y validación de cuestionarios de salud: revisión y recomendaciones metodológicas.)
- Rolstad, S., Adler, J., & Rydén, A. (2011). Response Burden and Questionnaire Length: Is Shorter Better? A Review and Meta-analysis. *Value in Health*, 14(8), 1101-1108. <https://doi.org/https://doi.org/10.1016/j.jval.2011.06.003>
- Roy, A., Higgins, J., & Nadeau, S. (2021). Reliability and minimal detectable change of the mini-BESTest in adults with spinal cord injury in a rehabilitation setting. *Physiother Theory Pract*, 37(1), 126-134. <https://doi.org/10.1080/09593985.2019.1622161>
- Santana, I., Duro, D., Lemos, R., Costa, V., Pereira, M., Simões, M. R., & Freitas, S. (2016). Mini-Mental State Examination: Screening and Diagnosis of Cognitive Decline, Using New Normative Data. *Acta Médica Portuguesa*, 29(4), 240-248. <https://doi.org/10.20344/amp.6889>
- Shumway-Cook, A., & Woollacott, M. H. (2017). *Motor Control: Translating Research Into Clinical Practice*. Wolters Kluwer. <https://books.google.pt/books?id=xy3EsgEACAAJ>
- Sibley, K. M., Beauchamp, M. K., Van Ooteghem, K., Straus, S. E., & Jaglal, S. B. (2015). Using the Systems Framework for Postural Control to Analyze the

- Components of Balance Evaluated in Standardized Balance Measures: A Scoping Review. *Arch Phys Med Rehabil*, 96(1), 122-132. <https://doi.org/https://doi.org/10.1016/j.apmr.2014.06.021>
- Sibley, K. M., Howe, T., Lamb, S. E., Lord, S. R., Maki, B. E., Rose, D. J., Scott, V., Stathokostas, L., Straus, S. E., & Jaglal, S. B. (2015). Recommendations for a Core Outcome Set for Measuring Standing Balance in Adult Populations: A Consensus-Based Approach. *PLoS One*, 10(3), e0120568. <https://doi.org/10.1371/journal.pone.0120568>
- Smidt, N., van der Windt, D. A., Assendelft, W. J., Mourits, A. J., Devillé, W. L., de Winter, A. F., & Bouter, L. M. (2002). Interobserver reproducibility of the assessment of severity of complaints, grip strength, and pressure pain threshold in patients with lateral epicondylitis. *Archives of Physical Medicine and Rehabilitation*, 83(8), 1145-1150. <https://doi.org/https://doi.org/10.1053/apmr.2002.33728>
- Terwee, C. B., Bot, S. D., de Boer, M. R., van der Windt, D. A., Knol, D. L., Dekker, J., Bouter, L. M., & de Vet, H. C. (2007). Quality criteria were proposed for measurement properties of health status questionnaires. *J Clin Epidemiol*, 60(1), 34-42. <https://doi.org/10.1016/j.jclinepi.2006.03.012>
- Tsang, C. S. L., Liao, L.-R., Chung, R. C. K., & Pang, M. Y. C. (2013). Psychometric Properties of the Mini-Balance Evaluation Systems Test (Mini-BESTest) in Community-Dwelling Individuals With Chronic Stroke. *Phys Ther*, 93(8), 1102-1115. <https://doi.org/10.2522/ptj.20120454>
- Viveiro, L. A. P., Gomes, G. C. V., Bacha, J. M. R., Carvas Junior, N., Kallas, M. E., Reis, M., Jacob Filho, W., & Pompeu, J. E. (2019). Reliability, Validity, and Ability to Identify Fall Status of the Berg Balance Scale, Balance Evaluation Systems Test (BESTest), Mini-BESTest, and Brief-BESTest in Older Adults Who Live in Nursing Homes. *J Geriatr Phys Ther*, 42(4), E45-e54. <https://doi.org/10.1519/jpt.0000000000000215>
- Wallin, A., Kierkegaard, M., Franzén, E., & Johansson, S. (2021). Test-Retest Reliability of the Mini-BESTest in People With Mild to Moderate Multiple Sclerosis. *Phys Ther*, 101(5). <https://doi.org/10.1093/ptj/pzab045>

- Wong, C. K. (2014). Interrater Reliability of the Berg Balance Scale When Used by Clinicians of Various Experience Levels to Assess People With Lower Limb Amputations. *Phys Ther*, 94(3), 371-378. <https://doi.org/10.2522/ptj.20130182>
- Yingyongyudha, A., Saengsirisuwan, V., Panichaporn, W., & Boonsinsukh, R. (2016). The Mini-Balance Evaluation Systems Test (Mini-BESTest) Demonstrates Higher Accuracy in Identifying Older Adult Participants With History of Falls Than Do the BESTest, Berg Balance Scale, or Timed Up and Go Test. *J Geriatr Phys Ther*, 39(2), 64-70. <https://doi.org/10.1519/jpt.0000000000000050>

Study III

Neurobiomechanical Characterization of Feedforward Phase of Gait Initiation in Chronic Stroke: A Linear and Non-linear Approach

Marta Freitas^{1,2,3,4}, Pedro Fonseca^{4,5}, Leonel Alves³, Liliana Pinho^{1,2,3,4}, Sandra Silva^{1,2,6,7}, Vânia Figueira^{1,2,4}, José Félix^{1,2,3}, Francisco Pinho^{1,2}, João Paulo Vilas-Boas^{4,5}, Augusta Silva^{3,8}

¹ Escola Superior de Saúde do Vale do Ave, Cooperativa de Ensino Superior Politécnico e Universitário, Rua José António Vidal, 81, 4760-409 Vila Nova de Famalicão, Portugal.

² H2M—Health and Human Movement Unit, Polytechnic University of Health, Cooperativa de Ensino Superior Politécnico e Universitário, CRL, 4760-409 Vila Nova de Famalicão, Portugal.

³ Center for Rehabilitation Research (CIR), R. Dr. António Bernardino de Almeida 400, 4200-072 Porto Portugal.

⁴ Porto Biomechanics Laboratory (LABIOME), Faculty of Sports, University of Porto, 4200-450 Porto, Portugal.

⁵ Centre for Research, Training, Innovation, and Intervention in Sport (CIFI2D), Faculty of Sport, University of Porto, 4200-450 Porto, Portugal.

⁶ Department of Medical Sciences, University of Aveiro, 3810-193 Aveiro, Portugal.

⁷ School of Health Sciences, University of Aveiro, 3810-193 Aveiro, Portugal.

⁸ Department of Physiotherapy, School of Health, Polytechnic of Porto, 4200-072 Porto, Portugal.

Article Under Review

Abstract

Introduction: Postural control arises from the complex interplay of stability, adaptability, and dynamic adjustments, which are disrupted post-stroke, emphasizing the importance of examining these mechanisms during functional tasks. **Objective:** This study aimed to analyse the complexity and variability of postural control in post-stroke individuals during the feedforward phase of gait initiation. **Methods:** A cross-sectional study analysed 17 post-stroke individuals and 16 matched controls. Participants had a unilateral ischemic stroke in the chronic phase and could walk in-dependently. Exclusions included cognitive impairments, recent surgery, and neurological/orthopaedic conditions. Kinematic and kinetic data were collected during 10 self-initiated gait trials, examining CoP and joint angles (-600ms to +50ms) using linear (displacement, amplitude, velocity) and non-linear (LyE, MSE) measures. Mann-Whitney U tests were applied ($p < 0.05$). **Results:** The stroke group showed greater CoP displacement ($p < 0.05$) and reduced velocity ($p = 0.021$). Non-linear analysis indicated lower LyE values and reduced complexity and adaptability in CoP position and amplitude across scales ($p < 0.05$). In the sagittal plane, the stroke group had higher displacement and amplitude in the head, trunk, pelvis, and limbs, with reduced LyE and MSE values ($p < 0.05$). Frontal plane findings showed increased displacement and amplitude in the head, trunk, and ankle, with reduced LyE and MSE ($p < 0.05$). In the transverse plane, exaggerated rotational patterns were observed with increased displacement and amplitude in the head, trunk, pelvis, and hip, alongside reduced LyE convergence and MSE complexity ($p < 0.05$). **Conclusion:** Stroke survivors exhibit increased linear variability, indicating instability, and reduced non-linear complexity, reflecting limited adaptability. These results highlight the need for rehabilitation strategies that address both stability and adaptability across time scales.

Keywords: Postural Control, Anticipatory Adjustments, Stroke, Motor Variability, System Complexity, Non-linear Analysis.

1. Introduction

Postural control (PC) is a complex system involving continuous and dynamic interactions between the sensorimotor system and environmental stimuli (Gill-Body et al., 2021). It underpin two key components: postural stability, defined as the capacity to maintain the centre of mass (COM) within the base of support, and postural orientation, which ensures appropriate alignment between body segments and the environment with respect to gravity for optimal task performance (Horak, 2006; Sibley, Beauchamp, et al., 2015). Together, these mechanisms form the basis of an individual's control, enabling the maintenance, achievement, or restoration of postural stability across various postures, activities, and functional tasks (Shumway-Cook & Woollacott, 2017; Vaughan-Graham & Cott, 2016). This ability, which strictly relies on the recruitment of postural adjustments, enables selectively managing of degrees of freedom involved in voluntary movement (Stergiou & Decker, 2011) and is intrinsically linked to feedforward mechanisms. These mechanisms play a pivotal role in preparing the body for movement and ensuring stability (Farinelli et al., 2021; Maeda et al., 2020). Early postural adjustments (EPAs), which occur between 600 to -450ms before self-initiated movements, activate postural muscles to stabilize the body irrespective of disturbance direction (Klous et al., 2012; Latash & Zatsiorsky, 2015). Closer to movement onset, anticipatory postural adjustments (APAs), occurring within -150ms to +50ms, generate forces to counteract destabilizing effects, to ensure movement safety and efficiency (Kanekar & Aruin, 2015; Klous et al., 2012). In addition to their functional importance, these mechanisms exhibit complexity and variability, highlighting the adaptability of the sensorimotor system to maintain postural stability and responding to environmental challenges (Harbourne et al., 2009; Harbourne & Stergiou, 2009).

Dysfunction in these feedforward mechanisms has well-documented repercussions on PC, particularly in conditions such as stroke (Halmi et al., 2020; Sousa et al., 2015; Sousa et al., 2022; Sumardi, 2021). PC dysfunction is among the most common consequences of stroke (Halmi et al., 2020; Hong et al., 2020; Hugues et al., 2019), significantly impairing functional tasks like gait or sit-to-stand (Cabanas-Valdés et al., 2021; Tasseel-Ponche et al., 2015). This, in turn, compromises independence, reduces activity levels, and increases the risk of falls (Djurovic et al., 2021; Ghamari et al., 2023; Hugues et al., 2019). Addressing these challenges is crucial for effective

rehabilitation, emphasizing the need for precise assessment tools that can capture the complexities of PC dynamics.

Traditional available approaches to understanding PC biomechanical parameters often emphasize linear measures (Ghamari et al., 2023; Isho & Usuda, 2016; Kang et al., 2019; Kleiner et al., 2015; Portnoy et al., 2017). While valuable, these measures fail to account the temporal dynamics, complexity, and adaptability required for real-life functional tasks (Hua et al., 2024; Vonesch et al., 2023). This limitation arises from the reliance of conventional methods on averaging the CoP over time, overlooking its dynamic properties, which could provide more detailed insights into post-stroke postural stability control (Jagroop et al., 2023; Moreno et al., 2022). From a non-linear perspective, systems dynamic variability is seen as a marker of adaptability, contrasting with linear approaches that often interpret variability as error (26). Analysing the complexity and variability of these adjustments offer a deeper understanding of the complexity, stability and adaptability of this dynamic system (Lacour et al., 2008; van Emmerik et al., 2016). Therefore, it is crucial for understanding how the body dynamically stabilizes itself across different temporal scales, particularly in the context of functional tasks (Moreno et al., 2022). These approaches enable researchers to investigate how biological systems maintain stability across multiple temporal scales, uncovering the intricate mechanisms underlying PC (Caballero et al., 2014). One of the key challenges in studying PC is effectively linking its various components (Sibley, Beauchamp, et al., 2015). Addressing this complexity requires approaches capable of capturing the non-linear and stochastic behaviours of the PC system (Hong et al., 2020; Kedziorek & Blazkiewicz, 2020; Tasseel-Ponche et al., 2015).

Despite their potential, non-linear analyses remain underutilized in the study of PC in functional tasks, particularly, in individuals with post-stroke impairments. A recent scoping review revealed that, to date, research has predominantly focused on upper limb (UL) tasks, focused on isolated components of task execution, such as muscular strength, muscle activity or range of motion (M. Freitas et al., 2024). To the best of our knowledge, only a few studies have investigated PC post-stroke using non-linear methods (Ghamari et al., 2023; Ghomashchi, 2016). However, a significant gap remains in the literature regarding the application of non-linear measures to functional postural tasks, such as Gait Initiation (GI). GI is considered an optimal task subphase for

detecting PC dysfunction (Khanmohammadi et al., 2016; Lelard et al., 2017; Sousa et al., 2015) and for studying how the central nervous system (CNS) employs stable and efficient strategies to manage the inherent instability of bipedal posture (Fettrow et al., 2019; Yiou et al., 2017). For post-stroke individuals, the feedforward phase of GI is particularly challenging, often leading to compensatory strategies that compromise movement stability and efficiency (Halmi et al., 2020). Despite its importance, most research has predominantly focused on APAs, with limited attention to earlier adjustments, such as EPAs, which are equally crucial for preparing the body for movement (Yiou et al., 2017).

Furthermore, studies frequently prioritize CoP dynamics (Ghamari et al., 2023; Ghomashchi, 2016; Mehdizadeh et al., 2018) while overlooking joint angle variability, which provides valuable insights into segmental coordination and adaptive strategies (Kilby et al., 2015). Given the complexity of PC, combining linear and non-linear analyses provides complementary insights: CoP dynamics reflect overall stability, while joint angle variability reveals neuromuscular mechanisms underlying segmental coordination and postural adjustments (Aghaie Ataabadi et al., 2021; Palmieri-Smith et al., 2002). This integrated approach is crucial for post-stroke populations, where stability and adaptability are often disrupted (Halmi et al., 2020).

This study aims to analyse and describe the complexity and variability of PC in post-stroke individuals during the feedforward phase of GI (-600ms to +50ms relative to movement onset). Both linear and non-linear measures were employed to analyse CoP dynamics and joint amplitude variations. The findings are expected to offer valuable insights into how individuals post-stroke adapt their postural strategies, contributing to the development of targeted rehabilitation interventions aimed at enhancing stability and movement efficiency (Altenburger et al., 2023; Chen et al., 2019).

2. Methods

2.1 Study Design

This cross-sectional observational study was conducted at the Biomechanical Laboratory, Rehabilitation Research Centre (CIR), School of Health, Polytechnic Institute of Porto, following approval from the Ethics Committee of the Polytechnic

Institute of Porto (approval number CE0054D). All participants provided informed consent to the experimental procedures, in accordance with the Declaration of Helsinki.

2.2 Participants

Participants consisted of volunteers recruited through convenience sampling, with the collaboration of the Portugal AVC association for the stroke group (participants with a history of stroke), and healthy group (participants with no history of stroke or self-reported disabilities) recruited by direct invitation through a network of personal acquaintances. The healthy group served as a reference for typical movement performance.

Seventeen Caucasian adults (4 females and 13 males) with a history of a single unilateral ischaemic stroke, impacting either the right ($n = 6$) or left ($n = 11$) hemisphere, and leading to motor control impairment in the contra-lesional hemi-body were included in this study. Complementarily, a comparison group of sixteen Caucasian healthy participants (4 females and 12 males), were recruited. The demographic characteristics of both groups are depicted in Table 1.

Table 1: Participants' characteristics (sociodemographic and clinical).

	Stroke Group (n=17)	Healthy Group (n=16)
Age (years)	56,76 (12,219)	56,00 (12,247)
Body Mass (Kg)	78,32 (11,802)	79,48 (11,264)
Height (m)	1,71 (0,084)	1,72 (0,085)
BMI M (kg/m ²)	26,60 (3,229)	26,90 (2,673)
Post-stroke time (years); M(SD)	5,14 (4,125)	---
Stroke Location; (n; %)		
Undetermined	8 (47,01)	---
Lenticulocapsular	6 (35,29)	---
Corona-radiata	1 (5,9)	---
Frontotemporal	2 (11,8)	---
Risk Factors; (n; %)		---
None	6 (35,3)	---
Diabetes	3 (17,6)	---
Hypertension	2 (11,8)	---
Clinical Obesity	4 (23,5)	---
Smoking	4 (23,5)	---
Alcohol Consumption	2 (11,8)	---
Hyperlipidaemia	3 (17,6)	---
Ability to walk independently at stroke onset	8 (47,06)	---

Thrombolysis / reperfusion therapy	7 (41,18)	---
Mini-BESTest M(SD)	15, 71 (2,932)	---
TUG; M(SD)	14,90 (3,635)	---
FMA-LE; M(SD)	18,29 (2,616)	---

Participants sociodemographic and clinical characteristics expressed as mean (standard-deviation). M: mean; SD: standard deviation; NIHSS: National Institutes of Health Stroke Scale; Mini-BESTest: Balance Evaluation Systems Test; TUG: Timed Up and Go; FMA-LL: Fugl-Meyer Assessment of Sensorimotor Recovery After Stroke – Lower Extremity.

Recruitment of participants into the healthy group was performed following a sample match regarding the stroke group in terms of age, gender, body mass index (BMI), and levels of physical activity. Exclusion criteria included not being born at term (i.e., before 37 weeks of gestation), due to the potential impact on postural control (Hadders-Algra, 2013); an altered mental state that interfered with communication and cooperation (Mini-Mental State Examination (MMSE) score < 24) (Guerreiro et al., 1994; Morgado et al., 2009); the presence of pain or any orthopaedic, neurological (e.g., stroke, Parkinson’s disease, sensory disturbances, etc.), or systemic conditions that could impair task performance; surgery within the past six months; the presence of implants or prostheses; uncontrolled cardiac conditions, thrombophlebitis, the use of medication that affects motor function (Rowe et al., 2021; Silva et al., 2015); or participating in moderate (i.e. vigorous activity of at least 20 minutes per day) to high-intensity physical activity (i.e., vigorous-intensity accumulating at least 1500 MET-minutes/week) at least 3 days of the week (Committee, 2005).

Participants were included in the “stroke group” if they met the following criteria: a diagnosis of first-ever ischaemic stroke, in the chronic phase (Silva et al., 2015; Walcott et al., 2014), affecting the middle cerebral artery territory as confirmed by Computerized Axial Tomography (Silva et al., 2015). Participants were also required to be able to independently perform sit-to-stand movements from a standard chair and to walk at least 10 meters, with supervision, if necessary, but without physical assistance (Silva et al., 2015). Participants were excluded if they met any of the exclusion criteria for the healthy group or if their stroke involved the brainstem or cerebellum (Sousa et al., 2013).

2.3 Instruments

2.3.1 Sample Selection and Characterization

A questionnaire, developed in accordance with the consensus-based core recommendations from the Stroke Recovery and Rehabilitation Roundtable (Kwakkel et al., 2017), was applied to assess the inclusion and exclusion criteria, as well as the sociodemographic and clinical profiles of the participants. Body mass (kg) and height (m) were measured using a seca® 760 scale (seca—Medical Scales and Measuring Systems®, UK) with a precision of 0,1 kg, and a seca® 222 stadiometer (seca—Medical Scales and Measuring Systems®, UK) with a 1 mm accuracy.

The MMSE scale, adapted for the Portuguese population (Guerreiro et al., 1994) was used to assess cognitive level of the participants in the study (Guerreiro et al., 1994; Morgado et al., 2009). A cognitive deficit is identified when the score is: ≤ 15 for individuals who are illiterate, ≤ 22 for those with 1 to 11 years of education, and ≤ 27 for individuals with more than 11 years of education (Guerreiro et al., 1994; Morgado et al., 2009).

The physical activity level was assessed using the short form of the International Physical Activity Questionnaire (IPAQ-SF) for the Portuguese population (Campaniço, 2016) a widely employed self-report instrument designed to evaluate physical activity over the previous seven days (Craig et al., 2003). To interpret the obtained results, the Guidelines for Data Processing and Analysis of the International Physical Activity Questionnaire (IPAQ) – Short Form were followed (IPAQ, 2005) (Committee, 2005).

The Fugl-Meyer Assessment of Sensorimotor Recovery After Stroke - Lower Extremity (FMA-LE), adapted and validated for the Portuguese population (Costa, 2003) was used to evaluate sensorimotor impairment in the stroke group (Kwakkel et al., 2017). Individuals scoring below 34 are generally considered to have sensorimotor impairment of the lower limb (Duncan et al., 1983), while a score below 21 indicates more severe motor impairment, accompanied by significant limitations in mobility and functional abilities (Kwong & Ng, 2019).

Postural control was clinically assessed using the European Portuguese Mini-BESTest (Marta Freitas et al., 2024), a reliable and valid tool proposed to measure dynamic postural stability consisting of 14 items, divided into four sections: anticipatory postural adjustments, reactive postural control, sensory orientation, and dynamic gait, with a

total score of 28 points, representing optimal balance performance (Franchignoni et al., 2010).

2.3.2 Kinematic and Kinetic Data

Whole-body kinematic data were synchronously collected using the Qualisys Motion Capture System (Qualisys AB, Gothenburg, Sweden), and a set of 72 reflective markers were placed bilaterally in anatomical references (identified by manual palpation) based on a biomechanical model adapted based on Cappozzo et al. (Cappozzo et al., 1995) and IOR (lower limbs) and the conventional gait model (upper limbs) (see Table 1 in the *supplementary material*) (Leardini et al., 2007). The camera system included twelve optoelectronic cameras (eight Oqus500, four MiquisM3) for motion capture, operating at a sampling rate of 100 Hz, and one Miquis video camera for synchronous video recording at 25 Hz. Ground reaction forces were simultaneously and synchronously recorded with 60 x 40 cm force platforms (Bertec, Columbus, OH, USA), operating at 100 Hz (Sousa et al., 2015). Based on the findings of Koltermann et al. (Koltermann et al., 2023), a sampling frequency of 100 Hz is sufficient for capturing PC variables, including CoP dynamics. The force platforms were installed in tandem in the direction of gait and embedded in the ground. Both kinematic and kinetic data were recorded using Qualisys Track Manager version 2021.2 (Qualisys AB, Sweden) (Silva et al., 2015; Sousa et al., 2013).

2.4 Procedures

The data collection was conducted in a controlled environment, with each task being performed by a single researcher to minimise inter-rater variability. Prior to data collection, anthropometric measurements, including body mass and height, were taken for each participant. Based on these measurements, the Body Mass Index (BMI), expressed in kg/m^2 , was calculated using the standard formula ($\text{BMI} = \text{body mass} / \text{height}^2$).

To ensure accuracy and precision in measurements, a single investigator was responsible for the preparation and meticulous placement of the markers (Schroeder et al., 2022). Additionally, a pilot study was conducted to familiarise participants with the experimental protocol and to refine the experimental setup, enhancing data robustness and alignment with the latest technological advancements (Couto et al., 2024).

Data collection started with the participant standing in an upright position on top of the first force platform, in a comfortable posture with their arms resting at their sides and feet in their natural stance position, while looking forward at an eye-level point two meters away (Sousa et al., 2013). This initial stance position was marked on the top of the force platform to ensure consistency across trials (Gama et al., 2019). Gait initiation was performed upon hearing the voice command "Please, you may walk.", after which the participant walked at a self-selected speed. Data recording began 30-s before the voice command onset and continued until the participant reached the end of the calibrated walkway, which allowed for approximately 3–5 steps (Fernandes et al., 2017). Each participant was free to choose which foot to use for the first step, with the swing leg being self-selected by the subject (Caderby et al., 2017). There was a one-minute rest between each trial, and 10 trials were performed (Fernandes et al., 2017). A physiotherapist stood nearby to ensure safety in case the participant required physical assistance during the trial. If participants hesitated due to a misunderstanding of the instructions, or required physical assistance from the physiotherapist, the trial was repeated (Rajachandrakumar et al., 2017). Prior to data collection, participants were given the opportunity to complete several practice trials to warm up and familiarize themselves with the experimental setup and procedures (Silva et al., 2015; Sousa et al., 2013). All participants used standardized footwear (flat shoes with rubber soles and laces), appropriately sized (Osada et al., 2022; Sousa et al., 2013). No assistive devices or orthotics were used by the participant during data collection (Sousa et al., 2013).

2.4.1 Data Processing

Marker trajectories were labelled using Qualisys Track Manager (version 2021.2, Qualisys AB, Sweden). Trajectory deviations or interruptions were interpolated using the software's built-in polynomial algorithms. All marker trajectories were then low-pass filtered with a 6 Hz bidirectional filter. Similarly, the force platform's CoP data was filtered using a 10 Hz low-pass bidirectional filter (Couto et al., 2024; Rajachandrakumar et al., 2017). The filtered marker trajectories were imported into Visual3D Professional (version 6.01.36, C-Motion, Canada), where a six degrees-of-freedom biomechanical model was constructed based on the marker set and manufacturer recommendations (Derrick et al., 2020).

To identify GI onset (T0) and the surrounding time window (A: -600ms to B: +50ms), the CoP velocity was calculated as the first derivative of the CoP position (Sousa et al., 2015). A threshold was defined as the mean plus three standard deviations of the first 10 seconds of the recording. The T0 event was identified when this threshold was crossed in the AP (Y-axis) or ML direction (X-axis), provided the crossing persisted for at least 250ms (Chen et al., 2019). Visual observation was conducted to validate and correct the automatic identification of T0. To account for the signal shift introduced by the derivative calculation and threshold placement, the event was adjusted backward by 3 frames (Chen et al., 2019; Sousa et al., 2015). Finally, joint angles and CoP variables were exported from event A (-600ms) to event B (+50ms).

The linear kinetic variables were characterized by measures of magnitude and variation of displacements, including total displacement (TDISP), mean displacement (MDISP), position (POS), amplitude (AMP), and mean velocity of the CoP (MVEL) in the mediolateral (ML-CoP) and anteroposterior (AP-CoP) directions. The non-linear kinetic variables were characterized by position (POS) and displacement (DISP).

For the kinematic analysis, joint angles of the LL, UL, and axial skeleton were calculated based on the angles formed between the distal and proximal segments. The extracted linear variables included joint position (POS), total displacement (TDISP), mean displacement (MDISP), and amplitude (AMPL). The non-linear variables were position (POS) and displacement (DISP). Joint moments were normalized to the subject's body mass (Halmi et al., 2020). The kinematic variables analysed encompassed the angles and moments of the head, shoulder, elbow, wrist, upper trunk, lower trunk, pelvis, hip, knee, and ankle across the sagittal (X), frontal (Y), and transverse (Z) planes. Joint angle values were interpreted according to the following conventions: positive values (+) correspond to specific movements such as extension, adduction, or internal rotation, while negative values (-) indicate opposing movements like flexion, abduction, or external rotation. Detailed descriptions for each joint and axis are provided in the *supplementary material* (Table 2). The outcomes were used to describe the feedforward phase of GI for the swing limb (lower and upper limbs on the same side as the first step) and the stance limb (lower and upper limbs on the contralateral side of the first step).

In addition to linear analyses, two non-linear measures were calculated for CoP POS, DISP and VEL and for joints POS and MDISP to evaluate the behavioural characteristics of the feedforward phase of GI. The largest Lyapunov exponent (LyE) was used to assess the stability of movement trajectories, capturing their divergence or convergence over time (Kedziorek & Blazkiewicz, 2020). The Multiscale Entropy (MSE) quantified the complexity of the system, reflecting its adaptability and variability. Both measures were computed using custom scripts developed in Matlab (version R2020b, The MathWorks, Inc.).

Multiscale entropy (MSE) is a validated method for analysing the complexity of time series data across multiple scales, effectively distinguishing complex dynamics in physiological signals (Costa et al., 2002; Costa et al., 2005). MSE used “sample entropy” to estimate the regularity in different time scales, based on the approximate entropy, to assess the complexity degree (Busa & van Emmerik, 2016).

The Complexity Index (CI) served as the primary dependent variable to examine the differences between stroke and healthy groups. The CI was evaluated for the COP parameters (POS, DISP, and MVEL) and the angular variables (POS and MDISP) across the AP, ML, and X, Y, Z directions, respectively. The analysis followed the methodologies described by Costa et al. (Costa et al., 2005) and Goldberger et al. (Goldberger et al., 2000). Initially, the Sample Entropy (SE) (Richman & Moorman, 2000) was computed (Eq. (1)):

$$SE(m, r, N) = -\ln \frac{U_{m+1}(r)}{U_m(r)} \quad (1)$$

where SE is the sample entropy value, m is the number of samples being compared ($m = 2$), r is the similarity threshold ($0.2 \times$ of standard deviation signal), N is the number of samples (66 points), and U indicates the probability of the samples falling within r .

The original time series was processed using a coarse-graining procedure (Eq. (2)), enabling the evaluation of complexity across two-time scales:

$$y_j^{\tau_m} = \left(\frac{1}{\tau_m}\right) \sum_{i=(j-1)\tau_m+1}^{j\tau_m} x_i, 1 \leq j \leq \frac{N}{\tau_m} \quad (2)$$

where $y_j^{\tau_m}$ represents the new time series, which is generated by averaging non-overlapping data points from the original time series based on the scale factor (τ_m). This

coarse-graining process facilitates the calculation of Sample Entropy (SE) across all time scales, ranging from 1 to τ_m .

The Complexity Index (CI) is derived through the numerical integration of individual SE values across all calculated time scales, as outlined in Eq. (3):

$$C_1 = \sum_{j=1}^N S_E(i) \quad (3)$$

where S_E represents the complexity value calculated at each individual time scale (i).

The LyE algorithm, as initially proposed by Wolf et al. (1985), can be expressed through a single equation. In this formulation, L represents the distance between points, t denotes the time lag, and M refers to the total count of replacement steps (Caesarendra et al., 2013; Rosenstein et al., 1993):

$$\lambda(i) = \frac{1}{M} \sum_{K=K_{min}}^{K_{max}} \left(\frac{1}{K.t} \ln \frac{L_{i+K}}{L_i} \right) \quad (4)$$

The LyE exponent is a key measure used to evaluate the chaotic behaviour of postural sway, determining how movement trajectories diverge or converge over time (Kedziorek & Blazkiewicz, 2020). Positive values indicate divergence of trajectories, reflecting greater instability and chaotic dynamics (Mademli et al., 2021). Conversely, negative values exhibit convergent trajectories, suggesting more robust postural control (Marouvo et al., 2021). This measure highlights the adaptive complexity of the PC system, balancing between stability and chaos in response to varying task demands (Kedziorek & Blazkiewicz, 2020). To calculate the LyE, the phase space was reconstructed following the method described by Broomhead (Broomhead & King, 1986; Matilla-García et al., 2021). This process involved generating multiple delayed copies of the time series, defined by a time lag (τ), to enable state space reconstruction for non-linear parameter estimation. In this study, a time lag of $\tau=1$ and an embedding dimension of $m=2$ were chosen, considering prior methodological insights and the relatively simple nature of the system being examined (Vlachos & Kugiumtzis, 2008). The algorithm measures the divergence or convergence of trajectories within the reconstructed phase space, offering a quantitative assessment of the system's sensitivity to initial conditions (Costa & Goldberger, 2015).

2.4.2 Statistical Analysis

Data analysis was performed using IBM SPSS Statistics version 29.0 (IBM Corporation, Armonk, NY, USA), with the significance level set at 0.05. The normality of continuous variables was assessed using the Shapiro-Wilk test. Descriptive statistics were used to summarise the data means and standard deviations were reported for quantitative variables, while absolute and relative frequencies were presented for qualitative data. For variables where the assumption of normality was not met, the median and interquartile range (25th and 75th percentiles) were calculated (Marôco, 2018). To compare the groups (stroke vs. healthy) on quantitative variables, either the t-test for independent samples or the Mann-Whitney U test was applied, depending on the results of the Shapiro-Wilk test. For kinematic and kinetic variables, the mean across the 10 repetitions performed by each participant was considered for linear analysis.

3. Results

The characteristics of the participants are summarized in Table 1. No statistically significant differences ($p > 0,05$) were found between stroke and healthy groups in terms of age, weight, height and BMI.

3.1 Kinetic Analysis

The performance of CoP behaviour during the feedforward period of GI, analysed through both linear and non-linear methods, is presented in Figure 1 and Tables 2 and 3, respectively.

3.1.1 Linear Analysis

The linear analysis of CoP TDISP (Figure 1) showed significantly higher values in the stroke group compared to the healthy group. For the stroke group, ML-CoP direction had a median value of 0,008, with 25th (P25) and 75th percentiles (P75) at 0,005 and 0,010, respectively. In the AP-CoP direction, the median was also 0,008, with P25 at 0,005 and P75 at 0,010. In contrast, the healthy group presented lower ML-CoP values (median 0,004, P25 0,004, P75 0,005) and slightly different AP-CoP values (median=0,008, P25=0,006, P75=0,008). These differences were statistically significant in the ML-CoP direction ($p=0,001$).

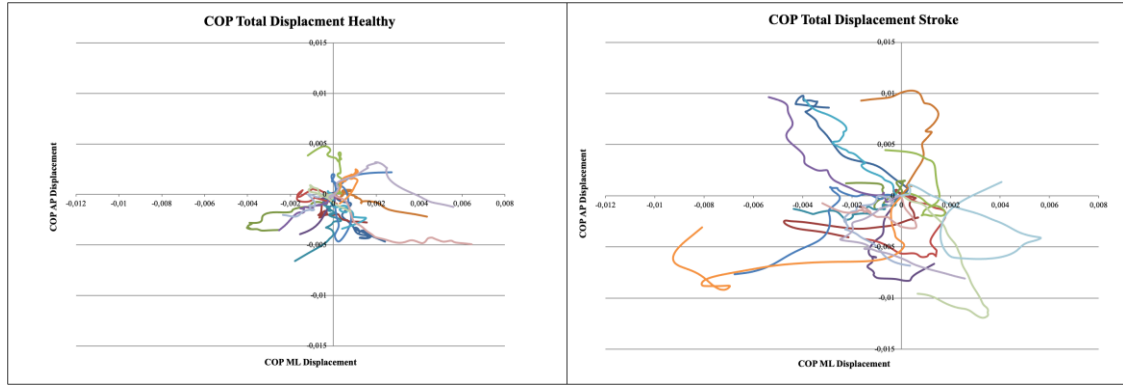


Figure 1. Scatter Plot of CoP representative of the CoP total displacement trajectories in the mediolateral (X-axis) and anteroposterior (Y-axis) directions for healthy and stroke groups. Each line corresponds to an individual's ten trials, illustrating the variability in CoP trajectory during the feedforward phase (-600ms to +50ms) of GI.

Further analysis (Table 2) indicated significant differences in CoP dynamics between the two groups. The stroke group demonstrated a significantly higher ML-CoP MDISP ($p=0,004$) and a reduction in AP-CoP MVEL ($p=0,021$). No significant differences were observed in the remaining CoP linear parameters ($p > 0,05$).

Table 2: Median (MED), 25th (P25) and 75th (P75) percentiles of position (POS), mean displacement (DISP), and mean velocity (MVEL) values of linear outcome of CoP.

		MED (P25; P75)		<i>p</i> value [#]
		Healthy	Stroke	
ML-CoP	POS	-0,1985 (-0,2057; -0,1916)	-0,2075 (-0,2211; -0,1865)	0,331
	MDISP	0,0026 (0,0023; 0,0030)	0,0039 (0,0029; 0,0057)	0,004
	AMP	0,0001 (0,0001; 0,0001)	0,0001 (0,0000; 0,0001)	0,368
	MVEL (m/s)	0,0001 (-0,0024; 0,0023)	0,0002 (-0,0018; 0,0027)	1,000
AP-CoP	POS	0,2268 (0,1847; 0,2824)	0,2037 (0,1527; 0,2546)	0,171
	MDISP	0,0047 (0,0040; 0,0062)	0,0049 (0,0039; 0,0070)	0,666
	AMP	0,0001 (0,0001; 0,0001)	0,0001 (0,0001; 0,0001)	0,449
	MVEL (m/s)	-0,004 (-0,0072; -0,0015)	-0,001 (-0,003; 0,000)	0,021

[#] Mann–Whitney Test; Significant differences in bold.

3.1.2 Non-Linear Analysis

Through the non-linear analysis (Table 3), the stroke group demonstrated a notable reduction in stability, evidenced by significantly lower convergent LyE values ($p=0.012$) in the ML-CoP POS. Additionally, a significant reduction in divergence was observed in LyE CoP MVEL values in both the ML ($p=0.031$) and AP ($p=0.002$) directions for the stroke group. No

significant differences were observed in the remaining CoP non-linear parameters ($p > 0.05$), although, in the stroke group divergence reductions tendencies in ML-CoP and AP-CoP DISP were observed.

Furthermore, complexity and adaptability were observed in all variables, as indicated by lower MSE values, significantly in both ML-COP POS (S1: $p=0,002$; S2: $p=0,016$; CI: $p=0,004$) and AMP POS (S1: $p=0,002$; S2: $p=0,004$; CI: $p=0,002$) (Table 3).

Table 3: Median (MED), 25th (P25) and 75th (P75) percentiles of position (POS), mean displacement (MDISP) and mean velocity (MVEL) values of non-linear outcomes of CoP.

		MED (P25; P75)		<i>p</i> value [#]
		Healthy	Stroke	
ML-CoP POS	LyE	-7.515 (-9.336; -3.164)	-2.881 (-4.699; -2.057)	0,012
	MSE S1	0,337 (0,314; 0,404)	0,281 (0,230; 0,308)	0,002
	MSE S2	0,666 (0,609; 0,845)	0,562 (0,402; 0,666)	0,016
	CI	1.001 (0,920; 1.276)	0,843 (0,618; 0,966)	0,004
AP-CoP POS	LyE	-4.817 (-8.132; -2.378)	-5.537 (-8.247; -3.972)	0,494
	MSE S1	0,294 (0,234; 0,344)	0,279 (0,199; 0,319)	0,368
	MSE S2	0,612 (0,442; 0,655)	0,538 (0,381; 0,639)	0,449
	CI	0,921 (0,676; 1.001)	0,817 (0,576; 0,961)	0,428
ML-CoP DISP	LyE	23.984 (21.299; 25.079)	21.147 (14.126; 26.359)	0,280
	MSE S1	1.046 (0,946; 1.114)	0,883 (0,376; 1.077)	0,052
	MSE S2	1.590 (1.462; 1.710)	1.444 (0,643; 1.730)	0,098
	CI	2.595 (2.356; 2.703)	2.266 (1.022; 2.708)	0,098
AP-CoP DISP	LyE	17.589 (13.544; 22.936)	10,254 (7.230; 19.680)	0,140
	MSE S1	1.019 (0,898; 1.278)	1.027 (0,397; 1.204)	0,564
	MSE S2	1.498 (1.333; 1.659)	1.502 (0,640; 1.612)	0,428
	CI	2.470 (2.181; 2.743)	2.434 (1.055; 2.858)	0,564
ML-CoP MVEL	LyE	32.384 (31.123; 33.495)	30,329 (21.765; 31.937)	0,031
	MSE S1	0,738 (0,680; 0,788)	0,729 (0,645; 0,812)	0,692
	MSE S2	1.526 (1.332; 1.615)	1.354 (1.187; 1.539)	0,090
	CI	2.214 (1.943; 2.365)	1.991 (1.879; 2.278)	0,183
AP-CoP MVEL	LyE	28.690 (24.158; 30,212)	22.618 (18.712; 24,454)	0,002
	MSE S1	0,751 (0,637; 0,912)	0,830 (0,733; 0,925)	0,349
	MSE S2	1.426 (1.220; 1.568)	1.549 (1.413; 1.659)	0,090
	CI	2.191 (1.848; 2.423)	2.340 (2.149; 2.497)	0,130

Mann–Whitney Test; Significant differences in bold. LyE: Largest Lyapunov Exponent; MSE: Multiscale Entropy; S1: Scale 1; S2: Scale 2; CI: Complexity Index.

3.2 Kinematic Analysis

3.2.1 Linear Analysis

The behaviour of joints during the feedforward phase of GI is illustrated in Figures 2, 3, and 4, which present the results of the linear analysis (detailed information is available in Tables 3, 4 and 5 in the *supplementary material*). The findings indicate that individuals post-stroke exhibited greater joint displacement, both in terms of TDISP and dynamic measures such as MDISP and AMPL.

Head, Pelvis and Trunk Joints

In the sagittal plane, the stroke group exhibited a tendency toward head FLE, while the healthy group showed a preference for EXT; however, these POS differences were not consistently significant ($p>0.05$). For the head, significantly greater values were observed for TDISPL ($p=0.019$), MDISP ($p=0.019$), and AMPL ($p=0.009$). Similarly, for the trunk, TDISPL ($p=0.004$), MDISP ($p=0.004$), and AMPL ($p=0.002$) were significantly higher. The pelvis also showed significantly elevated values for TDISPL ($p=0.017$), MDISP ($p=0.014$), and AMPL ($p=0.009$) in the stroke group (Figure 2).

For the head, TDISPL ($p=0.006$), MDISP ($p=0.005$), and AMPL ($p=0.006$) were significantly greater. Similarly, for the trunk, TDISPL ($p=0.016$), MDISP ($p=0.016$), and AMPL ($p=0.012$) were also significantly higher in the stroke group (Figure 2).

In the transverse plane, the stroke group showed exaggerated rotational patterns, with significantly higher TDISPL values for the head ($p=0.009$), trunk ($p=0.037$), and pelvis ($p=0.011$). MDISP and AMPL were also significantly greater for the head ($p=0.009$ and $p=0.004$), trunk (MDISP: $p=0.040$; AMPL: $p=0.008$), and pelvis (MDISP: $p=0.009$; AMPL: $p=0.002$) (Figure 2).



Figure 2. Median, 25th and 75th percentiles of position (°), total displacement (°), mean displacement (°) and amplitude (°) values of linear outcome of head, trunk and pelvis joints. Legend: EXT, extension; FLE, flexion; RT, right tilt; LT, left tilt; LR, left rotation; RR, right rotation; RV, retroversion; AV, anteversion; AD, adduction; ABD, abduction; * p -value < 0,05; Mann-Whitney Test.

Lower Limb Joints

In the sagittal plane, the stroke group demonstrated a tendency towards increased hip FLE in both swing and stance phases and decreased swing ankle DF; however, these POS differences were not statistically significant ($p > 0.05$). For the hip, significantly higher values were noted in the swing limb for MDISP ($p = 0.019$) and AMPL ($p = 0.044$). For the knee, AMPL was significantly elevated in the stance limb ($p = 0.021$). For the ankle, significantly greater values were observed in the swing limb for TDISPL ($p = 0.034$), MDISP ($p = 0.037$), and AMPL ($p = 0.028$) (Figure 3).

In the frontal plane, the stroke group exhibited significantly greater TDISPL, MDISP and AMPL for the ankle in both the swing limb ($p=0.009$; $p=0.026$; $p=0.006$, respectively) and stance limb ($p=0.007$; $p=0.002$; $p=0.002$, respectively) (Figure 3).

In the transverse plane, significantly greater values were found in the stroke group for swing hip TDISPL, MDISP, and AMPL ($p=0.011$, $p=0.011$, and $p=0.014$, respectively), as well as for stance hip TDISPL ($p=0.031$) and AMPL ($p=0.026$). Similarly, significant increases were observed for knee swing MDISP ($p=0.017$) and AMPL ($p=0.037$), and for knee stance TDISPL ($p=0.028$) and AMPL ($p=0.036$) (Figure 3).



Figure 3. Median, 25th and 75th percentiles of position (°), total displacement (°), mean displacement (°) and amplitude (°) values of linear outcome of lower limb joints. Legend: FLE, flexion; EXT, extension; AD, adduction; ABD, abduction; IR, internal rotation; ER, external rotation; DF, dorsiflexion; PF, plantar flexion; IN, inversion; EV, eversion; * p -value<0,05: Mann–Whitney Test.

Upper Limb Joints

In the sagittal plane, in the stroke group, the shoulder TDISPL was significantly greater in both the swing ($p=0.026$) and stance limbs ($p=0.019$). MDISP was significantly increased in the swing limb ($p=0.013$), and AMPL was significantly higher in the swing limb ($p=0.004$) and stance limb ($p=0.003$). For the elbow, AMPL was significantly elevated in the stance limb ($p=0.031$). For the wrist, significant increases were observed in MDISP ($p=0.016$) and AMPL ($p=0.008$), both in the swing limb (Figure 4).

In the frontal plane, in the stroke group, significant increases in elbow MDISP were noted in the swing limb ($p=0.031$), while AMPL was significantly higher in both the swing limb ($p=0.004$) and stance limb ($p=0.026$). For the wrist, MDISP was significantly elevated in the swing limb ($p=0.040$), and AMPL was significantly increased in the swing limb ($p=0.021$) (Figure 4).

In the transverse plane, the stroke group exhibited significant differences across joints. For the shoulder, POS was significantly altered in the swing limb ($p=0.019$). At the elbow, MDISP increased in the swing limb ($p=0.019$), while AMPL was elevated in both the swing ($p=0.026$) and stance limbs ($p=0.028$). For the wrist, POS differed in the swing ($p=0.009$) and stance limbs ($p<0.001$), alongside higher TDISPL ($p=0.021$), MDISP ($p=0.021$), and AMPL ($p=0.044$) in the swing limb (Figure 4).



Figure 4. Median, 25th and 75th percentiles of position (°), total displacement (°), mean displacement (°) and amplitude (°) values of linear outcome of upper limb joints. Legend: FLE, flexion; EXT, extension; AD, adduction; ABD, abduction; IR, internal rotation; ER, external rotation; UD, ulnar deviation; RD, radial deviation; * p -value < 0.05: Mann–Whitney Test.

3.2.1 Non-Linear Analysis

The non-linear analysis of joint behaviour during the feedforward phase of GI revealed significant differences between the stroke and healthy groups. The stroke group consistently exhibited reduced convergence or greater divergence in movement trajectories, as indicated by less negative or more positive LyE, respectively ((detailed information is available in Tables 6 to 10 in the *supplementary material*). This was

accompanied by a marked loss of complexity, reflected in decreased MSE (Figures 5, 6, 7, 8, and 9).

Head, Pelvis and Trunk Joints

In the sagittal plane, the stroke group exhibited less negative and convergent LyE values. For the head, significant differences were observed in POS ($p=0.004$). MSE measures demonstrated significant reductions across all dimensions for both POS (S1: $p=0.002$; S2: $p=0.009$; CI: $p=0.006$) and DISP (S1: $p=0.009$; S2: $p=0.034$; CI: $p=0.021$) (Figure 5).

In the frontal plane, the stroke group exhibited less negative LyE values, reflecting reduced convergence. For the head, significant differences were observed in POS ($p=0.006$), and MSE measures demonstrated significant reductions across all dimensions for POS (S1: $p=0.023$; S2: $p=0.021$; CI: $p=0.013$) and DISP (S1: $p<0.001$; S2: $p=0.007$; CI: $p=0.006$). For the trunk, MSE reductions were significant for POS (S1: $p=0.007$; S2: $p=0.002$; CI: $p=0.003$). For the pelvis, LyE values were significantly less negative for POS ($p=0.011$), while those for MDISPL were less positive, indicating reduced divergence; however, these differences were not statistically significant ($p>0.05$) (Figure 5).

In the transverse plane, LyE values in the stroke group exhibited a tendency toward less negative values, indicating reduced convergence, with significantly less negative values for pelvis POS ($p<0.001$). For the head, MSE measures showed significant reductions for POS (S1: $p=0.009$; S2: $p<0.001$; CI: $p=0.005$) and DISP (S1: $p=0.002$; S2: $p=0.006$; CI: $p=0.005$). For the trunk, MSE reductions were significant for POS (S1: $p=0.021$; CI: $p=0.040$), while reductions in DISP were not statistically significant ($p>0.05$). For the pelvis, MSE reductions were significant for POS (S1: $p=0.002$; S2: $p=0.019$; CI: $p=0.004$) and DISP (S1: $p=0.021$; S2: $p=0.044$) (Figure 5).

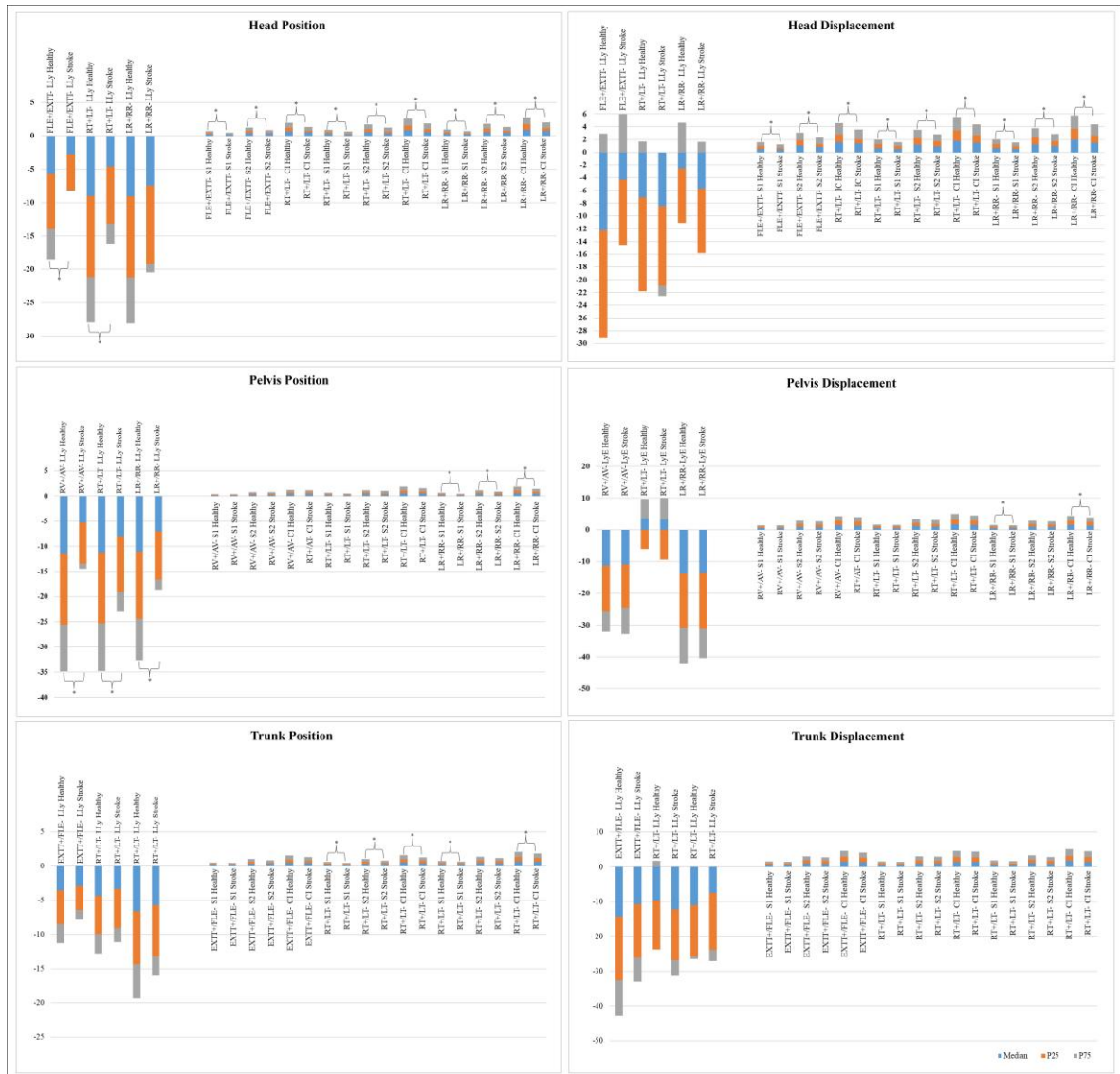


Figure 5. Non-linear analysis of position and mean displacement of head, pelvis and trunk joints. Legend: LyE, Largest Lyapunov Exponent; S1: Multiscale Entropy Scale 1; S2: Multiscale Entropy Scale 2; CI, Multiscale Entropy Complexity Index; EXT, extension; FLE, flexion; RT, right tilt; LT, left tilt; LR, left rotation; RR, right rotation; RV, retroversion; AV, anteversion; * p -value < 0.05; Mann-Whitney Test.

Lower Limb Joints

In the sagittal plane, the stroke group exhibited less convergence in LyE values. For the hip, significantly less negative POS values were observed in both the swing ($p=0.021$) and stance ($p=0.006$) limbs, and MSE measures showed significant reductions for POS in the swing limb (S2: $p=0.026$; CI: $p=0.040$). For the knee, DISP LyE values showed contrasting patterns: the healthy group exhibited positive values, indicating divergence, while the stroke group displayed negative values in the swing limb, reflecting

convergence. However, these differences were not statistically significant ($p>0.05$). MSE measures for the knee showed a significant reduction for POS in the swing limb (CI: $p=0.026$). For the ankle, the stroke group exhibited significantly less negative LyE values for POS in the stance limb ($p=0.016$) (Figures 6 and 7).

In the frontal plane, the stroke group exhibited less convergence in POS LyE values across all joints, though these differences were not statistically significant ($p>0.05$). For the hip, MSE measures were significantly lower in the stroke group, with reductions observed for POS (S1: $p=0.023$; S2: $p=0.009$; CI: $p=0.040$) and DISP (S1: $p=0.034$; S2: $p=0.040$; CI: $p=0.034$) in the swing limb. For the knee, LyE values for DISP in the healthy group were positive in both limbs, indicating divergence, while the stroke group exhibited negative LyE values in the swing limb, reflecting convergence, and positive values in the stance limb, though these differences were not statistically significant ($p>0.05$). For the ankle, the healthy group demonstrated divergence in DISP with positive LyE values in both limbs, while the stroke group exhibited convergence with negative LyE values, which were significant for both limbs ($p=0.021$ and $p=0.002$, respectively). MSE measures for the ankle were significantly reduced in the stroke group, with reductions observed for POS in the swing limb (S2: $p=0.001$; CI: $p<0.001$) and stance limb (S1: $p=0.008$; CI: $p<0.001$), as well as for MDISP in the swing limb (S1: $p=0.012$; S2: $p=0.021$; CI: $p=0.011$) (Figures 6 and 7).

In the transverse plane, the stroke group showed reduced convergence in POS for LyE values. For the hip, significant differences were observed in the swing limb ($p=0.006$), while for DISP, LyE values were predominantly negative (convergence) in the stroke group, except in the stance limb, where they remained positive. MSE measures for the hip showed significant reductions in POS (CI: $p=0.040$) and DISP (CI: $p=0.034$) in the swing limb. For the knee, LyE values for DISP were positive (divergence) in the healthy group but predominantly negative (convergence) in the stroke group, with significant differences observed in the stance limb ($p=0.009$). For the ankle, POS LyE values showed significant differences in both swing ($p=0.013$) and stance ($p<0.001$) limbs. For DISP, LyE values were predominantly negative in the stroke group, with significant differences in the stance limb ($p=0.031$). MSE measures for the ankle showed significant reductions in the stroke group, with decreased POS values in the

stance limb (S1: $p=0.016$; S2: $p<0.001$; CI: $p<0.001$) and DISP values also significantly reduced in the stance limb (S1: $p=0.023$; CI: $p=0.040$) (Figures 6 and 7).

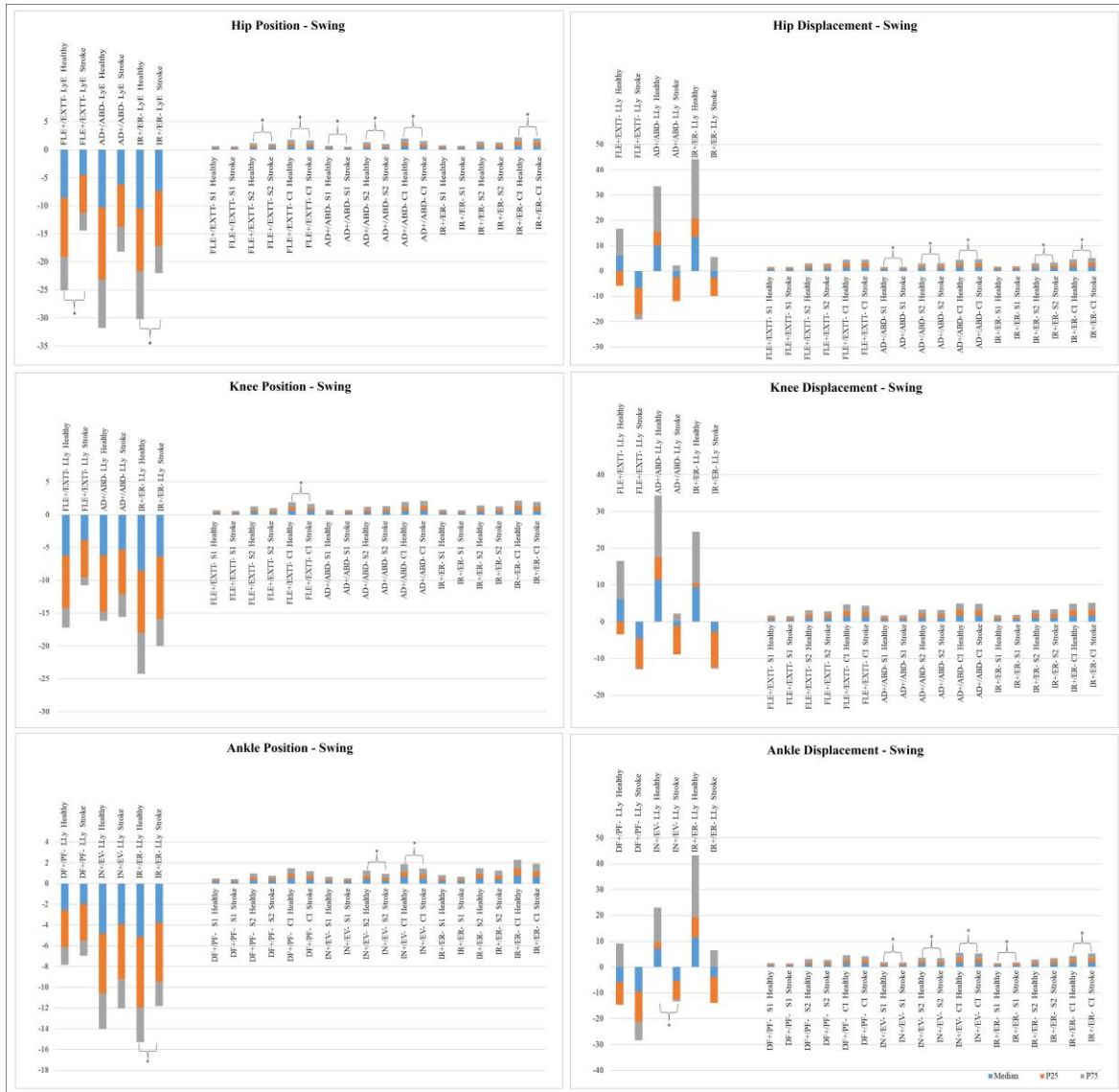


Figure 6. Non-linear analysis of position and mean displacement of swing lower limb joints. Legend: LyE, Largest Lyapunov Exponent; S1: Multiscale Entropy Scale 1; S2: Multiscale Entropy Scale 2; CI, Multiscale Entropy Complexity Index; EXT, extension; FLE, flexion; AD, adduction; ABD, abduction; IR, internal rotation; ER, external rotation; DF, dorsiflexion; PF, plantar flexion; IN, inversion; EV, version; * p -value<0,05: Mann–Whitney Test.

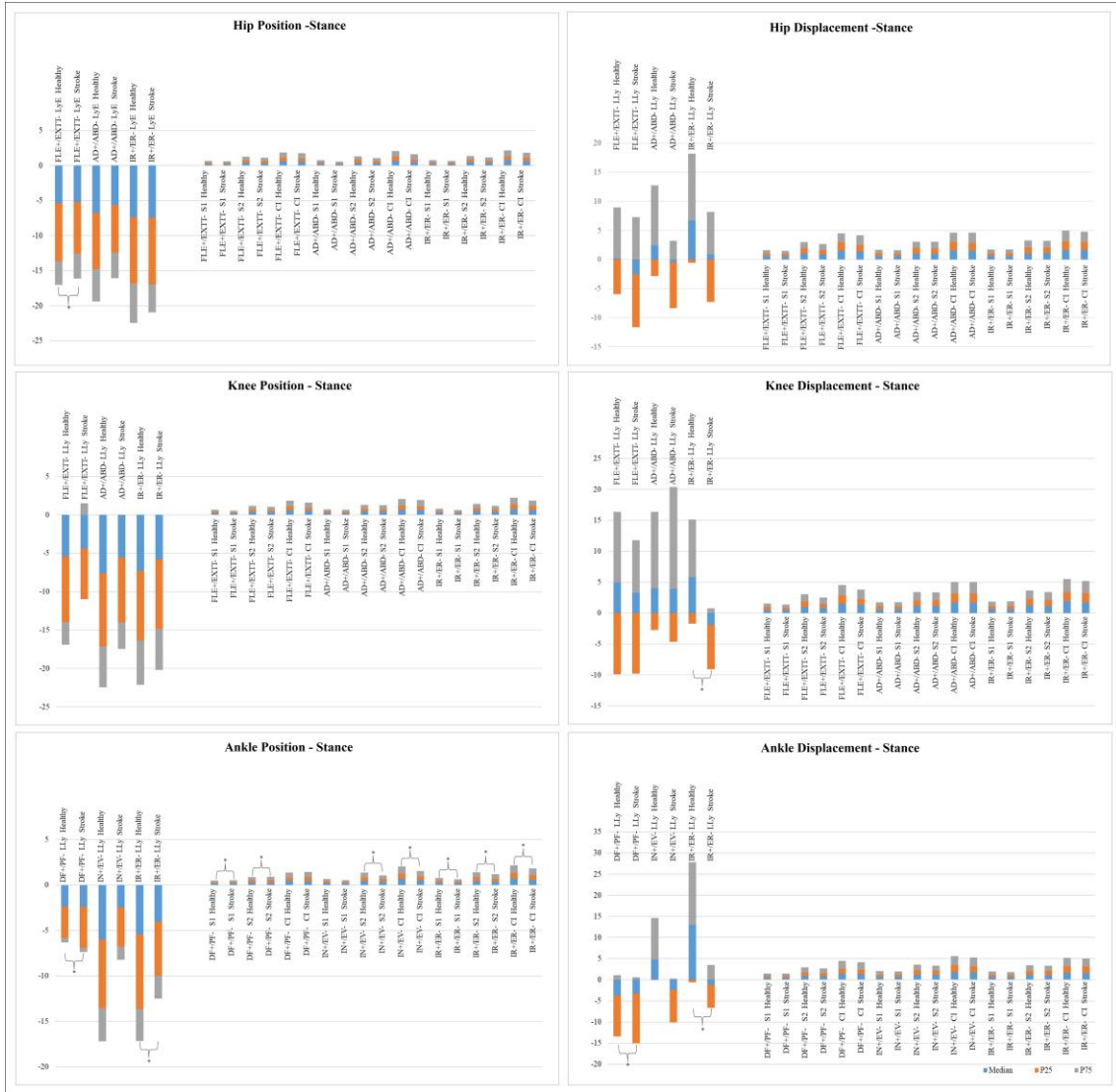


Figure 7. Non-linear analysis of position and mean displacement of stance lower limb joints. Legend: LyE, Largest Lyapunov Exponent; S1: Multiscale Entropy Scale 1; S2: Multiscale Entropy Scale 2; CI, Multiscale Entropy Complexity Index; EXT, extension; FLE, flexion; AD, adduction; ABD, abduction; IR, internal rotation; ER, external rotation; DF, dorsiflexion; PF, plantar flexion; IN, inversion; EV, version; * p -value<0,05: Mann–Whitney Test.

Upper Limb Joints

In the sagittal plane, the stroke group exhibited significantly reduced convergence for DISP in the shoulder ($p=0.011$), along with MSE reductions in the swing limb (S1: $p=0.002$; S2: $p=0.003$; CI: $p=0.002$). For the elbow, DISP also showed a significant reduction in convergence in the swing limb ($p=0.034$). For the wrist, DISP LyE values were positive (indicating divergence) in the stance limb for both groups, whereas in the swing limb, LyE values were divergent in the stroke group and convergent in the

healthy group, with a significant difference ($p=0.012$). Additionally, MSE measures showed significant reductions for POS in the wrist swing limb (CI: $p=0.014$) (Figures 8 and 9).

In the frontal plane, the stroke group exhibited more negative (convergent) LyE values for shoulder DISP in both limbs, whereas the healthy group demonstrated positive (divergent) LyE values for the swing limb and negative (convergent) values for the stance limb, with significant differences observed for the stance limb ($p=0.017$). MSE measures for the shoulder showed significant reductions for POS in both the swing (S2: $p<0.001$; CI: $p<0.001$) and stance limbs (S2: $p=0.016$; CI: $p=0.028$). For the elbow, MSE measures revealed significant reductions for POS in the swing limb (CI: $p=0.026$). For the wrist, POS LyE values were significantly less negative in the stance limb for the stroke group ($p=0.005$). Regarding DISP, LyE values in the stroke group were positive (divergent) in the swing limb and negative (convergent) in the healthy group, though these differences were not statistically significant ($p>0.05$) (Figures 8 and 9).

In the transverse plane, the stroke group showed reduced convergence in POS and MDISP for the shoulder, with less negative LyE values and significant differences in POS LyE for both limbs ($p < 0.001$; $p = 0.011$). For the elbow, reduced convergence was observed in POS and MDISP in both limbs, with significantly less negative LyE values for POS in the swing limb ($p=0.034$). MSE measures also showed significant reductions in POS for the swing limb (S1: $p=0.017$; S2: $p=0.026$; CI: $p=0.019$). For the wrist, reduced convergence was observed in POS, and DISP LyE values were less divergent (positive) in both limbs, though no significant differences were reported ($p>0.05$) (Figures 8 and 9).

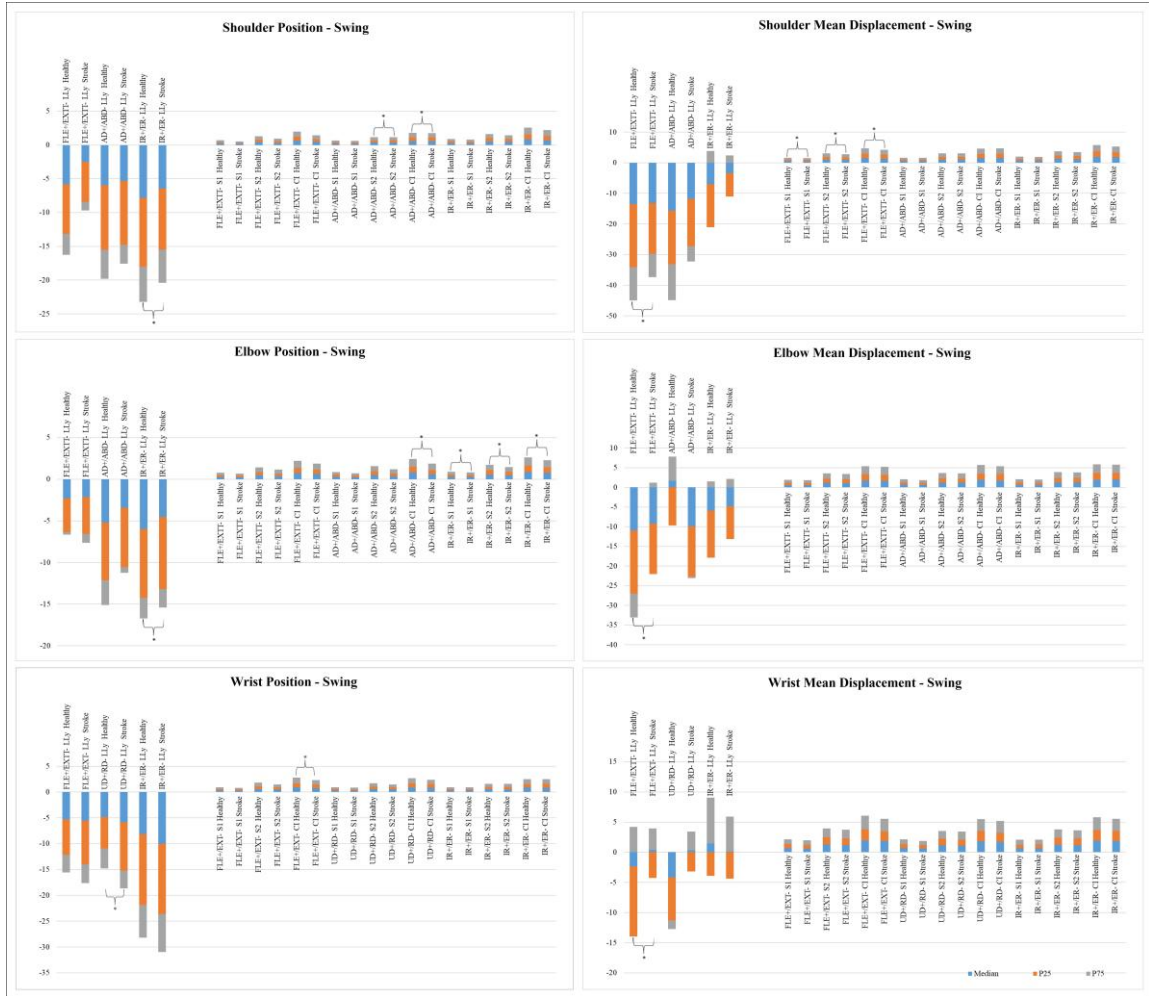


Figure 8. Non-linear analysis of position and mean displacement of swing upper limb joints. Legend: LyE, Largest Lyapunov Exponent; S1: Multiscale Entropy Scale 1; S2: Multiscale Entropy Scale 2; CI, Multiscale Entropy Complexity Index; EXT, extension; FLE, flexion; AD, adduction; ABD, abduction; IR, internal rotation; ER, external rotation; UD: ulnar deviation; RD: radial deviation; * p -value<0,05; Mann–Whitney Test.

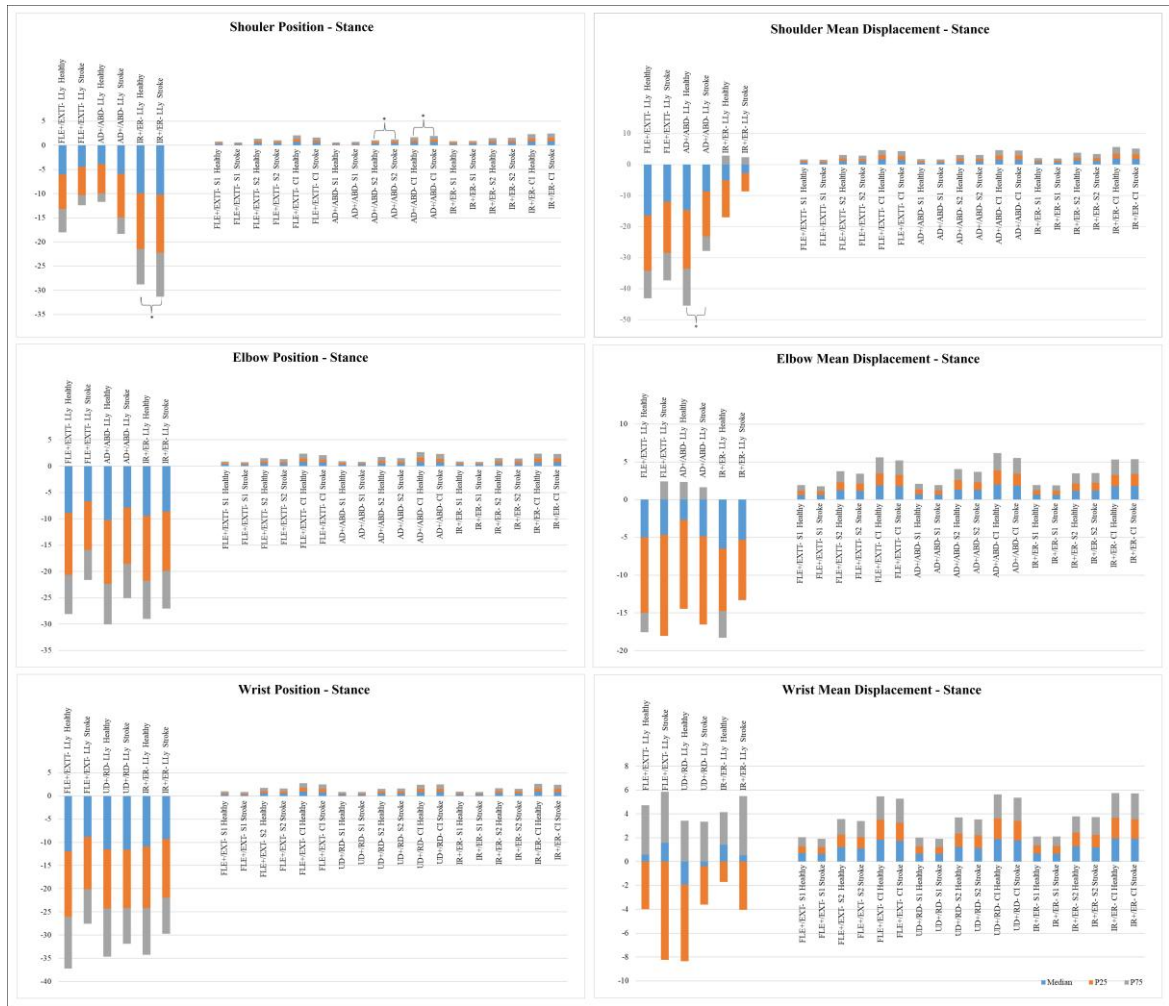


Figure 9. Non-linear analysis of position and mean displacement of stance upper limb joints. Legend: LyE, Largest Lyapunov Exponent; S1: Multiscale Entropy Scale 1; S2: Multiscale Entropy Scale 2; CI, Multiscale Entropy Complexity Index; EXT, extension; FLE, flexion; AD, adduction; ABD, abduction; IR, internal rotation; ER, external rotation; UD: ulnar deviation; RD: radial deviation; * p -value<0,05: Mann–Whitney Test.

4. Discussion

This study aimed to analyse the complexity and variability of PC in post-stroke individuals during the feedforward phase of GI. Both linear and non-linear measures were employed to analyse CoP dynamics and joint amplitude variations. The findings revealed significant differences between stroke and healthy individuals. Specifically, the stroke group exhibited increased DISP and reduced velocity VEL in CoP dynamics, alongside greater joint displacement in all planes of movement, particularly in the sagittal and transverse planes. These linear findings suggest compensatory mechanisms

driven by impaired APAs, as stroke survivors seem to depend on increased magnitude of variation to maintain stability (Tomita et al., 2024). However, the reduced adaptability and complexity observed in non-linear measures highlight constrained and less efficient motor control strategies (Stergiou & Decker, 2011). Together, these results offer a comprehensive characterisation of PC dysfunction after stroke and provide critical insights for designing targeted rehabilitation interventions to enhance both stability and adaptability in dynamic motor control.

4.1 CoP Dynamics

PC integrates sensory systems, the CNS, and the musculoskeletal system to support both postural maintenance and movement execution, ensuring stable posture and correct segmental orientation during tasks like GI (Lundy-Ekman & Weyer, 2022; Takakusaki, 2017). Despite some metrics not reached statistical significance, the increased magnitude of variation, reduced stability and complexity observed in CoP measures suggest critical dysfunctions (Figure 10).

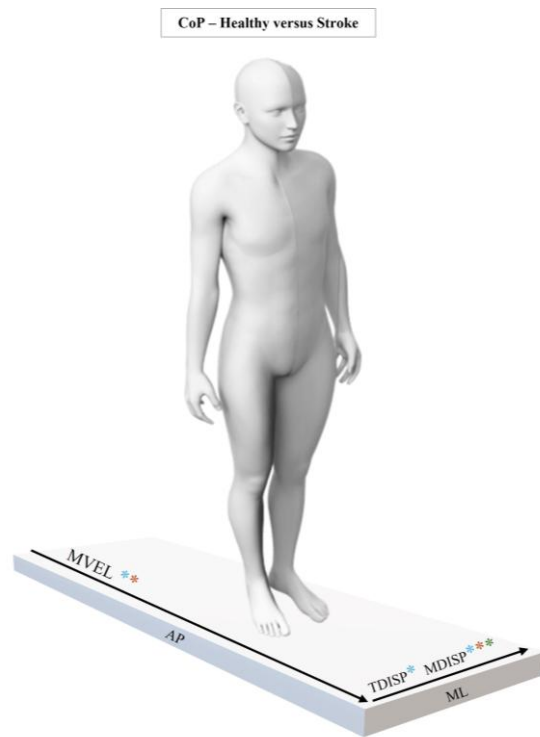


Figure 10. Significant results of linear and non-Linear CoP Analysis, between healthy and stroke groups.
*: significant linear differences; *: significant LyE differences; *: significant MSE differences.

The linear analysis revealed significant increases for the stroke group in ML TDISPL and MDISP, paired with decreased AP-MVEL. These findings suggest greater postural instability, particularly in the ML direction, during preparatory phases of movement, essential during GI (Delafontaine et al., 2019; Onuma et al., 2021; Silva et al., 2015). Higher ML magnitude of variation aligns with recent studies that emphasise the impaired ability of post-stroke individuals to stabilise the COM in the ML direction during dynamic tasks, factor that is critical for fall prevention (Gandolfi et al., 2019; Moisan et al., 2022; Rajachandrakumar et al., 2017; Silva et al., 2015). This phenomenon could be attributed to impairments in various elements of PC caused by stroke, including deficits in muscle activation, asymmetrical weight distribution in the LL, increased APAs of trunk muscles, dysregulation of CoP and COM displacement (Sousa et al., 2022), greater visual dependence, and deficits in the integration of visual, vestibular, and somatosensory information (Gandolfi et al., 2019; Mohapatra & Aruin, 2013).

Complementary to the linear findings, the non-linear analysis further revealed a reduction in entropy and LyE measures in the stroke group. This reduction reflects diminished system complexity and adaptability, which are critical for responding to predictable and unpredictable environmental demands (Stergiou & Decker, 2011; Vonesch et al., 2023). Specifically, a marked reduction in LyE of ML-CoP POS, in the stroke group, highlight a disrupted interplay between motor stability and flexibility when responding to dynamic perturbations (Mehdizadeh et al., 2018). This often leads to the initiation of more rigid motor patterns, resulting in more consistent and repetitive sway behaviours, particularly in the ML direction (Nandi et al., 2018). This aligns with the literature, which indicates that stroke survivors demonstrate increased regularity in the temporal structure of CoP variability, particularly in the ML direction (Mehdizadeh et al., 2018; Roerdink et al., 2006). This increased regularity has been interpreted as a compensatory mechanism, where the PC system adopts rigid strategies to address impaired adaptability (Sethi et al., 2017; Stergiou, 2016; Stergiou & Decker, 2011). Such rigid strategies may explain the impaired CoP dynamics observed during the feedforward phase of GI, where reduced adaptability constrains the ability to adjust, explore, and adopt alternative, more efficient motor strategies to meet the specific demands of the task (Andreasen et al., 2020). Decreased MSE values further supported

this finding, reflecting lower complexity and adaptability in PC system. This aligns with the study by Roerdink et al. (Roerdink et al., 2006), which reported reduced complexity in stroke survivors early in recovery. These findings suggest that the motor system of stroke survivors becomes less capable of responding to perturbations during the feedforward phase of GI, in line with the hypothesis that reduced complexity correlates with impaired adaptability (Kedziorek & Blazkiewicz, 2020). This interplay between instability and compensatory overuse has been previously identified as a hallmark of post-stroke motor dysfunction (Jones, 2017).

Furthermore, the reduction in the MVEL of AP-CoP observed in the stroke group suggests slower feedforward control strategies, likely reflecting motor impairments and reduced efficiency in APAs (Delafontaine et al., 2019). This is consistent with evidence that stroke survivors exhibit diminished APAs velocity due to neural reorganisation dysfunction (Delafontaine et al., 2019; Onuma et al., 2021; Silva et al., 2015). This trade-off between stability and movement efficacy has been previously documented, highlighting that reduced AP momentum may compromise functional mobility (Beyaert et al., 2015). Moreover, it appears that individuals prioritize safety over movement efficiency, leading to suboptimal motor strategies that prolong task execution times (Plummer et al., 2020). The observed divergence in DISP and VEL could likely reflect maladaptive compensatory mechanisms (Stergiou & Decker, 2011; Stergiou et al., 2006) that may represent an attempt to counteract systemic postural instability but also suggest reliance on less efficient and less variable motor strategies (Stergiou & Decker, 2011). This highlights impairments in anticipatory control processes essential for maintaining stability, potentially driven by compromised lateral stability—a key characteristic of post-stroke motor dysfunction (Rajachandrakumar et al., 2017). Additionally, the reduction in MSE values, particularly at smaller scales (S1), suggest impaired fine-tuned adjustments in postural dynamics (Kedziorek & Blazkiewicz, 2020). These findings are consistent with those of Mehdizadeh et al. (Mehdizadeh et al., 2018), who observed similar reductions in entropy in stroke survivors during static postural tasks, associating them with diminished neuromuscular flexibility. The observed reduction in neuromotor system complexity may indicate a constrained number of degrees of freedom, reflecting rigidity that limits exploratory movement strategies and heightens instability, aligning with Bernstein's framework (Biryukova & Sirotkina, 2020). This

reduction suggests that stroke survivors face challenges in effectively responding to sudden, minor perturbations during the feedforward phase of GI, a critical component for maintaining postural stability during movement transitions (Delafontaine et al., 2019; Sousa et al., 2015). On the other hand, the reductions observed in S2 suggest a broader dysfunction in integrating and coordinating adjustments over longer time scales. This points out a reduced capacity to stabilise PC over the preparatory window leading into GI (Gandolfi et al., 2019). Furthermore, while some metrics did not achieve statistical significance, such as AP-CoP LyE, it is important to acknowledge relevant trends that may indicate subtle dysfunctions. These results, alongside significant findings, suggest that the post-stroke group exhibits challenges in both stabilising and adapting the CoP during the preparatory phase of GI.

The integration of linear and non-linear results reveals a coherent picture of PC dysfunction. Increased linear magnitude of variation (e.g., CoP DISP) corresponds with reduced complexity, highlighting a dual challenge of reduced variability and diminished control flexibility (Mehdizadeh et al., 2018; Mehdizadeh, 2018). These findings suggest that the PC system operates within a constrained dynamic range, unable to control postural stability and adaptability effectively (Moisan et al., 2022). This limitation not only hampers the capacity to respond to perturbations but may also reduce the system's ability to explore alternative, potentially more efficient motor strategies, increasing the risk of falls and decreasing functional independence (Andreasen et al., 2020; Curuk & Aruin, 2022).

4.2 Joint Dynamics

The linear and non-linear findings suggest distinct compensatory mechanisms and deficits in dynamic stability during GI. Similarly to what was observed in the CoP dynamics, the stroke group exhibited greater magnitudes of variation while showing reduced adaptability and complexity, highlighting inefficient and rigid motor control strategies when compared to healthy controls. These findings highlight the interplay between increased linear movements, such as TDISPL and AMPL, and reduced non-linear adaptability and complexity, such as Ly and MSE, providing a more comprehensive understanding of post-stroke motor strategies.

4.2.1 Sagittal Plane

In the sagittal plane (Figure 11), although POS differences in the head, trunk, and pelvis were not statistically significant, the observed patterns suggest subtle compensatory mechanisms that static measures may not fully capture (Lafage et al., 2023). These findings likely reflect the heterogeneity within the stroke group, where individual responses are influenced by varying degrees of motor impairment, chronicity of the stroke, or compensatory habits developed over time (Mooney et al., 2020; Peng et al., 2024). Significant increases in TDISPL, MDISP, and AMPL across all segments—particularly the trunk and pelvis—highlight that compensations in stroke survivors are more pronounced in movement magnitude and variability rather than static positioning (Takahashi et al., 2021).

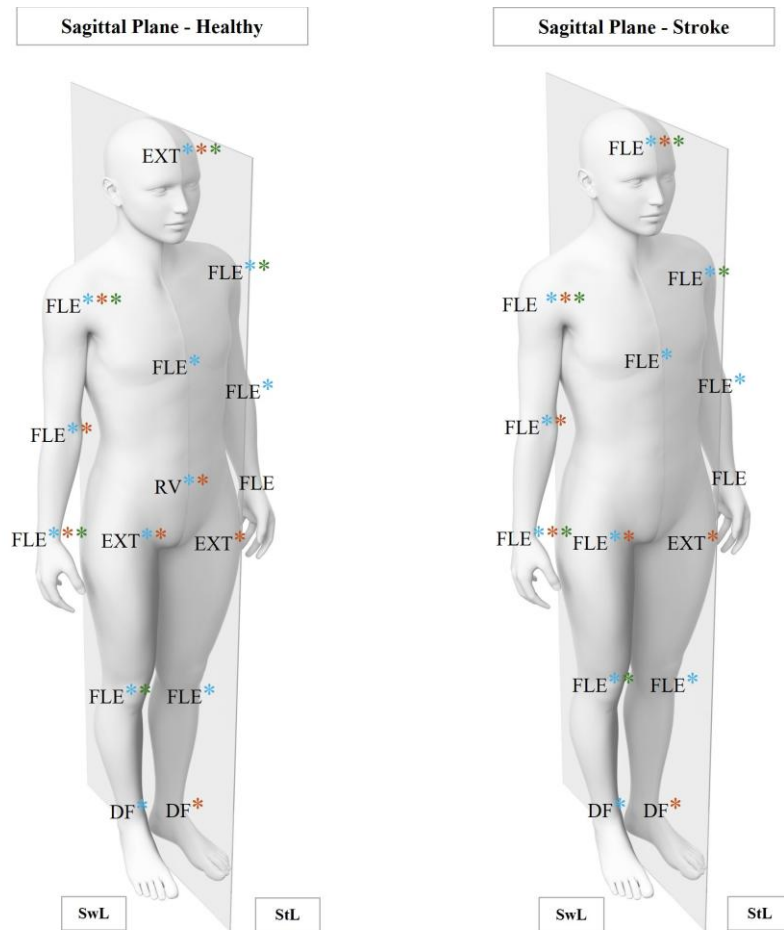


Figure 11. Significant results of linear and non-Linear joints analysis in sagittal plane, between healthy and stroke groups. EXT: extension; FLE: flexion; RV: retroversion; DF: dorsiflexion; SwL: swing limb; StL: stance limb; *: significant linear differences; *: significant LyE differences; *: significant MSE differences.

The stroke group demonstrated a tendency toward head FLE, contrasting with the EXT preference observed in healthy individuals. While not statistically significant, this pattern suggests a common post-stroke strategy to address impaired PC and maintain gaze stabilization (Chen et al., 2018; Stamenkovic et al., 2018). Head FLE disrupts the biomechanical chain by shifting the COM anteriorly, which increases reliance on compensatory movements in the trunk and pelvis to maintain stability (Van Criekeing et al., 2017). This anterior displacement imposes greater demands on trunk stabilization and may compromise activation of the trunk extensors, which are essential for APAs during GI (Sharififar et al., 2019; Yiou et al., 2017). Forward head posture has also been linked to reduced proprioceptive input, which further limits adaptability in postural adjustments (An & Park, 2021; Yong et al., 2016).

Compensatory mechanisms in the stroke group were reflected in significantly higher TDISPL values across all segments (head, trunk, and pelvis), reflecting greater movement amplitudes as compensatory strategies for postural instability due to impaired APAs (Delafontaine et al., 2019). However, the increased magnitude of variation, particularly in MDISP and AMPL for the trunk and pelvis, reflects reliance on exaggerated FLE-EXT movements to stabilize the body, which can reduce efficiency by shifting the COM further from optimal biomechanical alignment (Tomita et al., 2024). Excessive anterior pelvic tilt, a commonly reported compensatory mechanism in stroke survivors, may partially counterbalance deficits in proximal trunk control and hip extensors (Darak & Karthikbabu, 2020). However, this strategy is often energy-inefficient and shifts the COM anteriorly, further compromising stability (Kim et al., 2018). These findings align with previous research linking compensatory trunk displacements to inefficient and poorly coordinated motor actions during GI (Farinelli et al., 2021; Presti et al., 2022; Rougier & Pérennou, 2019).

Non-linear measures revealed that the stroke group exhibited less negative and convergent LyE values in POS for the head and pelvis, indicating relative stability in these segments (Kedziorek & Blazkiewicz, 2020). However, this stability comes at the cost of adaptability, as reflected in significant reductions in MSE across S1, S2, and CI for head POS and DISP. These reductions highlight compromised rapid, fine-grained adjustments and adaptability across multiple temporal scales (Mengarelli et al., 2023; Watanabe et al., 2015), suggesting a rigid strategy for head stabilization during weight

shifts. This rigidity increases reliance on the trunk and pelvis for compensatory adjustments, reflecting diminished neuromuscular flexibility—a common characteristic of post-stroke compensatory behaviours (Mehdizadeh et al., 2018).

The interplay between increased linear movements and reduced non-linear adaptability underscores the inefficiency of these compensatory strategies. For instance, while MDISP and AMPL were significantly elevated for the trunk and pelvis, the lack of significant changes in LyE values suggests that greater movement magnitudes fail to improve temporal organization or adaptability (Harbourne & Stergiou, 2009; Stergiou & Decker, 2011). This disparity highlights the value of integrating linear and non-linear metrics to uncover maladaptive strategies that static measures alone might overlook (Hadamus et al., 2022; Karimi et al., 2021).

The LL findings further support these interpretations. Hip FLE in the swing limb emerged as a prominent compensatory strategy to achieve foot clearance in response to reduced dorsiflexor strength or impaired motor control (Mizuta et al., 2022). While overactivation of the hip flexors ensures temporary clearance, it delays weight transfer, reducing efficiency during GI (Hsiao et al., 2020; Lanza & Gray, 2022; MacKinnon, 2018). Significant increases in MDISP and AMPL at the hip and ankle reflect exaggerated movements that aim to mitigate instability but may further compromise efficiency (Matsuda et al., 2017; Montané et al., 2023).

Non-linear measures further illustrate impaired dynamic control. Reduced convergence (less negative LyE) in POS for the hip and ankle highlights limited adaptability during weight shifts (Gow et al., 2015). In the knee, LyE variability—with convergence in the swing limb and divergence in the stance limb—suggests proximal-distal imbalances in control strategies (Yiou et al., 2017). Reduced MSE across all joints underscores reliance on rigid motor strategies, with significant reductions in hip POS MSE during the swing phase (S2 and CI) emphasizing its critical role in weight transfer and propulsion (Awad et al., 2020). Similarly, the knee's reduced movement complexity indicates limited adaptability to perturbations during the stance transition phase (Celestino et al., 2021). These findings align with those who identified reduced adaptability as a hallmark of post-stroke neuromotor impairments (Kempski et al., 2018; Stergiou, 2016).

For the ULs, reduced LyE convergence across all joints suggests subtle postural instability not captured by static measures (Mallo-López et al., 2024). Increased TDISPL in the shoulder during both the swing and stance phases highlights its compensatory role in redistributing the COM to maintain postural stability (Harbourne & Kamm, 2015). The elevated MDISP and AMPL in the shoulder and wrist during the swing limb reflect coordinated adjustments across proximal and distal segments (Phan et al., 2022). However, divergent LyE values for wrist DISP and reduced MSE in shoulder DISP point to poor synchronization and limited adaptability, indicative of rigid, stereotyped motor strategies (McPherson & Dewald, 2022; Winter et al., 2023). Further reductions in wrist POS (CI) and shoulder DISP (S1, S2, CI) underscore the exaggerated yet inefficient nature of these compensations. The shoulder often acts as a stabilizer to counter trunk and LL instabilities, while the wrist attempts to compensate for fine motor deficits (Jayasinghe et al., 2021; Zhou et al., 2021). These findings are consistent with research linking rigid UL motor strategies to impaired anticipatory PC and dynamic postural stability (139, 140).

4.2.2 Frontal Plane

In the frontal plane (Figure 12), the stroke group demonstrated tenuous compensatory mechanisms, reflected in increased tilt tendencies of the head, trunk, and pelvis, despite non-significant POS differences. Amplified TDISPL, MDISP, and AMPL values in the head and trunk highlight exaggerated lateral movements aimed at redistributing the COM and stabilizing the body. These findings align with evidence linking excessive lateral trunk tilts to impaired hip abductor strength on the stance limb, which disrupts smooth weight transitions and increases instability during dynamic tasks (Lanza & Gray, 2022). The trunk plays a dual role in such tasks, serving as both a stabiliser and an active participant in postural adjustments, particularly when thresholds of PC are exceeded (Van Crielinge et al., 2017; Van Crielinge et al., 2019).

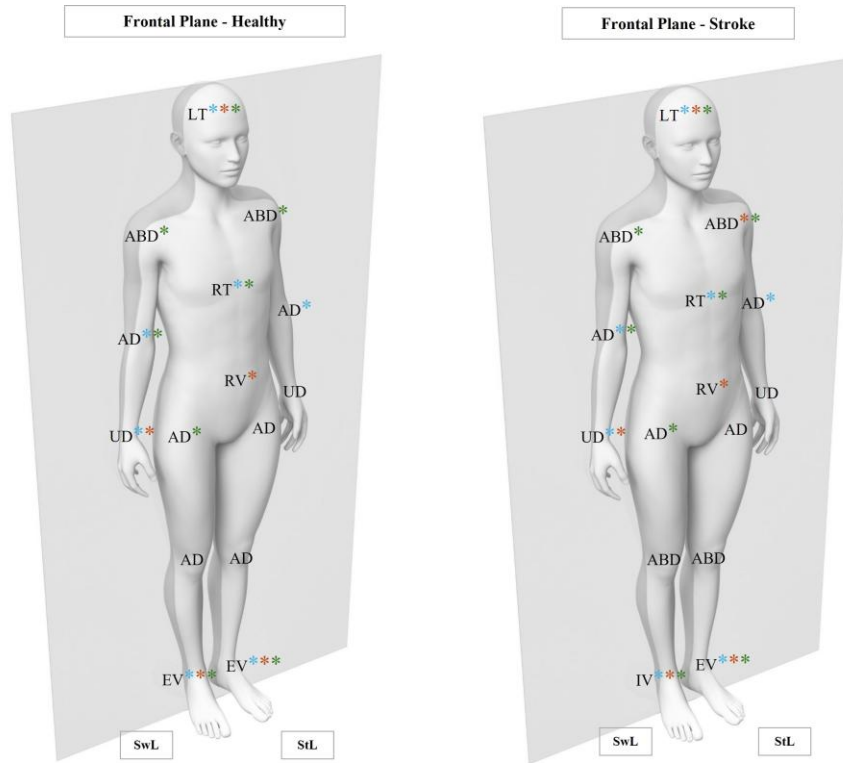


Figure 12. Significant results of linear and non-linear joints analysis in frontal plane, between healthy and stroke groups. LT: left tilt; ABD: abduction; AD: adduction; UD: ulnar deviation; IV: inversion; EV: eversion; SwL: swing limb; StL: stance limb; *: significant linear differences; *: significant LyE differences; *: significant MSE differences.

Non-linear measures provide deeper insights into these compensatory challenges. Reduced LyE values for head and pelvis POS suggest impaired stabilization and adaptability during lateral weight transfers, with trends toward less divergent LyE in pelvis MDISP indicating reliance on rigid, biomechanically limited strategies (Moreno et al., 2022). Significant reductions in MSE across S1, S2, and CI for head POS, DISP, and trunk DISP highlight constrained adaptability and a diminished capacity for fine-tuned adjustments during ML tasks (Chen et al., 2021; Leteneur et al., 2013). For the trunk, reduced POS MSE across all time scales further emphasizes its limited ability to execute precise lateral adjustments, resulting in exaggerated movements (De Luca et al., 2020).

For the LLs, increased TDISPL, MDISP, and AMPL at the ankle suggest compensatory reliance on distal segments to counteract proximal instability. Reduced LyE convergence at the ankle highlights impaired dynamic control, while variability in LyE patterns at the knee—convergent during swing and divergent during stance—reflects

shifts between proximal stabilization and distal adjustments based on individual impairments (Caderby et al., 2017; Yiou et al., 2017). MSE reductions in hip POS and DISP during swing (S1, S2, CI) and in ankle POS (S2, CI) further indicate limited adaptability during lateral weight transfers, compromising dynamic stability (Busa & van Emmerik, 2016).

Regarding the ULs, increased MDISP and AMPL in the elbow and wrist during the swing limb reflect compensatory adjustments involving both proximal and distal UL segments. These amplified movements indicate efforts to stabilise the COM and manage postural instability during lateral weight shifts. The increased reliance on distal segments, such as the wrist, underscores broader deficits in proximal stability and PC (Guo et al., 2020; Phan et al., 2022; Tomita et al., 2024). Non-linear measures reveal control deficits, with reduced LyE convergence for wrist POS in stance indicating inefficient distal control and divergent LyE values for wrist DISP in swing highlighting poor synchronization between distal and proximal UL segments. These findings align with evidence that compensatory trunk movements often offset deficits in UL stability and motor control (Michaelson et al., 2006). MSE results further reinforce these adaptability limitations, showing significant reductions in shoulder POS MSE (S2, CI) and elbow POS MSE (CI), which indicate constrained control across temporal scales (Bisi & Stagni, 2018). These results emphasize the interdependence of proximal and distal UL segments, where the shoulder compensates as a stabilizer for deficits in dynamic PC (Yang et al., 2019).

4.2.3 Transverse Plane

In the transverse plane (Figure 13), the exaggerated rotational patterns observed in the stroke group—reflected by increased TDISPL, MDISP, and AMPL values—likely represent compensatory strategies to stabilize the COM during dynamic tasks (Jayasinghe et al., 2021). However, these rotations appear to occur at the expense of segmental coordination, potentially exacerbating instability during weight transfers (Karthikbabu et al., 2012; Li et al., 2018). Similar findings have been reported in studies where excessive rotational movements were linked to impaired intersegmental control and reduced neuromuscular adaptability in stroke survivors (Shin et al., 2021; Yiou et al., 2017). Greater pelvic rotations, combined with increased head and trunk excursions,

interfere with the smooth transfer of forces during ML stability tasks (Choi et al., 2020; Dubey et al., 2018). While such adjustments may temporarily enhance CoP stability, they compromise biomechanical alignment, increase energy expenditure, and hinder optimal lower limb alignment and forward progression during GI (Onuma et al., 2021). Non-linear measures revealed deficits in dynamic stability across multiple segments. Reduced convergence, as indicated by less negative LyE values for pelvis POS, reflects impaired stabilization during lateral weight transfers, while trends in pelvis MDISP suggest a reliance on rigid control strategies, limiting adaptability in rotational movements. Significant reductions in MSE across S1, S2, and CI for head, trunk, and pelvis POS and DISP underscore constrained adaptability and a reliance on stereotyped motor strategies to maintain stability during perturbations. These limitations in force distribution between the trunk and lower limbs during dynamic transitions exacerbate instability during weight shifts.

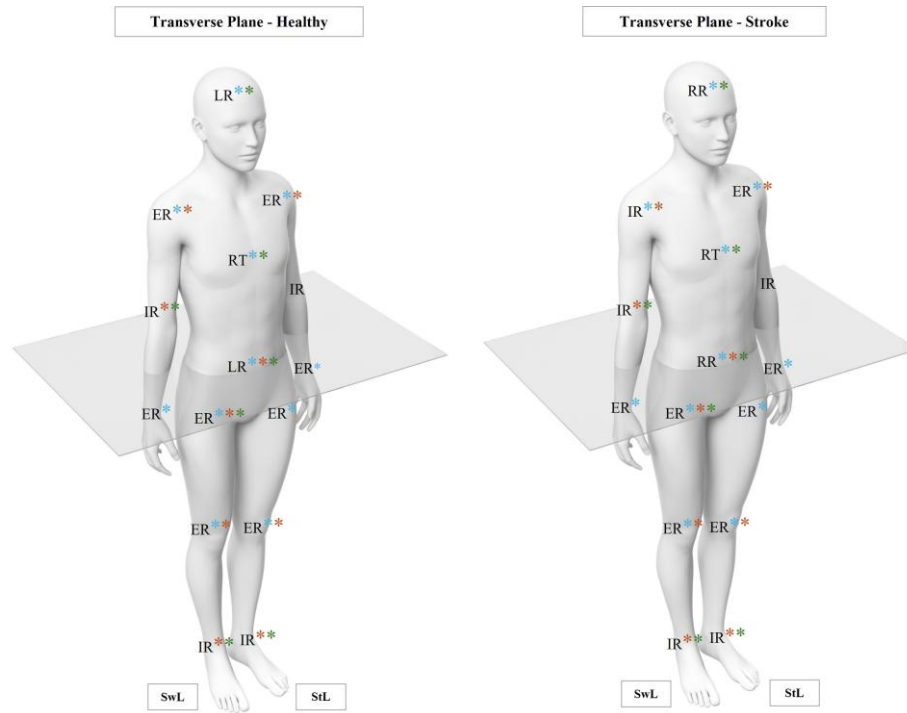


Figure 13. Significant results of linear and non-linear joints analysis in transverse plane, between healthy and stroke groups. LR: left rotation; RR: right rotation; ER: external rotation; IR: internal rotation; SwL: swing limb; StL: stance limb; *: significant linear differences; *: significant LyE differences; *: significant MSE differences.

In the LLs, exaggerated rotational displacements at the hip and knee, evidenced by increased TDISPL, MDISP, and AMPL, highlight compensatory strategies to counteract reduced trunk and pelvic control. These findings align with Yiou et al. (Yiou et al., 2017), suggesting that stroke survivors rely on rotational adjustments to address proximal instability during GI. Non-linear measures further reveal dynamic control deficits (M. Freitas et al., 2024; Kempinski et al., 2018), with reduced convergence in LyE for hip, knee, and ankle POS and DISP, particularly in the hip (swing limb) and ankle (both limbs). Variability in LyE at the knee—converging during the swing phase and diverging in stance—reflects heterogeneous strategies balancing proximal stabilization at the hip and distal adjustments at the knee and ankle (Xu et al., 2022). MSE findings reinforce these challenges, with significant reductions in hip POS and DISP at CI during the swing limb, highlighting limited adaptability during rotational weight shifts. Similarly, reduced ankle POS MSE across S1, S2, and CI underscores its compromised ability to provide a stable base during stance and adjust to dynamic demands in swing (Wu et al., 2019).

Significant POS differences in the shoulder (swing limb) and wrist (both limbs) highlight the active involvement of proximal and distal UL segments to manage postural instability. Increased MDISP and AMPL in the elbow and wrist during the swing limb reflect compensatory adjustments to redistribute the COM, though these amplified movements underscore inefficiencies in UL coordination, likely due to impaired trunk integration (Goh et al., 2015; Shaikh et al., 2014). Non-linear measures reinforce these deficits, with reduced LyE convergence in POS and DISP across the shoulder, elbow, and wrist, alongside divergent LyE values for the wrist during both swing and stance phases. These findings indicate poor segmental coordination and distal control deficits (Stergiou & Decker, 2011)(Stergiou & Decker, 2011). MSE reductions in elbow POS across S1, S2, and CI during the swing limb further highlight constrained adaptability, restricting synchronization with other segments and dynamic adjustment to rotational demands (Okita et al., 2024).

Finally, the interdependence of the head, trunk, pelvis, and limb segments reinforce the systemic nature of post-stroke impairments. Neuromotor deficits disrupt the natural biomechanical interplay, leading to asymmetry and exaggerated compensatory movements (Ding et al., 2024). These findings underscore the importance of combining

linear and non-linear analyses to capture the cascading effects of these strategies on stability and motor control, offering critical insights for developing targeted and effective rehabilitation approaches (Stergiou & Decker, 2011).

4.3 Multidimensional Postural Control: Neurobiomechanical Integration of Findings

The persistence of post-stroke PC dysfunction can be partially attributed to disruptions in both structural and functional pathways in the brain. These disruptions often result in an imbalance between the dorsolateral and ventromedial systems (Lefebvre & Liew, 2017), leading to impaired voluntary movement, particularly on the contralesional side, as well as bilateral PC deficits, with a predominant impact on the ipsilesional side (Seo & Koo, 2023; Yoo et al., 2023). In this study, all participants had lesions in the MCA territory, the most affected area after a stroke (Deuschl et al., 2020). Such lesions may disrupt the neuronal flow between motor area 6 (including the premotor cortex and supplementary motor area, among others) and the reticular formation, particularly the corticoreticular (CRS) and corticospinal (CSS) systems (Shumway-Cook & Woollacott, 2017). This disruption impairs the neuronal networks responsible for the interaction between CoP control and joint amplitude regulation (Rothwell, 2012; Takakusaki, 2017), as reflected in the findings of this study.

Clinical assessments, such as the Mini-BESTest and FMA-LL, revealed significant impairments in both anticipatory and reactive PC, as well as motor function. These findings align with biomechanical evidence of altered CoP dynamics and joint amplitudes during GI. Although no formal correlation analysis between clinical and biomechanical measures has been conducted, the consistent relationship between lower clinical scores and impaired biomechanical performance underscores the interdependence of neural, motor, and postural systems (Horak, 2006; Mancini & Horak, 2010).

The CRS system provides a structural and functional link between the cerebral cortex and the spinal cord, playing a critical role in CoP control by generating APAs essential for stabilizing the COM in anticipation of movement (Jang & Lee, 2019). Dysfunction in the CRS appears to compromise CoP stability, particularly in the ML direction, as evidenced by increased CoP magnitude of variation, lower LyE, and reduced MSE.

These findings reflect limited neuromuscular flexibility and a reliance on rigid compensatory strategies (Stergiou, 2016).

Similarly, the CSS, which also originates in motor area 6, is vital for precise movement execution, particularly in distal functions (Jang & Lee, 2019; Rosch & Mostofsky, 2019). The shared cortical origin of the CRS and CSS explains the observed interdependence between posture and movement (Asan et al., 2021; Tsai et al., 2018). Injuries affecting these pathways lead to irregular joint amplitudes, exaggerated FLE-EXT movements in the sagittal plane, and amplified rotational patterns in the transverse plane, further highlighting impaired segmental coordination (Levin, 2016). These dysfunctions compel compensatory reliance on proximal joint movements (Foysal & Baker, 2019), resulting in inefficient and exaggerated biomechanical patterns during GI.

Although the VSS is primarily associated with brainstem function, MCA lesions indirectly affect its role in PC by disrupting cortical regions such as the premotor cortex, SMA, and posterior parietal cortex (Takakusaki, 2017). These areas integrate vestibular, somatosensory, and visual inputs essential for postural stability (Lundy-Ekman & Weyer, 2022). The interactions between the CRS, CSS, and VSS play a critical role in modulating reflexive and anticipatory postural adjustments. Disruptions in these pathways destabilize the COM and impair segmental coordination (Takakusaki, 2017). Compensatory reliance on the VSS during dynamic tasks like GI often exposes its limitations, further exacerbating postural instability. This is compounded by anterior displacement of the head's COM, frequently observed in stroke survivors, which disrupts biomechanical alignment and increases reliance on compensatory flexor musculature (Levin, 2016; Lundy-Ekman & Weyer, 2022).

Ultimately, the shared neural circuitry of posture and movement highlights the interdependence between CoP dynamics and joint amplitude control (Jang & Lee, 2019; Le Mouel & Brette, 2017). Motor area 6, encompassing the SMA and premotor cortex, serves as a central hub for coordinating postural adjustments and voluntary movements (Takakusaki, 2017). Dysfunction in these regions delays APAs and impairs multi-joint coordination, increasing reliance on reactive adjustments and limiting dynamic movement range (Levin, 2016). These deficits manifest as increased CoP and joint variability, reduced stability, and diminished complexity across all planes.

4.4 Clinical Relevance

From a clinical perspective, the primary focus of rehabilitation should be on improving PC and enhancing the motor system's adaptability to dynamic demands (Altenburger et al., 2023). Deficits in stability and adaptability, commonly observed in stroke survivors, highlight the need for targeted interventions addressing lateral stability during transitions such as GI and intersegmental coordination during complex tasks (Halmi et al., 2020). The inability to effectively adjust to dynamic postural demands often results in compensatory motor strategies that, while stabilizing in the short term, limit flexibility and increase the risk of falls and functional limitations (Tasseel-Ponche et al., 2015).

Rehabilitation based on linear approaches, traditionally aimed to reduce instability or variability, playing a key role in addressing immediate biomechanical impairments. These methods, which focus on minimizing CoP displacement, improving joint ROM, or increasing muscle strength, are effective for stabilizing the postural system (Hugues et al., 2019; Hugues et al., 2016; Kamijo et al., 2023; Shumway-Cook & Woollacott, 2017). However, their limitations become apparent when dealing with dynamic, real-world demands, as they may inadvertently reinforce rigid motor patterns (Latash, 2012; Stergiou & Decker, 2011; Stergiou et al., 2006).

In contrast, the intervention grounded on a non-linear approach emphasizes adaptability and flexibility, which are essential for functional recovery (Harbourne & Stergiou, 2009). These methods capture the dynamic organization of PC by promoting variability within functional limits, addressing the constrained dynamic range and impaired neuromuscular coordination commonly observed in stroke survivors. Rooted in dynamic systems theory, this approach considers movement and PC as emergent properties arising from interactions between the individual, task, and environment (Altenburger et al., 2023; Stergiou & Decker, 2011). By targeting the interdependence of sensory, motor, and cognitive subsystems, these interventions focus on system-wide complexity and adaptability rather than isolated deficits (Altenburger et al., 2023). It fosters long-term resilience, enabling the motor system to effectively respond to dynamic and unpredictable environments, instead of merely optimizing performance under static or controlled conditions (Hristovski et al., 2012; Stergiou & Decker, 2011).

By integrating linear and non-linear approaches, clinicians can create a comprehensive framework for intervention. Linear strategies are essential for addressing immediate biomechanical impairments, while non-linear methods target the adaptability and flexibility required for functional recovery. Together, these complementary approaches provide a robust foundation for improving both stability and adaptability in stroke survivors, supporting long-term functional outcomes (Altenburger et al., 2023).

4.5 Limitations and Future Directions

This study has specific limitations that should be considered when interpreting the findings. First, the small convenience sample may limit the generalizability of findings to the broader stroke population. Second, the cross-sectional design prevents causal inferences regarding the relationship between observed differences and postural control impairments. Longitudinal studies are needed to examine the progression of these impairments and the effects of targeted rehabilitation interventions.

The MSE analysis, while methodologically robust, was limited to two scales, providing insights into short-term variability but potentially missing broader multiscale dynamics. Future studies should include larger datasets to explore higher scales, enabling a more detailed analysis of system complexity over longer time intervals.

Although both linear and nonlinear measures were used, the absence of neurophysiological data (e.g., muscle activation or cortical activity) limits the understanding of mechanisms underlying motor control strategies. Integrating such measures in future research could provide a more holistic perspective on postural control dysfunctions.

Future directions include conducting longitudinal studies to assess the progression of impairments and the effectiveness of interventions, expanding analyses to other functional tasks (e.g., sit-to-stand), and exploring dynamic conditions such as dual tasks or unpredictable environments. Multivariate analyses could clarify how kinematic variables influence CoP variability, while correlations between clinical assessments and biomechanical data could enhance translational impact. Additionally, principal component analysis (PCA) could simplify complex datasets and identify compensatory mechanisms in post-stroke individuals.

5. Conclusion

This study analysed the complexity and variability of postural control in post-stroke individuals during the feedforward phase of gait initiation, integrating linear and non-linear measures of CoP dynamics and joint amplitude variations. Stroke survivors demonstrated increased CoP displacement and reduced velocity, reflecting instability, and diminished adaptability, as highlighted by reduced complexity in non-linear measures. Augmented joint amplitudes across all planes, particularly sagittal and transverse, revealed inefficient compensatory mechanisms that disrupt coordination.

Supplementary Data

Supplementary data to this article can be found in Appendix IV.

6. References

- Aghaie Ataabadi, P., Sarvestan, J., Alaei, F., Yazdanbakhsh, F., & Abbasi, A. (2021). Linear and non-linear analysis of lower limb joints angle variability during running at different speeds. *Acta Gymnica*, 51, 1-6. <https://doi.org/10.5507/ag.2021.023>
- Altenburger, P., Ambike, S. S., & Haddad, J. M. (2023). Integrating Motor Variability Evaluation Into Movement System Assessment. *Phys Ther*, 103(10). <https://doi.org/10.1093/ptj/pzad075>
- An, H., & Park, S.-J. (2021). Effects of Cervical Spine Mobilization on Respiratory Function and Cervical Angles of Stroke Patients: A Pilot Study. *Healthcare*, 9. <https://doi.org/10.3390/healthcare9040377>
- Andreasen, S. C., Wright, T. R., Crenshaw, J. R., Reisman, D. S., & Knarr, B. A. (2020). Relationships of Linear and Non-linear Measurements of Post-stroke Walking Activity and Their Relationship to Weather. *Front Sports Act Living*, 2, 1-9. <https://doi.org/10.3389/fspor.2020.551542>
- Asan, A. S., McIntosh, J. R., & Carmel, J. B. (2021). Targeting Sensory and Motor Integration for Recovery of Movement After CNS Injury. *Front Neurosci*, 1-17. <https://doi.org/10.3389/fnins.2021.791824>
- Awad, L. N., Lewek, M. D., Kesar, T. M., Franz, J. R., & Bowden, M. G. (2020). These legs were made for propulsion: advancing the diagnosis and treatment of post-stroke propulsion deficits. *J Neuroeng Rehabil*, 17(1), 1-16. <https://doi.org/10.1186/s12984-020-00747-6>
- Beyaert, C., Vasa, R., & Frykberg, G. E. (2015). Gait post-stroke: Pathophysiology and rehabilitation strategies. *Neurophysiol Clin*, 45(4), 335-355. <https://doi.org/https://doi.org/10.1016/j.neucli.2015.09.005>
- Biryukova, E., & Sirotkina, I. (2020). Forward to Bernstein: Movement Complexity as a New Frontier. *Front Neurosci*, 14, 1-17. <https://doi.org/10.3389/fnins.2020.00553>
- Bisi, M. C., & Stagni, R. (2018). Changes of human movement complexity during maturation: quantitative assessment using multiscale entropy. *Comput Methods Biomech Biomed Engin*, 21(4), 325-331. <https://doi.org/10.1080/10255842.2018.1448392>

- Broomhead, D. S., & King, G. P. (1986). Extracting qualitative dynamics from experimental data. *Physica D: Nonlinear Phenomena*, 20(2), 217-236. [https://doi.org/https://doi.org/10.1016/0167-2789\(86\)90031-X](https://doi.org/https://doi.org/10.1016/0167-2789(86)90031-X)
- Busa, M. A., & van Emmerik, R. E. A. (2016). Multiscale entropy: A tool for understanding the complexity of postural control. *J Sport Health Sci*, 5(1), 44-51. <https://doi.org/10.1016/j.jshs.2016.01.018>
- Caballero, C., Barbado, D., & Moreno, F. (2014). Non-linear tools and methodological concerns measuring human movement variability: an overview. *Eur J Hum Mov*, 32, 61-81.
- Cabanas-Valdés, R., Boix-Sala, L., Grau-Pellicer, M., Guzmán-Bernal, J. A., Caballero-Gómez, F. M., & Urrútia, G. (2021). The Effectiveness of Additional Core Stability Exercises in Improving Dynamic Sitting Balance, Gait and Functional Rehabilitation for Subacute Stroke Patients (CORE-Trial): Study Protocol for a Randomized Controlled Trial. *Int J Environ Res Public Health*, 18(12), 1-17. <https://doi.org/10.3390/ijerph18126615>
- Caderby, T., Yiou, E., Peyrot, N., de Viviés, X., Bonazzi, B., & Dalleau, G. (2017). Effects of Changing Body Weight Distribution on Mediolateral Stability Control during Gait Initiation [Original Research]. *Front Hum Neurosci*, 11, 1-12. <https://doi.org/10.3389/fnhum.2017.00127>
- Caesarendra, W., Kosasih, B., Tieu, K., & Moodie, C. A. (2013). An application of nonlinear feature extraction-A case study for low speed slewing bearing condition monitoring and prognosis 2013 IEEE/ASME International Conference on Advanced Intelligent Mechatronics,
- Campaniço, H. (2016). Validade simultânea do questionário internacional de atividade física através da medição objetiva da atividade física por actigrafia proporcional. Universidade de Lisboa, Faculdade de Motricidade Humana]. Lisboa.
- Cappozzo, A., Catani, F., Della Croce, U., & Leardini, A. (1995). Position and orientation in space of bones during movement: anatomical frame definition and determination. *Clin Biomech*, 10(4), 171-178. [https://doi.org/https://doi.org/10.1016/0268-0033\(95\)91394-T](https://doi.org/https://doi.org/10.1016/0268-0033(95)91394-T)

- Celestino, M., Van Emmerik, R., Barela, J., Bacca, O., & Barela, A. (2021). Effects of limited knee flexion movement in intra-limb gait coordination. *J Biomech*, 128, 1-6. <https://doi.org/10.1016/j.jbiomech.2021.110712>
- Chen, A., Selvaraj, S., Krishnan, V., & Asgari, S. (2019). Accuracy and Reliability of Onset Detection Algorithms in Gait Initiation for Healthy Controls and Participants With Parkinson's Disease. *J Appl Biomech*, 35(6), 393–400. <https://doi.org/10.1123/jab.2018-0431>
- Chen, F.-C., Chu, C.-H., Pan, C.-Y., & Tsai, C.-L. (2018). Not just a light fingertip touch: A facilitation of functional integration between body sway and visual search in older adults. *Gait & Posture*, 62, 105-110. <https://doi.org/https://doi.org/10.1016/j.gaitpost.2018.03.018>
- Chen, P.-W., Baune, N., Zwir, I., Wang, J., Swamidass, V., & Wong, A. (2021). Measuring Activities of Daily Living in Stroke Patients with Motion Machine Learning Algorithms: A Pilot Study. *Int J Environ Res Public Health*, 18, 1-16. <https://doi.org/10.3390/ijerph18041634>
- Choi, Y.-H., Kim, N.-H., Son, S., & Cha, Y. (2020). Effects of Trunk Stabilization Exercise While Wearing a Pelvic Compression Belt on Walking and Balancing Abilities in Patients With Stroke. *Am J Phys Med Rehabil*, 99, 1048-1055. <https://doi.org/10.1097/PHM.0000000000001484>
- Committee, I. R. (2005). IPAQ Research Committee. Guidelines for Data Processing and Analysis of the International Physical Activity Questionnaire (IPAQ) – Short and Long Forms.
- Costa, M., Goldberger, A., & Peng, C.-K. (2002). Multiscale entropy analysis of complex physiologic time series. *Phys Rev Lett.*, 89(6), 705-708. <https://doi.org/10.1103/PHYSREVLETT.89.068102>
- Costa, M. D., & Goldberger, A. L. (2015). Generalized Multiscale Entropy Analysis: Application to Quantifying the Complex Volatility of Human Heartbeat Time Series. *Entropy*, 17(3), 1197-1203. <https://doi.org/10.3390/e17031197>
- Costa, S. V. (2003). Adaptação e Validação Cultural e Linguística do Fugl-Meyer Assessment of Sensorimotor Recovery after Stroke Escola Superior de Tecnologia da Saúde de Coimbra]. Coimbra, Portugal.

- Couto, A. G. B., Vaz, M. A. P., Pinho, L., Félix, J., Moreira, J., Pinho, F., Mesquita, I. A., Mesquita Montes, A., Crasto, C., & Sousa, A. S. P. (2024). Interlimb Coordination during Double Support Phase of Gait in People with and without Stroke. *J Mot Behav*, 56(2), 195-210. <https://doi.org/10.1080/00222895.2023.2282088>
- Craig, C. L., Marshall, A. L., Sjöström, M., Bauman, A. E., Booth, M. L., Ainsworth, B. E., Pratt, M., Ekelund, U. L. F., Yngve, A., Sallis, J. F., & Oja, P. (2003). International Physical Activity Questionnaire: 12-Country Reliability and Validity. *Med Sci Sports Exerc*, 35(8), 1381-1395. <https://doi.org/10.1249/01.MSS.0000078924.61453.FB>
- Curuk, E., & Aruin, A. S. (2022). Perturbation-based training enhances anticipatory postural control in individuals with chronic stroke: a pilot study. *Int J Rehabil Res*, 45(1), 72-78. <https://doi.org/10.1097/mrr.0000000000000515>
- Darak, V., & Karthikbabu, S. (2020). Lower limb motor function and hip muscle weakness in stroke survivors and their relationship with pelvic tilt, weight-bearing asymmetry, and gait speed: A cross-sectional study. *Curr J Neurol*, 19(1), 1-7. <https://doi.org/10.18502/ijnl.v19i1.3275>
- De Luca, A., Squeri, V., Barone, L. M., Verneti Mansin, H., Ricci, S., Pisu, I., Cassiano, C., Capra, C., Lentino, C., De Michieli, L., Sanfilippo, C. A., Saglia, J. A., & Checchia, G. A. (2020). Dynamic Stability and Trunk Control Improvements Following Robotic Balance and Core Stability Training in Chronic Stroke Survivors: A Pilot Study. *Front Neurol*, 11, 494. <https://doi.org/10.3389/fneur.2020.00494>
- Delafontaine, A., Vialleron, T., Hussein, T., Yiou, E., Honeine, J.-L., & Colnaghi, S. (2019). Anticipatory Postural Adjustments During Gait Initiation in Stroke Patients. *Front Neurol*, 10, 1-13. <https://doi.org/10.3389/fneur.2019.00352>
- Derrick, T. R., van den Bogert, A. J., Cereatti, A., Dumas, R., Fantozzi, S., & Leardini, A. (2020). ISB recommendations on the reporting of intersegmental forces and moments during human motion analysis. *J Biomech*, 99, 1-10. <https://doi.org/https://doi.org/10.1016/j.jbiomech.2019.109533>
- Deuschl, G., Beghi, E., Fazekas, F., Varga, T., Christoforidi, K. A., Sipido, E., Bassetti, C. L., Vos, T., & Feigin, V. L. (2020). The burden of neurological diseases in

- Europe: an analysis for the Global Burden of Disease Study 2017. *Lancet Public Health*, 5(10), e551-e567. [https://doi.org/10.1016/s2468-2667\(20\)30190-0](https://doi.org/10.1016/s2468-2667(20)30190-0)
- Ding, K., Wang, J., Wang, X., Zhou, L., Xiong, D., & Guo, L. (2024). System for Detection and Quantitative Evaluation of Compensatory Movement in Post-Stroke Patients Based on Wearable Sensor and Machine Learning Algorithm. *IEEE Sensors Journal*, 24, 22830-22842. <https://doi.org/10.1109/JSEN.2024.3408323>
- Djurovic, O., Mihaljevic, O., Radovanovic, S., Kostic, S., Vukicevic, M., Brkic, B. G., Stankovic, S., Radulovic, D., Vukomanovic, I. S., & Radevic, S. R. (2021). Risk Factors Related to Falling in Patients after Stroke. *Iran J Public Health*, 50(9), 1832-1841. <https://doi.org/10.18502/ijph.v50i9.7056>
- Dubey, L., Karthikbabu, S., & Mohan, D. (2018). Effects of Pelvic Stability Training on Movement Control, Hip Muscles Strength, Walking Speed and Daily Activities after Stroke: A Randomized Controlled Trial. *Annals of neurosciences*, 25(2), 80-89. <https://doi.org/10.1159/000486273>
- Duncan, P. W., Propst, M., & Nelson, S. G. (1983). Reliability of the Fugl-Meyer assessment of sensorimotor recovery following cerebrovascular accident. *Physical Therapy*, 63 10, 1606-1610.
- Farinelli, V., Bolzoni, F., Marchese, S. M., Esposti, R., & Cavallari, P. (2021). A Novel Viewpoint on the Anticipatory Postural Adjustments During Gait Initiation. *Front Hum Neurosci*, 15, 1-10. <https://doi.org/10.3389/fnhum.2021.709780>
- Fernandes, Â., Sousa, A. S. P., Rocha, N., & Tavares, J. (2017). The Influence of a Cognitive Task on the Postural Phase of Gait Initiation in Parkinson's Disease: An Electromyographic-Based Analysis. *Mot Control*, 21(3), 249-264. <https://doi.org/10.1123/mc.2015-0032>
- Fettrow, T., Reimann, H., Grenet, D., Thompson, E., Crenshaw, J., Higginson, J., & Jeka, J. (2019). Interdependence of balance mechanisms during bipedal locomotion. *PLoS One*, 14(12), e0225902. <https://doi.org/10.1371/journal.pone.0225902>
- Foysal, K. M. R., & Baker, S. N. (2019). A hierarchy of corticospinal plasticity in human hand and forearm muscles. *J Physiol*, 597(10), 2729-2739. <https://doi.org/10.1113/jp277462>

- Franchignoni, F., Horak, F., Godi, M., Nardone, A., & Giordano, A. (2010). Using psychometric techniques to improve the Balance Evaluation Systems Test: the mini-BESTest. *J Rehabil Med*, 42(4), 323-331. <https://doi.org/10.2340/16501977-0537>
- Freitas, M., Pinho, F., Pinho, L., Silva, S., Figueira, V., Vilas-Boas, J. P., & Silva, A. (2024). Biomechanical Assessment Methods Used in Chronic Stroke: A Scoping Review of Non-Linear Approaches. *Sensors*, 24(7), 2338. <https://doi.org/10.3390/s24072338>
- Gama, G. L., Celestino, M. L., Barela, J. A., & Barela, A. M. F. (2019). Gait initiation and partial body weight unloading for functional improvement in post-stroke individuals. *Gait Posture*, 68, 305-310. <https://doi.org/10.1016/j.gaitpost.2018.12.008>
- Gandolfi, M., Valè, N., Dimitrova, E., Zanolin, M. E., Mattiuz, N., Battistuzzi, E., Beccari, M., Geroin, C., Picelli, A., Waldner, A., & Smania, N. (2019). Robot-Assisted Stair Climbing Training on Postural Control and Sensory Integration Processes in Chronic Post-stroke Patients: A Randomized Controlled Clinical Trial. *Front Neurosci*, 13, 1143. <https://doi.org/10.3389/fnins.2019.01143>
- Ghamari, N., Ghaderpanah, R., Sadrian, S. H., & Fallah, N. (2023). Effect of a visual dual task on postural stability-A comparative study using linear and nonlinear methods. *Health Sci Rep*, 6(8), e1437. <https://doi.org/10.1002/hsr2.1437>
- Ghomashchi, H. (2016). Investigating the effects of visual biofeedback therapy on recovery of postural balance in stroke patients using a complexity measure. *Top Stroke Rehabil*, 23(3), 178-183. <https://doi.org/10.1080/10749357.2015.1122311>
- Gill-Body, K. M., Hedman, L. D., Plummer, L., Wolf, L., Hanke, T., Quinn, L., Riley, N., Kaufman, R., Verma, A., Quiben, M., & Scheets, P. (2021). Movement System Diagnoses for Balance Dysfunction: Recommendations From the Academy of Neurologic Physical Therapy's Movement System Task Force. *Phys Ther*, 101(9). <https://doi.org/10.1093/ptj/pzab153>
- Goh, S., Han, K., Ryu, J., Kim, S., & Choi, M. (2015). Failure of Arm Movement Control in Stroke Patients, Characterized by Loss of Complexity. *PLoS One*, 10(11), e0141996. <https://doi.org/10.1371/journal.pone.0141996>

- Goldberger, A. L., Amaral, L. A., Glass, L., Hausdorff, J. M., Ivanov, P. C., Mark, R. G., Mietus, J. E., Moody, G. B., Peng, C. K., & Stanley, H. E. (2000). PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals. *Circulation*, 101(23), E215-220. <https://doi.org/10.1161/01.cir.101.23.e215>
- Gow, B. J., Peng, C.-K., Wayne, P. M., & Ahn, A. C. (2015). Multiscale Entropy Analysis of Center-of-Pressure Dynamics in Human Postural Control: Methodological Considerations. *Entropy*, 17(12), 7926-7947. <https://www.mdpi.com/1099-4300/17/12/7849>
- Guerreiro, M., Silva, A. P., Botelho, M., Leitão, O., Castro-Caldas, A., & Garcia, C. (1994). Adaptação à população portuguesa da tradução do Mini Mental State Examination. *Rev Port Neurol*, 1-9.
- Guo, Z., Qian, Q., Wong, K., Zhu, H., Huang, Y., Hu, X., & Zheng, Y. (2020). Altered Corticomuscular Coherence (CMCoh) Pattern in the Upper Limb During Finger Movements After Stroke. *Front Neurol*, 11. <https://doi.org/10.3389/fneur.2020.00410>
- Hadamus, A., Błażkiewicz, M., Kowalska, A. J., Wydra, K. T., Grabowicz, M., Łukowicz, M., Białoszewski, D., & Marczyński, W. (2022). Nonlinear and Linear Measures in the Differentiation of Postural Control in Patients after Total Hip or Knee Replacement and Healthy Controls. *Diagnostics*, 12(7). <https://doi.org/10.3390/diagnostics12071595>
- Hadders-Algra, M. (2013). Typical and atypical development of reaching and postural control in infancy. *Dev Med Child Neurol*, 55 Suppl 4, 5-8. <https://doi.org/10.1111/dmcn.12298>
- Halmi, Z., Stone, T. W., Dinya, E., & Málly, J. (2020). Postural instability years after stroke. *J Stroke Cerebrovasc Dis*, 29(9). <https://doi.org/10.1016/j.jstrokecerebrovasdis.2020.105038>
- Harbourne, R., & Kamm, K. (2015). Upper extremity function: What's posture got to do with it? *J Hand Ther*, 28(2), 106-112. <https://doi.org/10.1016/j.jht.2015.01.008>
- Harbourne, R. T., Deffeyes, J. E., Kyvelidou, A., & Stergiou, N. (2009). Complexity of postural control in infants: linear and nonlinear features revealed by principal component analysis. *Nonlinear Dynamics Psychol Life Sci*, 13(1), 123-144.

- Harbourne, R. T., & Stergiou, N. (2009). Movement variability and the use of nonlinear tools: principles to guide physical therapist practice. *Phys Ther*, 89(3), 267-282. <https://doi.org/10.2522/ptj.20080130>
- Hong, S. Y., Moon, Y., & Choi, J. D. (2020). Effects of Cognitive Task Training on Dynamic Balance and Gait of Patients with Stroke: A Preliminary Randomized Controlled Study. *Med Sci Monit Basic Res*, 26, e925264. <https://doi.org/10.12659/msmbr.925264>
- Horak, F. B. (2006). Postural orientation and equilibrium: what do we need to know about neural control of balance to prevent falls? *Age Ageing*, 35, ii7-ii11. <https://doi.org/10.1093/ageing/afl077>
- Hristovski, R., Balagué, N., Daskalovski, B., Zivkovic, V., Velickovska, L., & Naumovski, M. (2012). Linear and nonlinear complex systems approach to sports. Explanatory differences and applications. *Research in Physical Education, Sport and Health*, 25-32.
- Hsiao, H., Gray, V., Borrelli, J., & Rogers, M. (2020). Biomechanical control of paretic lower limb during imposed weight transfer in individuals post-stroke. *J Neuroeng Rehabil*, 17, 140. <https://doi.org/10.1186/s12984-020-00768-1>
- Hua, A., Wang, G., Bai, J., Hao, Z., Liu, J., Meng, J., & Wang, J. (2024). Nonlinear dynamics of postural control system under visual-vestibular habituation balance practice: evidence from EEG, EMG and center of pressure signals. *Front Hum Neurosci*, 18, 1371648. <https://doi.org/10.3389/fnhum.2024.1371648>
- Hugues, A., Di Marco, J., Ribault, S., Ardaillon, H., Janiaud, P., Xue, Y., Zhu, J., Pires, J., Khademi, H., Rubio, L., Hernandez Bernal, P., Bahar, Y., Charvat, H., Szulc, P., Ciomas, C., Won, H., Cucherat, M., Bonan, I., Gueyffier, F., & Rode, G. (2019). Limited evidence of physical therapy on balance after stroke: A systematic review and meta-analysis. *PLoS One*, 14(8), e0221700. <https://doi.org/10.1371/journal.pone.0221700>
- Hugues, A., Marco, J., Janiaud, P., Bonan, I., Gueyffier, F., & Rode, G. (2016). Efficiency of physical rehabilitation on postural imbalance after stroke: Systematic review and meta-analysis. *Ann Rehabil Med*, 59, e67–e79. <https://doi.org/10.1016/j.rehab.2016.07.183>

- Isho, T., & Usuda, S. (2016). Association of trunk control with mobility performance and accelerometry-based gait characteristics in hemiparetic patients with subacute stroke. *Gait & Posture*, 44, 89-93. <https://doi.org/10.1016/j.gaitpost.2015.11.011>
- Jagroop, D., Aryan, R., Schinkel-Ivy, A., & Mansfield, A. (2022). Reliability of novel centre of pressure measures of quiet standing balance in people with chronic stroke.
- Jang, S. H., & Lee, S. J. (2019). Corticoreticular Tract in the Human Brain: A Mini Review. *Front Neurol*, 10, 1188. <https://doi.org/10.3389/fneur.2019.01188>
- Jayasinghe, S., Wang, R., Gebara, R., Biswas, S., & Ranganathan, R. (2021). Compensatory Trunk Movements in Naturalistic Reaching and Manipulation Tasks in Chronic Stroke Survivors. *J Appl Biomech*, 1-9. <https://doi.org/10.1123/jab.2020-0090>
- Jones, T. A. (2017). Motor compensation and its effects on neural reorganization after stroke. *Nat Rev Neurosci*, 18(5), 267-280. <https://doi.org/10.1038/nrn.2017.26>
- Kamijo, A., Furihata, C., Kimura, Y., Furuhashi, I., Ohtani, T., & Miyajima, T. (2023). Postural control exercise without using the upper limbs improves activities of daily living in patients with stroke. *Front Rehabil Sci*, 4, 1124515. <https://doi.org/10.3389/fresc.2023.1124515>
- Kanekar, N., & Aruin, A. S. (2015). Improvement of anticipatory postural adjustments for balance control: effect of a single training session. *J Electromyogr Kinesiol*, 25(2), 400-405. <https://doi.org/10.1016/j.jelekin.2014.11.002>
- Kang, N., Da Lee, R., Lee, J. H., & Hwang, M.-H. (2019). Functional Balance and Postural Control Improvements in Patients with Stroke after Non-Invasive Brain Stimulation: A Meta-Analysis. *Arch Phys Med Rehabil*, 101(1), 141-153. <https://doi.org/10.1016/j.apmr.2019.09.003>
- Karimi, Z., Mazloumi, A., Sharifnezhad, A., Jafari, A., Kazemi, Z., Keihani, A., & Mohebbi, I. (2021). Determining the interactions between postural variability structure and discomfort development using nonlinear analysis techniques during prolonged standing work. *Appl Ergon*, 96, 103489. <https://doi.org/10.1016/j.apergo.2021.103489>

- Karthikbabu, S., Chakrapani, M., Ganeshan, S., Rakshith, K. C., Nafeez, S., & Prem, V. (2012). A review on assessment and treatment of the trunk in stroke: A need or luxury. *Neural Regen Res*, 7(25), 1974-1977. <https://doi.org/10.3969/j.issn.1673-5374.2012.25.008>
- Kedziorek, J., & Blazkiewicz, M. (2020). Nonlinear Measures to Evaluate Upright Postural Stability: A Systematic Review. *Entropy*, 22(12), 1357. <https://doi.org/10.3390/e22121357>
- Kempski, K., Awad, L. N., Buchanan, T. S., Higginson, J. S., & Knarr, B. A. (2018). Dynamic structure of lower limb joint angles during walking post-stroke. *J Biomech*, 68, 1-5. <https://doi.org/10.1016/j.jbiomech.2017.12.019>
- Khanmohammadi, R., Talebian, S., Hadian, M. R., Olyaei, G., & Bagheri, H. (2016). Characteristic muscle activity patterns during gait initiation in the healthy younger and older adults. *Gait & Posture*, 43, 148-153. <https://doi.org/https://doi.org/10.1016/j.gaitpost.2015.09.014>
- Kilby, M. C., Molenaar, P. C. M., & Newell, K. M. (2015). Models of Postural Control: Shared Variance in Joint and COM Motions. *PLoS One*, 10(5), e0126379. <https://doi.org/10.1371/journal.pone.0126379>
- Kim, M. K., Kim, S. G., Shin, Y. J., Choi, E. H., & Choe, Y. W. (2018). The relationship between anterior pelvic tilt and gait, balance in patient with chronic stroke. *J Phys Ther Sci*, 30(1), 27-30. <https://doi.org/10.1589/jpts.30.27>
- Kleiner, A., Galli, M., Fern, P., Es, Rigoldi, C., Carmo, A., & Barros, R. (2015). Spontaneous Improvement in PosturalControl after Stroke: A LongitudinalProspective Study. *Int J Eng Sci Technol*, 4, 2705-2714. <https://doi.org/10.15680/IJIRSET.2015.0405008>
- Klous, M., Mikulic, P., & Latash, M. L. (2012). Early postural adjustments in preparation to whole-body voluntary sway. *J Electromyogr Kinesiol*, 22(1), 110-116. <https://doi.org/https://doi.org/10.1016/j.jelekin.2011.11.005>
- Koltermann, J. J., Floessel, P., Hammerschmidt, F., & Disch, A. C. (2023). The Influence of Anthropometric Variables and Filtering Frequency on Center of Pressure Data. *Sensors*, 23(11), 5105. <https://www.mdpi.com/1424-8220/23/11/5105>

- Kwakkel, G., Lannin, N. A., Borschmann, K., English, C., Ali, M., Churilov, L., Saposnik, G., Winstein, C., van Wegen, E. E., Wolf, S. L., Krakauer, J. W., & Bernhardt, J. (2017). Standardized measurement of sensorimotor recovery in stroke trials: Consensus-based core recommendations from the Stroke Recovery and Rehabilitation Roundtable. *Int J Stroke*, 12(5), 451-461. <https://doi.org/10.1177/1747493017711813>
- Kwong, P. W. H., & Ng, S. S. M. (2019). Cutoff Score of the Lower-Extremity Motor Subscale of Fugl-Meyer Assessment in Chronic Stroke Survivors: A Cross-Sectional Study. *Arch Phys Med Rehabil*, 100(9), 1782-1787. <https://doi.org/10.1016/j.apmr.2019.01.027>
- Lacour, M., Bernard-Demanze, L., & Dumitrescu, M. (2008). Posture control, aging, and attention resources: Models and posture-analysis methods. *Neurophysiol Clin*, 38(6), 411-421. <https://doi.org/https://doi.org/10.1016/j.neucli.2008.09.005>
- Lafage, R., Duvvuri, P., Elysee, J., Diebo, B., Bess, S., Burton, D., Daniels, A., Gupta, M., Hostin, R., Kebaish, K., Kelly, M., Kim, H.-J., Klineberg, E., Lenke, L., Lewis, S., Ames, C., Passias, P., Protosaltis, T., Shaffrey, C., . . . Lafage, V. (2023). Quantifying the Contribution of Lower Limb Compensation to Upright Posture. *Spine*, 48, 1082-1088. <https://doi.org/10.1097/BRS.0000000000004646>
- Lanza, M. B., & Gray, V. L. (2022). The effects of stroke on weight transfer before voluntary lateral and forward steps. *Front Neurol*, 13, 891439. <https://doi.org/10.3389/fneur.2022.891439>
- Latash, M. L. (2012). The bliss (not the problem) of motor abundance (not redundancy). *Exp Brain Res*, 217(1), 1-5. <https://doi.org/10.1007/s00221-012-3000-4>
- Latash, M. L., & Zatsiorsky, V. (2015). *Biomechanics and Motor Control: Defining Central Concepts*. Human Kinetics.
- Le Mouel, C., & Brette, R. (2017). Mobility as the Purpose of Postural Control [Hypothesis and Theory]. *Front Comput Neurosci*, 11, 67. <https://doi.org/10.3389/fncom.2017.00067>
- Leardini, A., Sawacha, Z., Paolini, G., Ingrosso, S., Nativio, R., & Benedetti, M. G. (2007). A new anatomically based protocol for gait analysis in children. *Gait & Posture*, 26(4), 560-571. <https://doi.org/https://doi.org/10.1016/j.gaitpost.2006.12.018>

- Lefebvre, S., & Liew, S. L. (2017). Anatomical Parameters of tDCS to Modulate the Motor System after Stroke: A Review. *Front Neurol*, 8, 29. <https://doi.org/10.3389/fneur.2017.00029>
- Lelard, T., Doutrelot, P.-L., Temfemo, A., & Ahmaidi, S. (2017). Electromyographic Pattern during Gait Initiation Differentiates Yoga Practitioners among Physically Active Older Subjects. *Front Hum Neurosci*, 11, 300. <https://doi.org/10.3389/fnhum.2017.00300>
- Leteneur, S., Simoneau, E., Gillet, C., Dessery, Y., & Barbier, F. (2013). Trunk's Natural Inclination Influences Stance Limb Kinetics, but Not Body Kinematics, during Gait Initiation in Able Men. *PLoS One*, 8, e55256. <https://doi.org/10.1371/journal.pone.0055256>
- Levin, M. F. (2016). Principles of Motor Recovery After Neurological Injury Based on a Motor Control Theory. *Adv Exp Med Biol*, 957, 121-140. https://doi.org/10.1007/978-3-319-47313-0_7
- Li, S., Francisco, G. E., & Zhou, P. (2018). Post-stroke Hemiplegic Gait: New Perspective and Insights. *Front Physiol*, 9, 1021. <https://doi.org/10.3389/fphys.2018.01021>
- Lundy-Ekman, L., & Weyer, A. (2022). *Neuroscience: Fundamentals for Rehabilitation*. Elsevier. <https://books.google.pt/books?id=eIimzgEACAAJ>
- MacKinnon, C. D. (2018). Chapter 1 - Sensorimotor anatomy of gait, balance, and falls. In B. L. Day & S. R. Lord (Eds.), *Handbook of Clinical Neurology* (Vol. 159, pp. 3-26). Elsevier. [https://doi.org/https://doi.org/10.1016/B978-0-444-63916-5.00001-X](https://doi.org/10.1016/B978-0-444-63916-5.00001-X)
- Mademli, L., Mavridi, D., Bohm, S., Patikas, D. A., Santuz, A., & Arampatzis, A. (2021). Standing on unstable surface challenges postural control of tracking tasks and modulates neuromuscular adjustments specific to task complexity. *Scientific Reports*, 11(1), 6122. <https://doi.org/10.1038/s41598-021-84899-y>
- Maeda, R. S., Gribble, P. L., & Pruszynski, J. A. (2020). Learning New Feedforward Motor Commands Based on Feedback Responses. *Curr Biol*, 30(10), 1941-1948.e1943. <https://doi.org/10.1016/j.cub.2020.03.005>
- Mallo-López, A., Cuesta-Gómez, A., Fernández-Pardo, T. E., Aguilera-Rubio, Á., & Molina-Rueda, F. (2024). Influence of Impaired Upper Extremity Motor

- Function on Static Balance in People with Chronic Stroke. *Sensors*, 24(13). <https://doi.org/10.3390/s24134311>
- Mancini, M., & Horak, F. B. (2010). The relevance of clinical balance assessment tools to differentiate balance deficits. *Eur J Phys Rehabil Med*, 46(2), 239-248.
- Marôco, J. (2018). *Análise Estatística com o SPSS Statistics.: 7ª edição*. ReportNumber, Lda. <https://books.google.pt/books?id=Ki5gDwAAQBAJ>
- Marouvo, J., Sousa, F., Fernandes, O., Castro, M. A., & Paszkiel, S. (2021). Gait Kinematics Analysis of Flatfoot Adults. *Appl Sci*, 11(15), 7077. <https://www.mdpi.com/2076-3417/11/15/7077>
- Matilla-García, M., Morales, I., Rodríguez, J. M., & Ruiz Marín, M. (2021). Selection of Embedding Dimension and Delay Time in Phase Space Reconstruction via Symbolic Dynamics. *Entropy*, 23(2), 221. <https://www.mdpi.com/1099-4300/23/2/221>
- Matsuda, F., Mukaino, M., Ohtsuka, K., Tanikawa, H., Tsuchiyama, K., Teranishi, T., Kanada, Y., Kagaya, H., & Saitoh, E. (2017). Biomechanical factors behind toe clearance during the swing phase in hemiparetic patients. *Top Stroke Rehabil*, 24(3), 177-182. <https://doi.org/10.1080/10749357.2016.1234192>
- McPherson, L., & Dewald, J. (2022). Abnormal synergies and associated reactions post-hemiparetic stroke reflect muscle activation patterns of brainstem motor pathways. *Front Neurol*, 13. <https://doi.org/10.3389/fneur.2022.934670>
- Mehdizadeh, H., Khalaf, K., Ghomashchi, H., Taghizadeh, G., Ebrahimi, I., Taghavi Azar Sharabiani, P., Mousavi, S. J., & Parnianpour, M. (2018). Effects of cognitive load on the amount and temporal structure of postural sway variability in stroke survivors. *Exp Brain Res*, 236(1), 285-296. <https://doi.org/10.1007/s00221-017-5126-x>
- Mehdizadeh, S. (2018). The largest Lyapunov exponent of gait in young and elderly individuals: A systematic review. *Gait Posture*, 60, 241-250. <https://doi.org/10.1016/j.gaitpost.2017.12.016>
- Mengarelli, A., Tigrini, A., Verdini, F., Rabini, R., & Fioretti, S. (2023). Multiscale Fuzzy Entropy Analysis of Balance: Evidences of Scale-Dependent Dynamics on Diabetic Patients With and Without Neuropathy. *IEEE Trans Neural Syst Rehabil Eng*, 31, 1462-1471. <https://doi.org/10.1109/TNSRE.2023.3248322>

- Michaelson, S. M., Dannenbaum, R., & Levin, M. F. (2006). Task-specific training with trunk restraint on arm recovery in stroke: randomized control trial. *Stroke*, 37(1), 186-192. <https://doi.org/10.1161/01.STR.0000196940.20446.c9>
- Mizuta, N., Hasui, N., Nishi, Y., Higa, Y., Matsunaga, A., Deguchi, J., Yamamoto, Y., Nakatani, T., Taguchi, J., & Morioka, S. (2022). Merged swing-muscle synergies and their relation to walking characteristics in subacute post-stroke patients: An observational study. *PLoS One*, 17. <https://doi.org/10.1371/journal.pone.0263613>
- Mohapatra, S., & Aruin, A. S. (2013). Static and dynamic visual cues in feed-forward postural control. *Exp Brain Res*, 224(1), 25-34. <https://doi.org/10.1007/s00221-012-3286-2>
- Moisan, G., Chayasit, P., Boonsinsukh, R., Nester, C. J., & Hollands, K. (2022). Postural control during quiet standing and voluntary stepping response tasks in individuals post-stroke: a case-control study. *Top Stroke Rehabil*, 29(7), 465-472. <https://doi.org/10.1080/10749357.2021.1943803>
- Montané, E., Cormier, C., Scandella, M., Cangelosi, A., Marque, P., Moissenet, F., & Gasq, D. (2023). ToulGaitViz: a tool for the systematic description of lower limb clearance during the swing phase of hemiparetic gait after stroke. A cohort study. *Eur J Phys Rehabil Med*, 59(6), 669-681. <https://doi.org/10.23736/s1973-9087.23.07979-0>
- Mooney, R., Cirillo, J., Stinear, C., & Byblow, W. (2020). Neurophysiology of motor skill learning in chronic stroke. *Clin Neurophysiol*, 131, 791-798. <https://doi.org/10.1016/j.clinph.2019.12.410>
- Moreno, F. J., Caballero, C., & Barbado, D. (2022). Postural control strategies are revealed by the complexity of fractional components of COP. *J Neurophysiol*, 127(5), 1289-1297. <https://doi.org/10.1152/jn.00426.2021>
- Morgado, J., Rocha, C., Maruta, C., Guerreiro, M., & Martins, I. (2009). Novos valores Normativos do mini-mental state examination. *Sinapse*, 9, 10-16.
- Nandi, T., Fisher, B., Hortobágyi, T., & Salem, G. (2018). Increasing mediolateral standing sway is associated with increasing corticospinal excitability, and decreasing M1 inhibition and facilitation. *Gait & Posture*, 60, 135-140. <https://doi.org/10.1016/j.gaitpost.2017.11.021>

- Okita, S., De Lucena, D. S., & Reinkensmeyer, D. (2024). Movement Diversity and Complexity Increase as Arm Impairment Decreases After Stroke: Quality of Movement Experience as a Possible Target for Wearable Feedback. *IEEE Trans Neural Syst Rehabil Eng*, 32, 2961-2970. <https://doi.org/10.1109/TNSRE.2024.3439669>
- Onuma, R., Masuda, T., Hoshi, F., Matsuda, T., Sakai, T., Okawa, A., & Jinno, T. (2021). Measurements of the centre of pressure of individual legs reveal new characteristics of reduced anticipatory postural adjustments during gait initiation in patients with post-stroke hemiplegia. *J Rehabil Med*, 53(7). <https://doi.org/10.2340/16501977-2856>
- Osada, Y., Motojima, N., Kobayashi, Y., & Yamamoto, S. (2022). Differences in mediolateral dynamic stability during gait initiation according to whether the non-paretic or paretic leg is used as the leading limb. *PLoS One*, 17(4), e0267577. <https://doi.org/10.1371/journal.pone.0267577>
- Palmieri-Smith, R., Ingersoll, C., Stone, M., & Krause, B. (2002). Center-of-Pressure Parameters Used in the Assessment of Postural Control. *J Sport Rehabil*, 11, 51-66. <https://doi.org/10.1123/jsr.11.1.51>
- Peng, X., Srivastava, S., Sutton, F., Zhang, Y., Badran, B., & Kautz, S. (2024). Compensatory increase in ipsilesional supplementary motor area and premotor connectivity is associated with greater gait impairments: a personalized fMRI analysis in chronic stroke. *Front Hum Neurosci*, 18, 1340374. <https://doi.org/10.3389/fnhum.2024.1340374>
- Phan, T., Nguyen, H., Vermillion, B., Kamper, D., & Lee, S. W. (2022). Abnormal proximal-distal interactions in upper-limb of stroke survivors during object manipulation: A pilot study. *Front Hum Neurosci*, 16, 1022516. <https://doi.org/10.3389/fnhum.2022.1022516>
- Plummer, P., Altmann, L., Feld, J., Zukowski, L., Najafi, B., & Giuliani, C. (2020). Attentional prioritization in dual-task walking: Effects of stroke, environment, and instructed focus. *Gait & Posture*, 79, 3-9. <https://doi.org/10.1016/j.gaitpost.2020.03.013>
- Portnoy, S., Reif, S., Mendelboim, T., & Rand, D. (2017). Postural control of individuals with chronic stroke compared to healthy participants: Timed-Up-

- and-Go, Functional Reach Test and center of pressure movement. *Eur J Phys Rehabil Med*, 53(5), 685-693. <https://doi.org/10.23736/S1973-9087.17.04522-1>
- Presti, D., Zaltieri, M., Bravi, M., Morrone, M., Caponero, M., Schena, E., Sterzi, S., & Massaroni, C. (2022). A Wearable System Composed of FBG-Based Soft Sensors for Trunk Compensatory Movements Detection in Post-Stroke Hemiplegic Patients. *Sensors*, 22(4), 138622. <https://doi.org/10.3390/s22041386>
- Rajachandrakumar, R., Fraser, J. E., Schinkel-Ivy, A., Inness, E. L., Biasin, L., Brunton, K., McIlroy, W. E., & Mansfield, A. (2017). Atypical anticipatory postural adjustments during gait initiation among individuals with sub-acute stroke. *Gait Posture*, 52(1), 325-331. <https://doi.org/10.1016/j.gaitpost.2016.12.020>
- Richman, J. S., & Moorman, J. R. (2000). Physiological time-series analysis using approximate entropy and sample entropy. *Am J Physiol Heart Circ Physiol*, 278(6), H2039-2049. <https://doi.org/10.1152/ajpheart.2000.278.6.H2039>
- Roerdink, M., De Haart, M., Daffertshofer, A., Donker, S. F., Geurts, A. C., & Beek, P. J. (2006). Dynamical structure of center-of-pressure trajectories in patients recovering from stroke. *Exp Brain Res*, 174(2), 256-269. <https://doi.org/10.1007/s00221-006-0441-7>
- Rosch, K. S., & Mostofsky, S. (2019). Chapter 19 - Development of the frontal lobe. In M. D'Esposito & J. H. Grafman (Eds.), *Handbook of Clinical Neurology* (Vol. 163, pp. 351-367). Elsevier. <https://doi.org/10.1016/B978-0-12-804281-6.00019-7>
- Rosenstein, M. T., Collins, J. J., & De Luca, C. J. (1993). A practical method for calculating largest Lyapunov exponents from small data sets. *Physica D: Nonlinear Phenomena*, 65(1), 117-134. [https://doi.org/https://doi.org/10.1016/0167-2789\(93\)90009-P](https://doi.org/https://doi.org/10.1016/0167-2789(93)90009-P)
- Rothwell, J. C. (2012). Overview of neurophysiology of movement control. *Clin Neurol Neurosurg*, 114(5), 432-435. <https://doi.org/10.1016/j.clineuro.2011.12.053>
- Rougier, P. R., & Pérennou, D. (2019). Upright standing after stroke: How loading-unloading mechanism participates to the postural stabilization. *Hum Mov Sci*, 64, 47-54. <https://doi.org/https://doi.org/10.1016/j.humov.2019.01.004>

- Rowe, E., Beauchamp, M. K., & Astephen Wilson, J. (2021). Age and sex differences in normative gait patterns. *Gait & Posture*, 88, 109-115. <https://doi.org/https://doi.org/10.1016/j.gaitpost.2021.05.014>
- Schroeder, S., Jaeger, S., Schwer, J., Seitz, A., Hamann, I., Werner, M., Thorwaechter, C., Santos, I., Wendler, T., Nebel, D., & Welke, B. (2022). Accuracy measurement of different marker based motion analysis systems for biomechanical applications: A round robin study. *PLoS One*, 17. <https://doi.org/10.1371/journal.pone.0271349>
- Seo, J. P., & Koo, D. K. (2023). Degeneration of nigrostriatal pathway in patients with middle cerebral infarct: A diffusion tensor imaging study. *Medicine*, 102(14), e33370. <https://doi.org/10.1097/md.00000000000033370>
- Sethi, A., Stergiou, N., Patterson, T. S., Patten, C., & Richards, L. G. (2017). Speed and Rhythm Affect Temporal Structure of Variability in Reaching Poststroke: A Pilot Study. *J Mot Behav*, 49(1), 35-45. <https://doi.org/10.1080/00222895.2016.1219304>
- Shaikh, T., Goussev, V., Feldman, A. G., & Levin, M. F. (2014). Arm-trunk coordination for beyond-the-reach movements in adults with stroke. *Neurorehabil Neural Repair*, 28(4), 355-366. <https://doi.org/10.1177/1545968313510973>
- Sharififar, S., Vincent, H. K., Shuster, J., Bishop, & Mark. (2019). Quantifying Poststroke Gait Deviations: A Meta-analysis of Observational and Cross-sectional Experimental Trials. *J Stroke Med*, 2(1), 23-31. <https://doi.org/10.1177/2516608519856246>
- Shin, S. Y., Kim, Y., Jayaraman, A., & Park, H. S. (2021). Relationship between gait quality measures and modular neuromuscular control parameters in chronic post-stroke individuals. *J Neuroeng Rehabil*, 18. <https://doi.org/10.1186/s12984-021-00860-0>
- Shumway-Cook, A., & Woollacott, M. H. (2017). *Motor Control: Translating Research Into Clinical Practice*. Wolters Kluwer. <https://books.google.pt/books?id=xy3EsgEACAAJ>
- Sibley, K. M., Beauchamp, M. K., Van Ooteghem, K., Straus, S. E., & Jaglal, S. B. (2015). Using the Systems Framework for Postural Control to Analyze the Components of Balance Evaluated in Standardized Balance Measures: A

- Scoping Review. *Arch Phys Med Rehabil*, 96(1), 122-132.
<https://doi.org/https://doi.org/10.1016/j.apmr.2014.06.021>
- Silva, A., Sousa, A. S., Silva, C., Tavares, J. M., Santos, R., & Sousa, F. (2015). Ankle antagonist coactivation in the double-support phase of walking: Stroke vs. healthy subjects. *Somatosens Mot Res*, 32(3), 153-157.
<https://doi.org/10.3109/08990220.2015.1012492>
- Sousa, A. S., Silva, A., & Santos, R. (2015). Reliability of Two Methods for Identifying the Postural Phase of Gait Initiation in Healthy and Poststroke Subjects. *J Appl Biomech*, 31(5), 349-356. <https://doi.org/10.1123/jab.2014-0222>
- Sousa, A. S. P., Moreira, J., Silva, C., Mesquita, I., Silva, A., Macedo, R., & Santos, R. (2022). Postural control during turn on the light task assisted by functional electrical stimulation in post stroke subjects. *Sci Rep*, 12(1), 6999.
<https://doi.org/10.1038/s41598-022-10893-7>
- Sousa, A. S. P., Silva, A., Santos, R., Sousa, F., & Tavares, J. (2013). Interlimb coordination during the stance phase of gait in subjects with stroke. *Arch Phys Med Rehabil*, 94(12), 2515-2522. <https://doi.org/10.1016/j.apmr.2013.06.032>
- Stamenkovic, A., Stapley, P. J., Robins, R., & Hollands, M. A. (2018). Do postural constraints affect eye, head, and arm coordination? *J Neurophysiol*, 120(4), 2066-2082. <https://doi.org/10.1152/jn.00200.2018>
- Stergiou, N. (2016). *Nonlinear Analysis for Human Movement Variability*. CRC Press.
<https://doi.org/10.1201/9781315370651>
- Stergiou, N., & Decker, L. M. (2011). Human movement variability, nonlinear dynamics, and pathology: is there a connection? *Hum Mov Sci*, 30(5), 869-888.
<https://doi.org/10.1016/j.humov.2011.06.002>
- Stergiou, N., Harbourne, R., & Cavanaugh, J. (2006). Optimal movement variability: a new theoretical perspective for neurologic physical therapy. *J Neurol Phys Ther*, 30(3), 120-129. <https://doi.org/10.1097/01.npt.0000281949.48193.d9>
- Sumardi, N. (2021). Postural Dysfunction in Stroke Rehabilitation. *Indonesian Journal Of Physical Medicine and Rehabilitation*, 9(2), 124-135.
<https://doi.org/10.36803/IJPMR.V9I2.272>
- Takahashi, S., Hoshino, M., Ohyama, S., Hori, Y., Yabu, A., Kobayashi, A., Tsujio, T., Kotake, S., & Nakamura, H. (2021). Relationship of back muscle and knee

- extensors with the compensatory mechanism of sagittal alignment in a community-dwelling elderly population. *Sci Rep*, 11. <https://doi.org/10.1038/s41598-021-82015-8>
- Takakusaki, K. (2017). Functional Neuroanatomy for Posture and Gait Control. *J Mov Disord*, 10(1), 1-17. <https://doi.org/10.14802/jmd.16062>
- Tasseel-Ponche, S., Yelnik, A. P., & Bonan, I. V. (2015). Motor strategies of postural control after hemispheric stroke. *Neurophysiol Clin*, 45(4-5), 327-333. <https://doi.org/10.1016/j.neucli.2015.09.003>
- Tomita, Y., Mullick, A. A., Feldman, A. G., & Levin, M. F. (2024). Altered Anticipatory Postural Adjustments During Whole-Body Reaching in Subjects With Stroke. *Neurorehabilit Neural Repair*, 38(3), 176-186. <https://doi.org/10.1177/15459683241231528>
- Tsai, W. C., Lien, H. Y., Liu, W. Y., Guo, S. L., Lin, Y. H., & Yang, T. F. (2018). Early and anticipatory postural adjustments in healthy subjects under stable and unstable sitting conditions. *J Electromyogr Kinesiol*, 43, 21-27. <https://doi.org/10.1016/j.jelekin.2018.08.005>
- Van Crielinge, T., Saeys, W., Hallemans, A., Velghe, S., Viskens, P. J., Vereeck, L., De Hertogh, W., & Truijen, S. (2017). Trunk biomechanics during hemiplegic gait after stroke: A systematic review. *Gait Posture*, 54, 133-143. <https://doi.org/10.1016/j.gaitpost.2017.03.004>
- Van Crielinge, T., Truijen, S., Schröder, J., Maebe, Z., Blanckaert, K., van der Waal, C., Vink, M., & Saeys, W. (2019). The effectiveness of trunk training on trunk control, sitting and standing balance and mobility post-stroke: a systematic review and meta-analysis. *Clin Rehabil*, 33(6), 992-1002. <https://doi.org/10.1177/0269215519830159>
- van Emmerik, R. E. A., Ducharme, S. W., Amado, A. C., & Hamill, J. (2016). Comparing dynamical systems concepts and techniques for biomechanical analysis. *J Sport Health Sci*, 5(1), 3-13. <https://doi.org/10.1016/j.jsbs.2016.01.013>
- Vaughan-Graham, J., & Cott, C. (2016). Defining a Bobath clinical framework - A modified e-Delphi study. *Physiother Theory Pract*, 32(8), 612-627. <https://doi.org/10.1080/09593985.2016.1228722>

- Vlachos, I., & Kugiumtzis, D. (2008). State Space Reconstruction for Multivariate Time Series Prediction. *ArXiv*, 11. <https://doi.org/10.48550/arXiv.0809.2220>
- Vonesch, A., Duhot, C., Lelard, T., Léonard, G., Błażkiewicz, M., & Mouras, H. (2023). Non-Linear Measures of Postural Control in Response to Painful and Non-Painful Visual Stimuli. *Entropy*, 25(11), 1561. <https://www.mdpi.com/1099-4300/25/11/1561>
- Walcott, B. P., Miller, J. C., Kwon, C. S., Sheth, S. A., Hiller, M., Cronin, C. A., Schwamm, L. H., Simard, J. M., Kahle, K. T., Kimberly, W. T., & Sheth, K. N. (2014). Outcomes in severe middle cerebral artery ischemic stroke. *Neurocrit Care*, 21(1), 20-26. <https://doi.org/10.1007/s12028-013-9838-x>
- Watanabe, E., Kiyono, K., Hayano, J., Yamamoto, Y., Inamasu, J., Yamamoto, M., Ichikawa, T., Sobue, Y., Harada, M., & Ozaki, Y. (2015). Multiscale Entropy of the Heart Rate Variability for the Prediction of an Ischemic Stroke in Patients with Permanent Atrial Fibrillation. *PLoS One*, 10(9), e0137144. <https://doi.org/10.1371/journal.pone.0137144>
- Winter, L., Taylor, P., Bellenger, C., Grimshaw, P., & Crowther, R. G. (2023). The application of the Lyapunov Exponent to analyse human performance: A systematic review. *J Sports Sci*, 41(22), 1994-2013. <https://doi.org/10.1080/02640414.2024.2308441>
- Wu, C.-H., Lee, C.-H., Jiang, B. C., & Sun, T.-L. (2019). Multiscale Entropy Analysis of Postural Stability for Estimating Fall Risk via Domain Knowledge of Timed-Up-And-Go Accelerometer Data for Elderly People Living in a Community. *Entropy*, 21(11), 1076. <https://www.mdpi.com/1099-4300/21/11/1076>
- Xu, P., Yu, H., Wang, X., & Song, R. (2022). Characterizing stroke-induced changes in the variability of lower limb kinematics using multifractal detrended fluctuation analysis. *Front Neurol*, 13, 893999. <https://doi.org/10.3389/fneur.2022.893999>
- Yang, C. L., Creath, R. A., Magder, L., Rogers, M. W., & McCombe Waller, S. (2019). Impaired posture, movement preparation, and execution during both paretic and nonparetic reaching following stroke. *J Neurophysiol*, 121(4), 1465-1477. <https://doi.org/10.1152/jn.00694.2018>

- Yiou, E., Caderby, T., Delafontaine, A., Fourcade, P., & Honeine, J. L. (2017). Balance control during gait initiation: State-of-the-art and research perspectives. *World J Orthop*, 8(11), 815-828. <https://doi.org/10.5312/wjo.v8.i11.815>
- Yong, M.-S., Lee, H., & Lee, M.-Y. (2016). Correlation between head posture and proprioceptive function in the cervical region. *J Phys Ther. Sci*, 28, 857-860. <https://doi.org/10.1589/jpts.28.857>
- Yoo, Y. J., Lim, S. H., Kim, Y., Kim, J.-S., Hong, B. Y., Yoon, M.-J., Rim, H., & Park, G.-Y. (2023). Structural Integrity of the Cerebellar Outflow Tract Predicts Long-Term Motor Function After Middle Cerebral Artery Ischemic Stroke. *Neurorehabilit Neural Repair*, 37(8), 554-563. <https://doi.org/10.1177/15459683231177607>
- Zhou, S., Guo, Z., Wong, K., Zhu, H., Huang, Y., Hu, X., & Zheng, Y. (2021). Pathway-specific cortico-muscular coherence in proximal-to-distal compensation during fine motor control of finger extension after stroke. *J Neural Eng*, 18(5). <https://doi.org/10.1088/1741-2552/ac20bc>

CHAPTER IV: GENERAL DISCUSSION

General Discussion

This thesis aimed to address critical gaps in the assessment and understanding of post-stroke PC and motor variability by integrating linear and non-linear methodologies. The overarching research question - “How can neurobiomechanical linear and non-linear approaches characterise the complexity and variability of the human movement system in post-stroke individuals, providing valuable insights into their adaptive postural and movement strategies and informing the development of targeted rehabilitation interventions?” - was investigated through three interconnected studies. Inspired by the HMS framework, which underscores the importance of movement variability and adaptability as fundamental components of functional recovery (Gill-Body et al., 2021), this thesis integrates findings from the three studies to provide a multidimensional perspective on stroke rehabilitation.

Specifically, this work advances the understanding of PC mechanisms in post-stroke individuals by addressing three key domains: (1) methodological gaps in the application of non-linear analysis to human movement (Study I), (2) the cultural adaptation and psychometric validation of a clinical assessment tool (Study II), and (3) the neurobiomechanical characterization of PC during GI (Study III). Together, these studies establish a comprehensive framework for investigating and addressing the complex deficits in PC and motor adaptability associated with stroke.

Study I: Addressing Methodological Gaps

Study I provided a comprehensive review of the current application of non-linear measures in the biomechanical analysis of human movement, with a particular focus on post-stroke populations. This review identified critical gaps in the characterization of study samples, selection of movement tasks, and application of non-linear measures, limiting the ability to draw robust conclusions about post-stroke motor control.

Commonly reported variables included sex, age, affected side, time after injury, and motor function. However, other critical factors—such as stroke location, severity, ethnicity, pre-existing comorbidities (e.g., diabetes, cognitive impairment, or depression), and pre-stroke lifestyle factors (e.g., social engagement and physical activity)—were often omitted (Kwakkel et al., 2017). Additionally, the inconsistent use of functional and clinical measures, such as the FMA, further undermined the comparability of results across studies (Bernhardt et al., 2017; Pongmoragot et al., 2016).

Another significant gap was the absence of matched control groups in approximately half of the reviewed studies. Including non-disabled matched controls is critical for contextualizing findings and assessing the relative severity of motor impairments in post-stroke populations. Without this comparative framework, it becomes challenging to discern the extent of deficits and compensatory mechanisms (Kwakkel et al., 2017).

The review also highlighted a predominant focus on isolated components of movement tasks, such as reaching or walking, without considering the integrated execution of functional tasks. While these tasks provide valuable insights into specific motor functions, they often fail to capture the systemic nature of motor control, which relies on interactions between multiple body segments and systems (Kwakkel et al., 2023). As an example, functional tasks like GI demand seamless coordination between CoP dynamics and joint amplitudes to maintain stability and ensure smooth transitions. By focusing on isolated tasks, researchers risk overlooking compensatory strategies and segmental interactions critical for understanding functional motor control (Hedman et al., 2018; Kwakkel et al., 2023; Ozturk et al., 2016; Quinn et al., 2021). This limited the understanding of post-stroke PC dysfunction, which is a critical component of functional recovery.

The review further revealed several methodological gaps in applying non-linear measures, such as SampEn, ApEn, LyE, and MFDFA. While these measures are powerful tools for quantifying movement variability, their application was often isolated rather than integrated, limiting their ability to provide a multidimensional understanding of motor control (Yentes & Raffalt, 2021). Van Emmerik and colleagues (2016) demonstrated that ApEn, SampEn, and their variants, are limited in their ability to provide a detailed analysis of physiological signals because they assess entropy only on a temporal scale (van Emmerik et al., 2016). As physiological systems exhibit structures across multiple time scales (Ahmed & Mandic, 2011), MSE was developed to quantify the intrinsic complexity of these systems at both small and large scales (Busa & van Emmerik, 2016; Costa et al., 2005). In the research included in Study I, which focused on the quantification of the local dynamic stability of complex non-linear systems (Kempski et al., 2018), LyE was the measure applied. LyE quantifies the rate of trajectory convergence or divergence in an n-dimensional state space and the system's sensitivity to initial conditions (Liu et al., 2015; Mehdizadeh, 2018). Although entropy measures provide valuable insights into one aspect of variability, they do not capture the

structural richness and the broad component characterization of a complex system operating across multiple spatial and temporal scales (Yentes & Raffalt, 2021). Therefore, it is recommended to combine entropy measures with other non-linear metrics for a more comprehensive assessment (Harbourne & Stergiou, 2009).

A lack of standardization in selecting critical parameters, such as embedding dimension (m), time delay (τ), and data length (N), further complicated the interpretation and comparison of findings. Variations in data length, for example, can significantly influence the sensitivity of measures like LyE and entropy to detect changes in PC, potentially leading to inconsistent results (Stergiou, 2016). Standardizing these parameters is essential to enhance reproducibility and comparability across studies (Caballero et al., 2014; Müller et al., 2017).

Study II: Cross-Cultural Adaptation and Validation of a Robust Clinical Tool

Given the gaps identified in Study I regarding the lack of focus on PC, Study II addressed this limitation by culturally adapting and psychometrically validating the Mini-BESTest for Portuguese-speaking populations. The Mini-BESTest is widely recognized as one of the most robust tools for assessing dynamic PC (Sibley et al., 2015). It is the recommended tool by the Task Force on Movement System Diagnoses (Dos Santos et al., 2023) and is included in the guidelines for a Core Set of Outcome Measures for Adults with Neurologic Conditions Undergoing Rehabilitation (Moore et al., 2018). These guidelines emphasize the importance of standardized measures that reflect the HMS construct to assess postural stability dysfunction comprehensively (Gill-Body et al., 2021).

The cross-cultural adaptation and validation of the Mini-BESTest_EP was a critical step before conducting Study III, ensuring the availability of a reliable and valid scale that could accurately reflect PC dysfunction in individuals with sensorimotor impairments. Unlike tools such as the BBS, which primarily evaluates quasi-static postural stability, the Mini-BESTest assesses multiple PC components, including anticipatory postural adjustments, reactive postural responses, sensory orientation, and dynamic gait (Dos Santos et al., 2023; Sibley et al., 2015). This multidimensional approach aligns with the needs identified in Study I, providing a robust foundation for exploring PC mechanisms in greater depth (Franchignoni et al., 2010; Moore et al., 2018).

Study II confirmed that the Mini-BESTest_EP is a valid and reliable tool for assessing dynamic postural stability performance in Portuguese-speaking populations. The high

internal consistency and excellent inter-rater and intra-rater reliability demonstrated the scale's robustness (Nakhostin-Ansari et al., 2022). Furthermore, the absence of floor and ceiling effects confirmed its capacity to discriminate between different levels of balance performance, establishing its superiority over the BBS in evaluating dynamic postural control (Dahl & Jørgensen, 2014; Tsang et al., 2013). These psychometric properties ensure its sensitivity to detect both subtle and significant changes in balance, making it crucial for tracking rehabilitation progress in clinical settings (Franchignoni et al., 2010).

A significant strength of the Mini-BESTest_EP is its ability to identify impairments in specific PC components. For example, tasks involving APAs and reactive responses are particularly relevant in post-stroke populations, where deficits in these domains often lead to falls and reduced functional independence (Tomita et al., 2024; Yang et al., 2019). This comprehensive evaluation of PC domains offers a clear advantage over more traditional scales like the BBS, which lacks a thorough assessment of dynamic and sensory components (Franchignoni et al., 2010). Beyond its psychometric robustness, the Mini-BESTest_EP bridges the gap between clinical and neurobiomechanical assessments. By aligning with the recommendations of the Task Force on Movement System Diagnoses (Dos Santos et al., 2023), the tool supports personalized intervention strategies targeting specific deficits, such as enhancing reactive responses or improving sensory orientation, critical for restoring functional mobility and reducing fall risks.

The findings of Study II laid the groundwork for Study III by providing a validated clinical tool to comprehensively assess dynamic PC and characterize the study sample. Using the Mini-BESTest_EP allowed Study III to systematically identify and categorize participants' PC deficits, enabling a clear understanding of the clinical profile of the sample. This step was essential for interpreting the neurobiomechanical findings in the broader context of PC dysfunction in post-stroke individuals. While the Mini-BESTest_EP was not directly correlated with biomechanical metrics, it served as a foundational tool for documenting deficits in APAs, reactive postural responses, sensory orientation, and dynamic gait. These findings informed the overall characterization of the study population and reinforced the multidimensional nature of PC assessment (Schneider et al., 2021; Moore et al., 2018).

Study III: Neurobiomechanical Characterization of PC During GI

Building on the insights from Study I and the psychometric foundation established in

Study II, Study III integrated linear (e.g., CoP DISP and VEL) and non-linear (e.g., LyE and MSE) measures to characterize PC during GI. This functional task, involving anticipatory adjustments and dynamic postural orientation, was chosen to capture the systemic interactions between CoP dynamics and joint amplitudes.

The findings of Study III provide critical insights into post-stroke PC during the feedforward phase of GI, contributing to the overarching aim of this thesis. By combining linear and non-linear analyses, Study III revealed significant impairments in both stability and adaptability in post-stroke individuals, offering a comprehensive neurobiomechanical characterization of PC dysfunction. These results complement and expand upon the gaps identified in Study I while validating the importance of robust clinical measures emphasized in Study II.

The linear analysis revealed significant increases in ML TDISPL and MDISP for the post-stroke group, along with decreased AP-MVEL, indicating greater postural instability, particularly in the mediolateral (ML) direction, during preparatory phases of gait initiation (GI) (Silva et al., 2015; Delafontaine et al, 2019; Onuma et al, 2021). These changes are attributed to postural control (PC) impairments, such as asymmetrical muscle activation, altered weight distribution, increased anticipatory postural adjustments (APAs) in trunk muscles, and dysregulation of CoP and COM displacement (Sousa et al, 2002; Gandolfi et al., 2019; Mohapatra & Aruin, 2013).

Complementing these findings, the non-linear analysis showed reductions in entropy and LyE measures in the stroke group, reflecting decreased system complexity and adaptability, which are critical for responding to environmental demands (Vaughan-Graham & Cott, 2016; Vonesh et al, 2023). Specifically, lower LyE values in ML-CoP POS highlight a disrupted balance between stability and flexibility, leading to rigid motor patterns and more repetitive sway behaviors, particularly in the ML direction (Ghomashchi, 2016; Nandi et al, 2018; Roerdink et al, 2006). Reduced MSE values further supported these findings, indicating impaired neuromotor system flexibility and limited exploratory movement strategies, consistent with Bernstein's framework (Jagroop et al, 2023; Stergiou, 2016; Biryukova & Sirotkina, 2020).

Additionally, the reduction in AP-CoP MVEL suggests slower feedforward control strategies, reflecting motor impairments and reduced APA efficiency (Silva et. al., 2015; Delafontaine et al, 2019; Onuma et al., 2021). This aligns with evidence that stroke survivors prioritize safety over movement efficiency, leading to suboptimal

motor strategies and prolonged task execution times (Beyart et al., 2015; Plummer et al., 2020). The divergence in DISP and VEL likely represents maladaptive compensatory mechanisms aimed at counteracting postural instability but also indicates reliance on less efficient motor strategies (Vaughan-Graham & Cott, 2016; Stergiou et al., 2016).

The integration of linear and non-linear findings highlights a dual challenge in post-stroke PC: increased linear variability (e.g., CoP DISP) and decreased non-linear complexity, suggesting a constrained dynamic range and limited adaptability (Ghomashchi, 2016; Moisan et al., 2022; Mehdizadeh, 2018). This combination impairs the ability to respond to perturbations, explore alternative motor strategies, and maintain stability, increasing fall risk and reducing functional independence (Andreasen et al., 2020; Curuk and Aruin, 2022).

The analysis of joint amplitude variability provided additional insights into compensatory mechanisms. In the sagittal plane, the stroke group exhibited significant increases in TDISPL, MDISP, and AMPL across the head, trunk, and pelvis, suggesting that compensatory mechanisms were more pronounced in movement magnitude and variability rather than static positioning (Lafage et al., 2023; Takahashi et al., 2021). The head showed a tendency for FLE, contrasting with EXT in healthy individuals, which disrupted the COM alignment and increased reliance on trunk and pelvic compensations for stability (Chen et al., 2018; Stamenkovic et al., 2018; Van Criel et al., 2017). In the trunk and pelvis, exaggerated FLE-EXT movements and anterior pelvic tilt were observed, compensating for impaired PC but resulting in energy inefficiency and further COM misalignment (Darak & Karthikbabu, 2020; Kim et al., 2018; Tomita et al., 2024). In the LL, hip FLE during the swing limb was a key compensatory strategy to achieve foot clearance, but it delayed weight transfer and reduced efficiency, with significant increases in MDISP and AMPL at the hip and ankle, reflecting maladaptive responses to instability (Hsiao et al., 2020; Lanza & Gray, 2022; MacKinnon, 2018; Mizuta et al., 2022). Non-linear analysis revealed reduced LyE and MSE in POS and DISP for the head, pelvis, hip, and ankle, indicating limited adaptability and reliance on rigid motor strategies (Gow et al., 2015; Mengarelli et al., 2023; Watanabe et al., 2015). For the UL, increased TDISPL in the shoulder during both limbs highlighted its role in redistributing the COM to maintain postural stability, while elevated MDISP and AMPL in the shoulder and wrist indicated compensatory adjustments across proximal and distal segments (Harbourne & Kamm, 2015; Phan et

al., 2022). However, reduced MSE and divergent LyE in the wrist and shoulder pointed to poor coordination and limited adaptability, consistent with rigid and stereotyped motor strategies observed in stroke survivors (McPherson & Dewald, 2022; Winter et al., 2023). These findings underscore the inefficiency of these compensatory strategies, emphasizing the need for integrated linear and non-linear analyses to uncover maladaptive responses not captured by static measures (Hadamus et al., 2022; Karimi et al., 2021).

In the frontal plane, the stroke group exhibited compensatory mechanisms characterized by increased tilt tendencies in the head, trunk, and pelvis, despite non-significant POS differences. Amplified TDISPL, MDISP, and AMPL in the head and trunk indicated exaggerated lateral movements aimed at redistributing the COM to stabilize the body during weight shifts (Beyaert et al., 2015). These compensations are linked to impaired hip abductor strength on the stance limb, which disrupts smooth transitions and increases instability during dynamic tasks (Lanza & Gray, 2022). The trunk played a dual role as both a stabilizer and an active participant in postural adjustments, particularly when PC thresholds were exceeded (Van Crielinge et al., 2017; Van Crielinge et al., 2019). Non-linear measures provided deeper insights, with reduced LyE in POS for the head and pelvis indicating impaired stabilization and adaptability during lateral weight transfers. Trends toward less divergent LyE in pelvis MDISP suggested reliance on rigid and biomechanically limited strategies (Moreno et al., 2022). Significant reductions in MSE across S1, S2, and CI for head POS, DISP, and trunk DISP further highlighted constrained adaptability and limited fine-tuned adjustments during ML tasks (Chen et al., 2021; Leteneur et al., 2013). In the LL, increased TDISPL, MDISP, and AMPL at the ankle reflected compensatory reliance on distal segments to counteract proximal instability (Farinelli et al., 2021). Reduced LyE convergence at the ankle indicated impaired dynamic control, while variability in LyE patterns at the knee—convergent during the SwL phase and divergent during the StL phase—reflected a shift between proximal stabilization and distal adjustments (Caderby et al., 2017; Yiou et al., 2017). Reduced MSE in hip POS and DISP during the swing limb and in ankle POS at S2 and CI further emphasized limited adaptability and compromised dynamic stability (Busa & van Emmerik, 2016). For the UL, increased MDISP and AMPL in the elbow and wrist during the swing limb highlighted compensatory adjustments across proximal and distal segments to stabilize the COM

(Ko et al., 2015). However, the increased reliance on distal segments, such as the wrist, underscored broader deficits in proximal stability and PC (Guo et al., 2020; Phan et al., 2022). Non-linear measures revealed control deficits, with reduced LyE convergence in the swing limb wrist POS, indicating inefficient distal control, and divergent LyE DISP, highlighting poor synchronization between proximal and distal UL segments (Mazzoleni et al., 2018). Reduced MSE in shoulder POS (S2, CI) and elbow POS (CI) further pointed to constrained control across temporal scales, emphasizing the interdependence between proximal and distal UL segments, where the shoulder compensated as a stabilizer for deficits in dynamic PC (Yang et al., 2019).

In the transverse plane, exaggerated rotational patterns were observed in the stroke group, with increased TDISPL, MDISP, and AMPL in the head, trunk, and pelvis, reflecting compensatory strategies aimed at stabilizing the COM during dynamic tasks (Jayasinghe et al., 2021). However, these rotations compromised segmental coordination, exacerbating instability during weight transfers and increasing energy expenditure (Karthikbabu et al., 2012; Li et al., 2018). Increased pelvic rotations, combined with greater head and trunk excursions, interfered with smooth force transfers, further disrupting ML stability and hindering forward progression during GI (Choi et al., 2020; Dubey et al., 2018). Non-linear measures revealed deficits in dynamic stability, with reduced LyE convergence in pelvis POS and trends toward rigid control strategies in pelvis MDISP, reflecting limited adaptability in rotational movements (Stergiou, 2016). Significant reductions in MSE across S1, S2, and CI for head, trunk, and pelvis POS and DISP indicated constrained adaptability and reliance on stereotyped motor strategies during perturbations (Kempski et al., 2018). In the LL, exaggerated rotational displacements at the hip and knee, evidenced by increased TDISPL, MDISP, and AMPL, highlighted compensatory strategies for reduced trunk and pelvic control (De Luca et al., 2020). Non-linear findings, such as reduced LyE convergence for hip, knee, and ankle POS and DISP, particularly in the swing hip and both ankles, suggested impaired stabilization and adaptability (Stergiou, 2016). Variability in LyE at the knee—converging in swing and diverging in stance limbs - reflected proximal-distal imbalances, with MSE reductions in hip and ankle indicating limited adaptability during rotational weight shifts (Wu et al., 2019; Xu et al., 2022). For the UL, increased MDISP and AMPL in the shoulder and swing wrist reflected active compensatory adjustments for postural instability (Halmi et al., 2020). However,

reduced MSE and divergent LyE in wrist POS and DISP in both limbs suggested poor synchronization and inefficient coordination between proximal and distal segments (Goh et al., 2015). These findings pointed to rigid motor strategies and inadequate trunk integration in compensatory mechanisms (Goh et al., 2015; Okita et al., 2024).

From a neurobiomechanical perspective, post-stroke PC dysfunction arises from disruptions in neural pathways, particularly within the MCA territory, common among the participants in Study III, affecting the CRS, CSS, and VSS systems (Shumway-Cook & Woollacott, 2017). These pathways, crucial for integrating CoP control and joint amplitude regulation, are compromised, leading to impaired APAs, increased CoP variability, and reduced neuromuscular adaptability (Lefebvre & Liew, 2017; Rothwell, 2012; Takakusaki, 2017). Damage to the CRS results in greater CoP variation and rigidity, while CSS dysfunction causes irregular joint amplitudes and reliance on proximal movements, reflecting poor segmental coordination (Jang & Lee, 2019; Levin, 2016). The VSS, indirectly impacted by MCA lesions, fails to stabilize the COM, further exacerbating postural instability and increasing compensatory reliance on flexor musculature (Levin, 2016; Lundy-Ekman & Weyer, 2022). Non-linear measures, including reduced LyE and MSE, highlight diminished adaptability and rigid motor strategies across systems. These deficits manifest as exaggerated CoP DISP, joint irregularities, and impaired stability, underscoring the interplay between posture and movement control, crucial for dynamic tasks like GI (Levin, 2016; Takakusaki, 2017).

Overall, the findings emphasize the systemic nature of post-stroke impairments, with exaggerated compensatory rotations and limited adaptability, disrupting biomechanical interplay across segments. The integration of linear and non-linear measures revealed systemic post-stroke impairments. Increased linear measures, such as TDISPL, MDISP, and AMPL, indicated greater variability and movement magnitude, while reductions in non-linear measures (LyE and MSE) highlighted diminished complexity and adaptability. This interplay reflects a dual challenge: compensatory strategies aimed at stabilizing the COM exacerbate inefficiencies in motor control and limit the ability to explore alternative more efficient solutions (Ding et al., 2024; Karimi et al., 2021). These findings offer critical insights for developing targeted and effective rehabilitation interventions

In summary, this thesis provides a multidimensional understanding of post-stroke PC by bridging methodological gaps, validating robust clinical tools, and employing advanced

neurobiomechanical analyses. The integration of findings from the three studies underscores the importance of combining linear and non-linear approaches to comprehensively characterize stability and adaptability deficits in stroke survivors. By addressing methodological inconsistencies, adapting validated assessment tools, and elucidating the interplay between CoP dynamics and joint amplitude variability during functional tasks like GI, this work highlights the intricate complexities of PC dysfunction post-stroke. These insights not only advance the scientific understanding of PC mechanisms but also play a critical foundation for developing targeted rehabilitation interventions aimed at restoring functional independence and reducing fall risks in this population.

Clinical Contributions

The clinical contributions outlined in this thesis collectively highlight the importance of addressing critical gaps in the assessment and rehabilitation of postural control (PC) and motor variability in post-stroke populations. Study I emphasized the need for comprehensive sample characterization, standardized methodologies, and the inclusion of matched control groups to enhance the reliability and applicability of biomechanical research. This framework not only informs personalized rehabilitation strategies but also provides a robust foundation for advancing the field through consistent reporting and analysis of critical clinical and demographic variables. Additionally, Study I underscored the necessity of evaluating integrated functional tasks, such as gait initiation, that capture the systemic and dynamic nature of PC, thereby bridging the gap between isolated task assessments and real-life movement challenges.

The successful adaptation of the Mini-BESTest into European Portuguese, in Study II, addressed a significant clinical need, providing Portuguese-speaking professionals with a validated, reliable, and multidimensional tool to assess PC impairments. By enabling the identification of specific deficits in anticipatory postural adjustments, reactive responses, sensory orientation, and dynamic gait, the Mini-BESTest stands out as a superior alternative to traditional tools like the Berg Balance Scale. Its integration into clinical practice facilitates the design of tailored rehabilitation interventions that directly target the underlying mechanisms of PC dysfunction, fostering more effective recovery pathways and functional outcomes.

Study III advanced these insights by integrating linear and non-linear analyses to provide a comprehensive neurobiomechanical characterization of PC dysfunction during

gait initiation. The findings highlighted the dual challenge of increased instability and diminished adaptability, which are central to post-stroke motor impairments. The identification of compensatory strategies, such as exaggerated joint movements and reliance on rigid motor patterns, informed the need for interventions that balance stability with adaptability. Rehabilitation strategies grounded in linear approaches address immediate biomechanical impairments, while non-linear methods foster system-wide flexibility and dynamic responsiveness, essential for long-term recovery.

Collectively, these studies advocate for a multidimensional approach to post-stroke rehabilitation, integrating the strengths of linear and non-linear methodologies to address both immediate and systemic challenges in PC. By aligning robust clinical tools, such as the Mini-BESTest, with advanced biomechanical insights, this thesis provides a framework for designing interventions that enhance stability, adaptability, and overall functional mobility in stroke survivors. These findings lay the groundwork for future research and clinical innovations aimed at improving the quality of life for individuals with post-stroke impairments.

Limitations and Future Studies

Some limitations from Studies I, II, and III should be considered. In Study I, the search was restricted to five databases, which might have led to the omission of relevant literature. While a broad search strategy was employed to mitigate this, some critical studies may have been missed. Nonetheless, the findings from this scoping review likely reflect the significant advances made in this field, particularly in the application of non-linear dynamics to understand the complexity of human movement and evaluate biological adaptivity.

To address the gaps identified in Study I, future research should adopt standardized protocols for data collection, emphasizing consistent reporting of clinical, demographic, and functional variables. This would enable cross-study comparisons and meta-analyses, enriching the overall knowledge base. Combining linear and non-linear metrics in future studies could offer a more comprehensive understanding of both the magnitude and quality of movement variability in post-stroke populations. Expanding research to include ecologically valid tasks, under dual-task conditions or transitions in dynamic environments, could also provide more relevant insights into the real-world challenges faced by individuals, improving interventions for functional mobility.

Study II used a convenience sample from two outpatient clinics to represent a broad

spectrum of the Portuguese population with postural stability dysfunction. However, the lack of randomized sampling could limit the generalizability of the findings. Additionally, concerns about the inclusion of diverse conditions might suggest a preference for a more homogeneous sample. Nonetheless, this study deliberately included a wide range of balance deficits to validate the Mini-BESTest_EP across diverse clinical conditions. Future studies should focus on fully randomized sampling methods and evaluate responsiveness, predictive validity, and specificity across different patient populations. Establishing the minimal clinically important difference (MCID) for the Mini-BESTest_EP is essential for enhancing its clinical utility. To achieve this, future research could combine effect sizes with clinical anchors, conduct longitudinal studies involving physiotherapy interventions, and use both distribution-based and anchor-based methods. This would allow for a better understanding of the clinical interpretation of health status changes in populations with sensorimotor impairments.

Study III, which employed linear (e.g., CoP displacement and velocity) and non-linear (e.g., LyE and MSE) analyses, highlighted important insights into post-stroke PC. However, the study's cross-sectional design limits causal inferences about the relationship between observed impairments and postural control deficits. Additionally, the limited sample size might affect the generalizability of the findings to the broader stroke population. Longitudinal studies are necessary to investigate the progression of PC impairments and evaluate the long-term effects of targeted rehabilitation interventions. Moreover, the MSE analysis in Study III, while methodologically robust, was limited to two scales, potentially missing broader multiscale dynamics. Future research should expand to higher scales and larger datasets, enabling a more detailed understanding of system complexity across extended time intervals.

Although Studies II and III used both linear and non-linear measures, the absence of neurophysiological data (e.g., muscle activation or cortical activity) limits the mechanistic understanding of PC strategies. Future studies should integrate such data to provide a holistic perspective on PC dysfunctions. Additionally, exploring functional tasks beyond those analyzed, such as sit-to-stand transitions, could enhance the translational relevance of findings. Multivariate analyses could clarify the influence of kinematic variables on CoP variability, while correlations between clinical assessments (e.g., Mini-BESTest_EP) and biomechanical data could strengthen the translational

impact of these tools. Principal component analysis (PCA) might also simplify complex datasets, providing deeper insights into compensatory mechanisms and recovery trajectories in post-stroke individuals.

By addressing these limitations and expanding the scope of future research, the contributions of this thesis can be further validated and leveraged to advance the understanding and rehabilitation of postural control impairments in stroke populations.

CHAPTER V: CONCLUSION

Conclusion

This thesis provides a comprehensive and multidisciplinary exploration of post-stroke PC, integrating findings from three interconnected studies. It highlights the potential of non-linear measures, such as entropy and LyE, to capture the complexity of human movement, complementing traditional linear metrics. This work bridges gaps in methodology, clinical tool validation, and neurobiomechanical characterization, providing critical insights into the challenges of postural instability and adaptability during the feedforward phase of GI, and offering valuable directions for advancing research and rehabilitation practices.

The cross-cultural adaptation and validation of the Mini-BESTest_EP into European Portuguese emerged as a significant milestone, offering a robust and reliable tool for assessing dynamic balance in Portuguese-speaking populations. With psychometric properties consistent with the original version, the Mini-BESTest_EP enhances clinical practice by enabling precise identification of postural impairments, supporting personalized rehabilitation strategies, and providing a standardized approach to balance assessment.

The investigation of PC during the feedforward phase of GI offered critical insights into the dual challenges faced by post-stroke individuals: heightened instability and diminished adaptability. Findings revealed increased CoP displacement and reduced velocity, underscoring postural instability and slower anticipatory adjustments. Non-linear measures demonstrated reduced complexity and adaptability, shedding light on constrained motor strategies and inefficient compensatory mechanisms that disrupt coordination.

This thesis advances the understanding of PC impairments through an innovative combination of biomechanical and clinical approaches, emphasizing the interplay between stability and adaptability. Its contributions extend beyond individual studies, offering a unified framework for evaluating and addressing the multifaceted challenges of post-stroke rehabilitation. By bridging gaps in research and practice, this work lays the foundation for more effective and impactful rehabilitation strategies tailored to the unique needs of stroke populations.

CHAPTER: VI REFERENCES

References

- Adegoke, B. O., Olaniyi, O., & Akosile, C. O. (2012). Weight bearing asymmetry and functional ambulation performance in stroke survivors. *Glob J Health Sci*, 4(2), 87-94. <https://doi.org/10.5539/gjhs.v4n2p87>
- Ahmed, M. U., & Mandic, D. P. (2011). Multivariate multiscale entropy: a tool for complexity analysis of multichannel data. *Phys Rev E Stat Nonlin Soft Matter Phys*, 84(6 Pt 1), 061918. <https://doi.org/10.1103/PhysRevE.84.061918>
- Alqahtani, B. A., Alhowimel, A. S., Alshehri, M. M., Alqahtani, M. A., Almuhaysh, A. A., Alshakarah, A. O., Alanazi, A., Khoja, A. H., & Alenazi, A. M. (2022). Cross-Cultural Adaptation and Validation of the Arabic Version of the Mini-BESTest among Community-Dwelling Older Adults in Saudi Arabia. *Healthcare*, 10(10), 1903. <https://www.mdpi.com/2227-9032/10/10/1903>
- Altenburger, P., Ambike, S. S., & Haddad, J. M. (2023). Integrating Motor Variability Evaluation Into Movement System Assessment. *Phys Ther*, 103(10). <https://doi.org/10.1093/ptj/pzad075>
- Andreasen, S. C., Wright, T. R., Crenshaw, J. R., Reisman, D. S., & Knarr, B. A. (2020). Relationships of linear and non-linear measurements of post-stroke walking activity and their relationship to weather. *Frontiers in Sports and Active Living*, 2, 551542. <https://doi.org/10.3389/fspor.2020.551542>
- APTA. (2015). White Paper - Physical Therapist Practice and the Movement System. Alexandria VA: American Physical Therapy Association.
- Beyaert, C., Vasa, R., & Frykberg, G. E. (2015). Gait post-stroke: Pathophysiology and rehabilitation strategies. *Neurophysiologie Clinique/Clinical Neurophysiology*, 45(4-5), 335–355. <https://doi.org/10.1016/j.neucli.2015.09.005>
- Aromataris, E., & Munn, Z. (2020). Furthering the science of evidence synthesis with a mix of methods. *JBIM Manual Evid Synth*, 18, 2106-2107. <https://doi.org/10.46658/JBIMES-20-02>
- Beaton, D. E., Bombardier, C., Guillemin, F., & Ferraz, M. B. (2000). Guidelines for the process of cross-cultural adaptation of self-report measures. *Spine*, 25(24), 3186-3191. <https://doi.org/10.1097/00007632-200012150-00014>

- Bergström, M., Lenholm, E., & Franzén, E. (2012). Translation and validation of the Swedish version of the mini-BESTest in subjects with Parkinson's disease or stroke: a pilot study. *Physiother Theory Pract*, 28(7), 509-514. <https://doi.org/10.3109/09593985.2011.653707>
- Bernhardt, J., Hayward, K. S., Kwakkel, G., Ward, N. S., Wolf, S. L., Borschmann, K., Krakauer, J. W., Boyd, L. A., Carmichael, S. T., Corbett, D., & Cramer, S. C. (2017). Agreed Definitions and a Shared Vision for New Standards in Stroke Recovery Research: The Stroke Recovery and Rehabilitation Roundtable Taskforce. *Neurorehabil Neural Repair*, 31(9), 793-799. <https://doi.org/10.1177/1545968317732668>
- Beyaert, C., Vasa, R., & Frykberg, G. E. (2015). Gait post-stroke: Pathophysiology and rehabilitation strategies. *Neurophysiol Clin*, 45(4), 335-355. <https://doi.org/https://doi.org/10.1016/j.neucli.2015.09.005>
- Biryukova, E., & Sirotkina, I. (2020). Forward to Bernstein: Movement Complexity as a New Frontier. *Front Neurosci*, 14, 1-17. <https://doi.org/10.3389/fnins.2020.00553>
- Bisi, M. C., & Stagni, R. (2018). Changes of human movement complexity during maturation: quantitative assessment using multiscale entropy. *Comput Methods Biomech Biomed Engin*, 21(4), 325-331. <https://doi.org/10.1080/10255842.2018.1448392>
- Blomgren, C., Jood, K., Jern, C., Holmegaard, L., Redfors, P., Blomstrand, C., & Claesson, L. (2018). Long-term performance of instrumental activities of daily living (IADL) in young and middle-aged stroke survivors: Results from SAHLSIS outcome. *Scand J Occup Ther*, 25(2), 119-126. <https://doi.org/10.1080/11038128.2017.1329343>
- Blum, L., & Korner-Bitensky, N. (2008). Usefulness of the Berg Balance Scale in Stroke Rehabilitation: A Systematic Review. *Phys Ther*, 88(5), 559-566. <https://doi.org/10.2522/ptj.20070205>
- Busa, M. A., & van Emmerik, R. E. A. (2016). Multiscale entropy: A tool for understanding the complexity of postural control. *J Sport Health Sci*, 5(1), 44-51. <https://doi.org/10.1016/j.jshs.2016.01.018>

- Caballero, C., Barbado, D., & Moreno, F. (2014). Non-linear tools and methodological concerns measuring human movement variability: an overview. *Eur J Hum Mov*, 32, 61-81.
- Caballero, C., Davids, K., Heller, B., Wheat, J., & Moreno, F. J. (2019). Movement variability emerges in gait as adaptation to task constraints in dynamic environments. *Gait & Posture*, 70, 1-5. <https://doi.org/10.1016/j.gaitpost.2019.02.002>
- Cabanas-Valdés, R., Boix-Sala, L., Grau-Pellicer, M., Guzmán-Bernal, J. A., Caballero-Gómez, F. M., & Urrútia, G. (2021). The Effectiveness of Additional Core Stability Exercises in Improving Dynamic Sitting Balance, Gait and Functional Rehabilitation for Subacute Stroke Patients (CORE-Trial): Study Protocol for a Randomized Controlled Trial. *Int J Environ Res Public Health*, 18(12), 1-17. <https://doi.org/10.3390/ijerph18126615>
- Caderby, T., Yiou, E., Peyrot, N., de Viviés, X., Bonazzi, B., & Dalleau, G. (2017). Effects of Changing Body Weight Distribution on Mediolateral Stability Control during Gait Initiation [Original Research]. *Frontiers in Human Neuroscience*, 11. <https://doi.org/10.3389/fnhum.2017.00127>
- Cavanaugh, J. T., Kelty-Stephen, D. G., & Stergiou, N. (2017). Multifractality, Interactivity, and the Adaptive Capacity of the Human Movement System: A Perspective for Advancing the Conceptual Basis of Neurologic Physical Therapy. *J Neurol Phys Ther*, 41(4), 245-251. <https://doi.org/10.1097/npt.0000000000000199>
- Chen, F.-C., Chu, C.-H., Pan, C.-Y., & Tsai, C.-L. (2018). Not just a light fingertip touch: A facilitation of functional integration between body sway and visual search in older adults. *Gait & Posture*, 62, 105-110. <https://doi.org/https://doi.org/10.1016/j.gaitpost.2018.03.018>
- Chen, P.-W., Baune, N., Zwir, I., Wang, J., Swamidass, V., & Wong, A. (2021). Measuring Activities of Daily Living in Stroke Patients with Motion Machine Learning Algorithms: A Pilot Study. *Int J Environ Res Public Health*, 18, 1-16. <https://doi.org/10.3390/ijerph18041634>

- Cho, K., Lee, K., Lee, B., Lee, H., & Lee, W. (2014). Relationship between Postural Sway and Dynamic Balance in Stroke Patients. *J Phys Ther Sci*, 26(12), 1989-1992. <https://doi.org/10.1589/jpts.26.1989>
- Choi, Y.-H., Kim, N.-H., Son, S., & Cha, Y. (2020). Effects of Trunk Stabilization Exercise While Wearing a Pelvic Compression Belt on Walking and Balancing Abilities in Patients With Stroke. *Am J Phys Med Rehabil*, 99, 1048-1055. <https://doi.org/10.1097/PHM.0000000000001484>
- Costa, M., Goldberger, A. L., & Peng, C. K. (2005). Multiscale entropy analysis of biological signals. *Phys Rev E Stat Nonlin Soft Matter Phys*, 71(2 Pt 1), 021906. <https://doi.org/10.1103/PhysRevE.71.021906>
- Couto, A. G. B., Vaz, M. A. P., Pinho, L., Félix, J., Moreira, J., Pinho, F., Mesquita, I. A., Mesquita Montes, A., Crasto, C., & Sousa, A. S. P. (2024). Interlimb Coordination during Double Support Phase of Gait in People with and without Stroke. *J Mot Behav*, 56(2), 195-210. <https://doi.org/10.1080/00222895.2023.2282088>
- Cramer, E., Weber, F., Faro, G., Klein, M., Willeke, D., Hering, T., & Zietz, D. (2020). Cross-cultural adaption and validation of the German version of the Mini-BESTest in individuals after stroke: an observational study. *Neurol Res Pract*, 2(1), 27. <https://doi.org/10.1186/s42466-020-00078-w>
- Curuk, E., & Aruin, A. S. (2022). Perturbation-based training enhances anticipatory postural control in individuals with chronic stroke: A pilot study. *International Journal of Rehabilitation Research*, 45(1), 72–78. <https://doi.org/10.1097/MRR.0000000000000488>
- da Costa, C. S., Batistão, M. V., & Rocha, N. A. (2013). Quality and structure of variability in children during motor development: a systematic review. *Res Dev Disabil*, 34(9), 2810-2830. <https://doi.org/10.1016/j.ridd.2013.05.031>
- Dabrowski, A., Balcerzak, M., Pikunov, D., & Stefanski, A. (2020). Improving efficiency of the largest Lyapunov exponent's estimation by its determination from the vector field properties. *Nonlinear Dyn*, 102(3), 1869-1880. <https://doi.org/10.1007/s11071-020-05994-9>

- Dahl, S. S. H., & Jørgensen, L. (2014). Intra- and Inter-Rater Reliability of the Mini-Balance Evaluation Systems Test in Individuals with Stroke. *Int J Ther Rehabil*, 2, 1-6.
- Darak, V., & Karthikbabu, S. (2020). Lower limb motor function and hip muscle weakness in stroke survivors and their relationship with pelvic tilt, weight-bearing asymmetry, and gait speed: A cross-sectional study. *Curr J Neurol*, 19(1), 1-7. <https://doi.org/10.18502/ijnl.v19i1.3275>
- De Luca, A., Squeri, V., Barone, L. M., Verneti Mansin, H., Ricci, S., Pisu, I., Cassiano, C., Capra, C., Lentino, C., De Michieli, L., Sanfilippo, C. A., Saglia, J. A., & Checchia, G. A. (2020). Dynamic Stability and Trunk Control Improvements Following Robotic Balance and Core Stability Training in Chronic Stroke Survivors: A Pilot Study. *Front Neurol*, 11, 494. <https://doi.org/10.3389/fneur.2020.00494>
- De Vet, H., Terwee, C., Mokkink, L., & Knol, D. (2011). *Measurement in Medicine: A Practical Guide*. <https://doi.org/10.1017/CBO9780511996214>
- Delafontaine, A., Vialleron, T., Hussein, T., Yiou, E., Honeine, J.-L., & Colnaghi, S. (2019). Anticipatory Postural Adjustments During Gait Initiation in Stroke Patients. *Front Neurol*, 10, 1-13. <https://doi.org/10.3389/fneur.2019.00352>
- Deuschl, G., Beghi, E., Fazekas, F., Varga, T., Christoforidi, K. A., Sipido, E., Bassetti, C. L., Vos, T., & Feigin, V. L. (2020). The burden of neurological diseases in Europe: an analysis for the Global Burden of Disease Study 2017. *Lancet Public Health*, 5(10), e551-e567. [https://doi.org/10.1016/s2468-2667\(20\)30190-0](https://doi.org/10.1016/s2468-2667(20)30190-0)
- Ding, K., Wang, J., Wang, X., Zhou, L., Xiong, D., & Guo, L. (2024). System for Detection and Quantitative Evaluation of Compensatory Movement in Post-Stroke Patients Based on Wearable Sensor and Machine Learning Algorithm. *IEEE Sensors Journal*, 24, 22830-22842. <https://doi.org/10.1109/JSEN.2024.3408323>
- Dominguez-Olivan, P., Gasch-Gallen, A., Aguas-Garcia, E., & Bengoetxea, A. (2020). Validity and reliability testing of the Spanish version of the BESTest and mini-BESTest in healthy community-dwelling elderly. *BMC Geriatrics*, 20(1), 444. <https://doi.org/10.1186/s12877-020-01724-3>

- Dos Santos, R. B., Fiedler, A., Badwal, A., Legasto-Mulvale, J. M., Sibley, K. M., Olaleye, O. A., Diermayr, G., & Salbach, N. M. (2023). Standardized tools for assessing balance and mobility in stroke clinical practice guidelines worldwide: A scoping review. *Front Rehabil Sci*, 4, 1084085. <https://doi.org/10.3389/fresc.2023.1084085>
- Dubey, L., Karthikbabu, S., & Mohan, D. (2018). Effects of Pelvic Stability Training on Movement Control, Hip Muscles Strength, Walking Speed and Daily Activities after Stroke: A Randomized Controlled Trial. *Annals of neurosciences*, 25(2), 80-89. <https://doi.org/10.1159/000486273>
- Ekker, M. S., Verhoeven, J. I., Vaartjes, I., van Nieuwenhuizen, K. M., Klijn, C. J. M., & de Leeuw, F.-E. (2019). Stroke incidence in young adults according to age, subtype, sex, and time trends. *Neurology*, 92(21), e2444-e2454. <https://doi.org/doi:10.1212/WNL.00000000000007533>
- Elm, E. v., Altman, D. G., Egger, M., Pocock, S. J., Gøtzsche, P. C., & Vandenbroucke, J. P. (2007). Strengthening the reporting of observational studies in epidemiology (STROBE) statement: guidelines for reporting observational studies. *Bmj*, 335(7624), 806-808. <https://doi.org/10.1136/bmj.39335.541782.AD>
- Farinelli, V., Bolzoni, F., Marchese, S. M., Esposti, R., & Cavallari, P. (2021). A Novel Viewpoint on the Anticipatory Postural Adjustments During Gait Initiation. *Front Hum Neurosci*, 15, 1-10. <https://doi.org/10.3389/fnhum.2021.709780>
- Fathi azar, E., Hejazi, M., & Jamshidian, E. (2018). Evaluation of the Relationship between Functional Independence and Quality of Life in Patients with Chronic Stroke. *J Clin Physio Res*, 3 (1), 29-33.
- Federolf, P. (2016). A novel approach to study human posture control: "Principal movements" obtained from a principal component analysis of kinematic marker data. *J Biomech*, 49 3, 364-370. <https://doi.org/10.1016/j.jbiomech.2015.12.030>
- Feigin, V. L., Brainin, M., Norrving, B., Martins, S., Sacco, R. L., Hacke, W., Fisher, M., Pandian, J., & Lindsay, P. (2022). World Stroke Organization (WSO): Global Stroke Fact Sheet 2022. *Int J Stroke*, 17(1), 18-29. <https://doi.org/10.1177/17474930211065917>

- Fernandes, Â., Sousa, A. S. P., Rocha, N., & Tavares, J. (2017). The Influence of a Cognitive Task on the Postural Phase of Gait Initiation in Parkinson's Disease: An Electromyographic-Based Analysis. *Mot Control*, 21(3), 249-264. <https://doi.org/10.1123/mc.2015-0032>
- Franchignoni, F., Godi, M., Guglielmetti, S., Nardone, A., & Giordano, A. (2015). Enhancing the usefulness of the Mini-BESTest for measuring dynamic balance: a Rasch validation study. *Eur J Phys Rehabil Med*, 51 4, 429-437. <https://consensus.app/papers/enhancing-the-usefulness-of-the-minibestest-for-measuring-franchignoni-godi/132cfad5ea785516becc56a457901699/>
- Franchignoni, F., Horak, F., Godi, M., Nardone, A., & Giordano, A. (2010). Using psychometric techniques to improve the Balance Evaluation Systems Test: the mini-BESTest. *J Rehabil Med*, 42(4), 323-331. <https://doi.org/10.2340/16501977-0537>
- Freyler, K., Gollhofer, A., Colin, R., Brüderlin, U., & Ritzmann, R. (2015). Reactive Balance Control in Response to Perturbation in Unilateral Stance: Interaction Effects of Direction, Displacement and Velocity on Compensatory Neuromuscular and Kinematic Responses. *PLoS One*, 10. <https://doi.org/10.1371/journal.pone.0144529>
- Gandolfi, M., Valè, N., Dimitrova, E., Zanolin, M. E., Mattiuz, N., Battistuzzi, E., Beccari, M., Geroïn, C., Picelli, A., Waldner, A., & Smania, N. (2019). Robot-assisted stair climbing training on postural control and sensory integration processes in chronic post-stroke patients: A randomized controlled clinical trial. *Frontiers in Neuroscience*, 13, 1143. <https://doi.org/10.3389/fnins.2019.01143>
- Ghamari, N., Ghaderpanah, R., Sadrian, S. H., & Fallah, N. (2023). Effect of a visual dual task on postural stability-A comparative study using linear and nonlinear methods. *Health Sci Rep*, 6(8), e1437. <https://doi.org/10.1002/hsr2.1437>
- Gil-Salcedo, A., Dugravot, A., Fayosse, A., Jacob, L., Bloomberg, M., Sabia, S., & Schnitzler, A. (2022). Long-Term Evolution of Functional Limitations in Stroke Survivors Compared With Stroke-Free Controls: Findings From 15 Years of Follow-Up Across 3 International Surveys of Aging. *Stroke*, 53(1), 228-237. <https://doi.org/10.1161/STROKEAHA.121.034534>

- Gill-Body, K. M., Hedman, L. D., Plummer, L., Wolf, L., Hanke, T., Quinn, L., Riley, N., Kaufman, R., Verma, A., Quiben, M., & Scheets, P. (2021). Movement System Diagnoses for Balance Dysfunction: Recommendations From the Academy of Neurologic Physical Therapy's Movement System Task Force. *Phys Ther*, 101(9). <https://doi.org/10.1093/ptj/pzab153>
- Godi, M., Franchignoni, F., Caligari, M., Giordano, A., Turcato, A. M., & Nardone, A. (2013). Comparison of Reliability, Validity, and Responsiveness of the Mini-BESTest and Berg Balance Scale in Patients With Balance Disorders. *Phys Ther*, 93(2), 158-167. <https://doi.org/10.2522/ptj.20120171>
- Goh, S., Han, K., Ryu, J., Kim, S., & Choi, M. (2015). Failure of Arm Movement Control in Stroke Patients, Characterized by Loss of Complexity. *PLoS One*, 10(11), e0141996. <https://doi.org/10.1371/journal.pone.0141996>
- Ghomashchi, H. (2016). Investigating the effects of visual biofeedback therapy on recovery of postural balance in stroke patients using a complexity measure. *Topics in Stroke Rehabilitation*, 23(3), 178–183. <https://doi.org/10.1080/10749357.2016.1141477>
- Gorniak, S. L. (2019). The relationship between task difficulty and motor performance complexity. *Atten Percept Psychophys*, 81(1), 12-19. <https://doi.org/10.3758/s13414-018-1634-4>
- Gow, B. J., Peng, C.-K., Wayne, P. M., & Ahn, A. C. (2015). Multiscale Entropy Analysis of Center-of-Pressure Dynamics in Human Postural Control: Methodological Considerations. *Entropy*, 17(12), 7926-7947. <https://www.mdpi.com/1099-4300/17/12/7849>
- Guccione, A. A., Neville, B. T., & George, S. Z. (2019). Optimization of Movement: A Dynamical Systems Approach to Movement Systems as Emergent Phenomena. *Phys Ther*, 99(1), 3-9. <https://doi.org/10.1093/ptj/pzy116>
- Guo, Z., Qian, Q., Wong, K., Zhu, H., Huang, Y., Hu, X., & Zheng, Y. (2020). Altered Corticomuscular Coherence (CMCoh) Pattern in the Upper Limb During Finger Movements After Stroke. *Front Neurol*, 11. <https://doi.org/10.3389/fneur.2020.00410>

- Hadamus, A., Błażkiewicz, M., Kowalska, A. J., Wydra, K. T., Grabowicz, M., Łukowicz, M., Białoszewski, D., & Marczyński, W. (2022). Nonlinear and Linear Measures in the Differentiation of Postural Control in Patients after Total Hip or Knee Replacement and Healthy Controls. *Diagnostics*, 12(7). <https://doi.org/10.3390/diagnostics12071595>
- Haid, T., & Federolf, P. (2018). Human Postural Control: Assessment of Two Alternative Interpretations of Center of Pressure Sample Entropy through a Principal Component Factorization of Whole-Body Kinematics. *Entropy*, 20. <https://doi.org/10.3390/e20010030>
- Halmi, Z., Stone, T. W., Dinya, E., & Mály, J. (2020). Postural instability years after stroke. *J Stroke Cerebrovasc Dis*, 29(9). <https://doi.org/10.1016/j.jstrokecerebrovasdis.2020.105038>
- Harbourne, R., & Kamm, K. (2015). Upper extremity function: What's posture got to do with it? *J Hand Ther*, 28(2), 106-112. <https://doi.org/10.1016/j.jht.2015.01.008>
- Harbourne, R. T., Deffeyes, J. E., Kyvelidou, A., & Stergiou, N. (2009). Complexity of postural control in infants: linear and nonlinear features revealed by principal component analysis. *Nonlinear Dynamics Psychol Life Sci*, 13(1), 123-144.
- Harbourne, R. T., & Stergiou, N. (2009). Movement variability and the use of nonlinear tools: principles to guide physical therapist practice. *Phys Ther*, 89(3), 267-282. <https://doi.org/10.2522/ptj.20080130>
- Harezlak, K., & Kasprowski, P. (2020). Application of Time-Scale Decomposition of Entropy for Eye Movement Analysis. *Entropy*, 22(2), 168. <https://www.mdpi.com/1099-4300/22/2/168>
- Hartman-Maeir, A., Soroker, N., Ring, H., Avni, N., & Katz, N. (2007). Activities, participation and satisfaction one-year post stroke. *Disabil Rehabil*, 29(7), 559-566. <https://doi.org/10.1080/09638280600924996>
- Hedman, L. D., Quinn, L., Gill-Body, K., Brown, D. A., Quiben, M., Riley, N., & Scheets, P. L. (2018). White Paper: Movement System Diagnoses in Neurologic Physical Therapy. *J Neurol Phys Ther*, 42(2), 110-117. <https://doi.org/10.1097/npt.0000000000000215>

- Horak, F. B. (2006). Postural orientation and equilibrium: what do we need to know about neural control of balance to prevent falls? *Age Ageing*, 35, ii7-ii11. <https://doi.org/10.1093/ageing/afl077>
- Horak, F. B., Wrisley, D. M., & Frank, J. (2009). The Balance Evaluation Systems Test (BESTest) to differentiate balance deficits. *Phys Ther*, 89(5), 484-498. <https://doi.org/10.2522/ptj.20080071>
- Hsiao, H., Gray, V., Borrelli, J., & Rogers, M. (2020). Biomechanical control of paretic lower limb during imposed weight transfer in individuals post-stroke. *J Neuroeng Rehabil*, 17, 140. <https://doi.org/10.1186/s12984-020-00768-1>
- Hugues, A., Di Marco, J., Ribault, S., Ardaillon, H., Janiaud, P., Xue, Y., Zhu, J., Pires, J., Khademi, H., Rubio, L., Hernandez Bernal, P., Bahar, Y., Charvat, H., Szulc, P., Ciumas, C., Won, H., Cucherat, M., Bonan, I., Gueyffier, F., & Rode, G. (2019). Limited evidence of physical therapy on balance after stroke: A systematic review and meta-analysis. *PLoS One*, 14(8), e0221700. <https://doi.org/10.1371/journal.pone.0221700>
- Jagroop, D., Aryan, R., Schinkel-Ivy, A., & Mansfield, A. (2022). Reliability of novel centre of pressure measures of quiet standing balance in people with chronic stroke.
- Jang, S. H., & Lee, S. J. (2019). Corticoreticular Tract in the Human Brain: A Mini Review. *Front Neurol*, 10, 1188. <https://doi.org/10.3389/fneur.2019.01188>
- Jayasinghe, S., Wang, R., Gebara, R., Biswas, S., & Ranganathan, R. (2021). Compensatory Trunk Movements in Naturalistic Reaching and Manipulation Tasks in Chronic Stroke Survivors. *J Appl Biomech*, 1-9. <https://doi.org/10.1123/jab.2020-0090>
- Jinzhong, Xu, Y., Li, Y., Tian, R., & Kurths, J. (2019). Predicting noise-induced critical transitions in bistable systems. *Chaos*, 29 8, 81102. <https://doi.org/10.1063/1.5115348>
- Kanekar, N., & Aruin, A. S. (2015). Improvement of anticipatory postural adjustments for balance control: effect of a single training session. *J Electromyogr Kinesiol*, 25(2), 400-405. <https://doi.org/10.1016/j.jelekin.2014.11.002>

- Karimi, Z., Mazloumi, A., Sharifnezhad, A., Jafari, A., Kazemi, Z., Keihani, A., & Mohebbi, I. (2021). Determining the interactions between postural variability structure and discomfort development using nonlinear analysis techniques during prolonged standing work. *Appl Ergon*, 96, 103489. <https://doi.org/10.1016/j.apergo.2021.103489>
- Karthikbabu, S., Chakrapani, M., Ganeshan, S., Rakshith, K. C., Nafeez, S., & Prem, V. (2012). A review on assessment and treatment of the trunk in stroke: A need or luxury. *Neural Regen Res*, 7(25), 1974-1977. <https://doi.org/10.3969/j.issn.1673-5374.2012.25.008>
- Katan, M., & Luft, A. (2018). Global Burden of Stroke. *Semin Neurol*, 38(2), 208-211. <https://doi.org/10.1055/s-0038-1649503>
- Kedziorek, J., & Blazkiewicz, M. (2020). Nonlinear Measures to Evaluate Upright Postural Stability: A Systematic Review. *Entropy*, 22(12), 1357. <https://doi.org/10.3390/e22121357>
- Kempinski, K., Awad, L. N., Buchanan, T. S., Higginson, J. S., & Knarr, B. A. (2018). Dynamic structure of lower limb joint angles during walking post-stroke. *J Biomech*, 68, 1-5. <https://doi.org/10.1016/j.jbiomech.2017.12.019>
- Khanmohammadi, R., Talebian, S., Hadian, M. R., Olyaei, G., & Bagheri, H. (2016). Characteristic muscle activity patterns during gait initiation in the healthy younger and older adults. *Gait & Posture*, 43, 148-153. <https://doi.org/https://doi.org/10.1016/j.gaitpost.2015.09.014>
- Kilby, M. C., Molenaar, P. C. M., & Newell, K. M. (2015). Models of Postural Control: Shared Variance in Joint and COM Motions. *PLoS One*, 10(5), e0126379. <https://doi.org/10.1371/journal.pone.0126379>
- Kim, M. K., Kim, S. G., Shin, Y. J., Choi, E. H., & Choe, Y. W. (2018). The relationship between anterior pelvic tilt and gait, balance in patient with chronic stroke. *J Phys Ther Sci*, 30(1), 27-30. <https://doi.org/10.1589/jpts.30.27>
- Klous, M., Mikulic, P., & Latash, M. L. (2012). Early postural adjustments in preparation to whole-body voluntary sway. *J Electromyogr Kinesiol*, 22(1), 110-116. <https://doi.org/https://doi.org/10.1016/j.jelekin.2011.11.005>

- Ko, J. H., Wang, Z., Challis, J. H., & Newell, K. M. (2015). Compensatory mechanisms of balance to the scaling of arm-swing frequency. *J Biomech*, 48(14), 3825-3829. <https://doi.org/10.1016/j.jbiomech.2015.09.008>
- Koltermann, J. J., Floessel, P., Hammerschmidt, F., & Disch, A. C. (2023). The Influence of Anthropometric Variables and Filtering Frequency on Center of Pressure Data. *Sensors*, 23(11), 5105. <https://www.mdpi.com/1424-8220/23/11/5105>
- Kwakkel, G., Lannin, N. A., Borschmann, K., English, C., Ali, M., Churilov, L., Saposnik, G., Winstein, C., van Wegen, E. E., Wolf, S. L., Krakauer, J. W., & Bernhardt, J. (2017). Standardized measurement of sensorimotor recovery in stroke trials: Consensus-based core recommendations from the Stroke Recovery and Rehabilitation Roundtable. *Int J Stroke*, 12(5), 451-461. <https://doi.org/10.1177/1747493017711813>
- Kwakkel, G., Stinear, C., Essers, B., Munoz-Novoa, M., Branscheidt, M., Cabanas-Valdés, R., Lakičević, S., Lampropoulou, S., Luft, A. R., Marque, P., Moore, S. A., Solomon, J. M., Swinnen, E., Turolla, A., Alt Murphy, M., & Verheyden, G. (2023). Motor rehabilitation after stroke: European Stroke Organisation (ESO) consensus-based definition and guiding framework. *Eur Stroke J*, 8(4), 880-894. <https://doi.org/10.1177/23969873231191304>
- Lafage, R., Duvvuri, P., Elysee, J., Diebo, B., Bess, S., Burton, D., Daniels, A., Gupta, M., Hostin, R., Kebaish, K., Kelly, M., Kim, H.-J., Klineberg, E., Lenke, L., Lewis, S., Ames, C., Passias, P., Protopsaltis, T., Shaffrey, C., . . . Lafage, V. (2023). Quantifying the Contribution of Lower Limb Compensation to Upright Posture. *Spine*, 48, 1082-1088. <https://doi.org/10.1097/BRS.0000000000004646>
- Lampropoulou, S. I., Billis, E., Gedikoglou, I. A., Michailidou, C., Nowicky, A. V., Skrinou, D., Michailidi, F., Chandrinou, D., & Meligkoni, M. (2018). Reliability, validity and minimal detectable change of the Mini-BESTest in Greek participants with chronic stroke. *Physiother Theory Pract*, 35(2), 171-182. <https://doi.org/10.1080/09593985.2018.1441931>
- Lanza, M., & Gray, V. (2022). The effects of stroke on weight transfer before voluntary lateral and forward steps. *Front Neurol*, 13. <https://doi.org/10.3389/fneur.2022.891439>

- Latash, M. L. (2012). The bliss (not the problem) of motor abundance (not redundancy). *Exp Brain Res*, 217(1), 1-5. <https://doi.org/10.1007/s00221-012-3000-4>
- Latash, M. L., & Zatsiorsky, V. (2015). *Biomechanics and Motor Control: Defining Central Concepts*. Human Kinetics.
- Le Mouel, C., & Brette, R. (2017). Mobility as the Purpose of Postural Control [Hypothesis and Theory]. *Front Comput Neurosci*, 11, 67. <https://doi.org/10.3389/fncom.2017.00067>
- Lefebvre, S., & Liew, S. L. (2017). Anatomical Parameters of tDCS to Modulate the Motor System after Stroke: A Review. *Front Neurol*, 8, 29. <https://doi.org/10.3389/fneur.2017.00029>
- Lemay, J.-F., Roy, A., Nadeau, S., & Gagnon, D. H. (2019). French version of the Mini BESTest: A translation and transcultural adaptation study incorporating a reliability analysis for individuals with sensorimotor impairments undergoing functional rehabilitation. *Ann Phys Rehabil Med*, 62(3), 149-154. <https://doi.org/https://doi.org/10.1016/j.rehab.2018.12.001>
- Lencioni, T., Carpinella, I., Rabuffetti, M., Marzegan, A., & Ferrarin, M. (2019). Human kinematic, kinetic and EMG data during different walking and stair ascending and descending tasks. *Sci Data*, 6. <https://doi.org/10.1038/s41597-019-0323-z>
- Leteneur, S., Simoneau, E., Gillet, C., Dessery, Y., & Barbier, F. (2013). Trunk's Natural Inclination Influences Stance Limb Kinetics, but Not Body Kinematics, during Gait Initiation in Able Men. *PLoS One*, 8, e55256. <https://doi.org/10.1371/journal.pone.0055256>
- Levin, M. F. (2016). Principles of Motor Recovery After Neurological Injury Based on a Motor Control Theory. *Adv Exp Med Biol*, 957, 121-140. https://doi.org/10.1007/978-3-319-47313-0_7
- Li, S., Francisco, G. E., & Zhou, P. (2018). Post-stroke Hemiplegic Gait: New Perspective and Insights. *Front Physiol*, 9, 1021. <https://doi.org/10.3389/fphys.2018.01021>
- Li, Y., Yu, Z., Wu, P., & Chen, J. (2022). Ability of an altered functional coupling between resting-state networks to predict behavioral outcomes in subcortical

- ischemic stroke: A longitudinal study. *Front Aging Neurosci*, 14, 933567. <https://doi.org/10.3389/fnagi.2022.933567>
- Liu, K., Wang, H., Xiao, J., & Taha, Z. (2015). Analysis of human standing balance by largest lyapunov exponent. *Comput Intell Neurosci*, 2015, 158478. <https://doi.org/10.1155/2015/158478>
- Löfgren, N., Lenholm, E., Conradsson, D., Ståhle, A., & Franzén, E. (2014). The Mini-BESTest - a clinically reproducible tool for balance evaluations in mild to moderate Parkinson's disease? *BMC Neurology*, 14(1), 235. <https://doi.org/10.1186/s12883-014-0235-7>
- Lundy-Ekman, L., & Weyer, A. (2022). *Neuroscience: Fundamentals for Rehabilitation*. Elsevier. <https://books.google.pt/books?id=eIimzgEACAAJ>
- MacKinnon, C. D. (2018). Chapter 1 - Sensorimotor anatomy of gait, balance, and falls. In B. L. Day & S. R. Lord (Eds.), *Handbook of Clinical Neurology* (Vol. 159, pp. 3-26). Elsevier. <https://doi.org/10.1016/B978-0-444-63916-5.00001-X>
- Maeda, R. S., Gribble, P. L., & Pruszynski, J. A. (2020). Learning New Feedforward Motor Commands Based on Feedback Responses. *Curr Biol*, 30(10), 1941-1948.e1943. <https://doi.org/10.1016/j.cub.2020.03.005>
- Matthew, R., Seko, S., Bajcsy, R., & Lotz, J. (2019). Kinematic and Kinetic Validation of an Improved Depth Camera Motion Assessment System Using Rigid Bodies. *IEEE J Biomed Health Inform*, 23, 1784-1793. <https://doi.org/10.1109/JBHI.2018.2872834>
- Mazzoleni, S., Tran, V., Dario, P., & Posteraro, F. (2018). Wrist Robot-Assisted Rehabilitation Treatment in Subacute and Chronic Stroke Patients: From Distal-to-Proximal Motor Recovery. *IEEE Trans Neural Syst Rehabil Eng*, 26, 1889-1896. <https://doi.org/10.1109/TNSRE.2018.2864935>
- McPherson, L., & Dewald, J. (2022). Abnormal synergies and associated reactions post-hemiparetic stroke reflect muscle activation patterns of brainstem motor pathways. *Front Neurol*, 13. <https://doi.org/10.3389/fneur.2022.934670>

- Mehdizadeh, S. (2018). The largest Lyapunov exponent of gait in young and elderly individuals: A systematic review. *Gait Posture*, 60, 241-250. <https://doi.org/10.1016/j.gaitpost.2017.12.016>
- Mengarelli, A., Tigrini, A., Verdini, F., Rabini, R., & Fioretti, S. (2023). Multiscale Fuzzy Entropy Analysis of Balance: Evidences of Scale-Dependent Dynamics on Diabetic Patients With and Without Neuropathy. *IEEE Trans Neural Syst Rehabil Eng*, 31, 1462-1471. <https://doi.org/10.1109/TNSRE.2023.3248322>
- Mizuta, N., Hasui, N., Nishi, Y., Higa, Y., Matsunaga, A., Deguchi, J., Yamamoto, Y., Nakatani, T., Taguchi, J., & Morioka, S. (2022). Merged swing-muscle synergies and their relation to walking characteristics in subacute post-stroke patients: An observational study. *PLoS One*, 17. <https://doi.org/10.1371/journal.pone.0263613>
- Mohapatra, S., & Aruin, A. S. (2013). Static and dynamic visual cues in feed-forward postural control. *Experimental Brain Research*, 224(1), 25–34. <https://doi.org/10.1007/s00221-012-3282-0>
- Moisan, G., Chayasit, P., Boonsinsukh, R., Nester, C. J., & Hollands, K. (2022). Postural control during quiet standing and voluntary stepping response tasks in individuals post-stroke: A case-control study. *Topics in Stroke Rehabilitation*, 29(6), 465–472. <https://doi.org/10.1080/10749357.2022.2052018>
- Mokkink, L. B., Terwee, C. B., Patrick, D. L., Alonso, J., Stratford, P. W., Knol, D. L., Bouter, L. M., & de Vet, H. C. W. (2010). The COSMIN checklist for assessing the methodological quality of studies on measurement properties of health status measurement instruments: an international Delphi study. *Qual Life Res*, 19(4), 539-549. <https://doi.org/10.1007/s11136-010-9606-8>
- Moore, J. L., Potter, K., Blankshain, K., Kaplan, S. L., O'Dwyer, L. C., & Sullivan, J. E. (2018). A Core Set of Outcome Measures for Adults With Neurologic Conditions Undergoing Rehabilitation: A CLINICAL PRACTICE GUIDELINE. *J Neurol Phys Ther*, 42(3), 174-220. <https://doi.org/10.1097/npt.0000000000000229>
- Moreno, F. J., Caballero, C., & Barbado, D. (2022). Postural control strategies are revealed by the complexity of fractional components of COP. *J Neurophysiol*, 127(5), 1289-1297. <https://doi.org/10.1152/jn.00426.2021>

- Müller, W., Jung, A., & Ahammer, H. (2017). Advantages and problems of nonlinear methods applied to analyze physiological time signals: human balance control as an example. *Sci Rep*, 7(1), 2464. <https://doi.org/10.1038/s41598-017-02665-5>
- Nandi, T., Fisher, B., Hortobágyi, T., & Salem, G. (2018). Increasing mediolateral standing sway is associated with increasing corticospinal excitability, and decreasing M1 inhibition and facilitation. *Gait & Posture*, 60, 135–140. <https://doi.org/10.1016/j.gaitpost.2017.11.019>
- Nakhostin-Ansari, A., Nakhostin Ansari, N., Mellat-Ardakani, M., Nematizad, M., Naghdi, S., Babaki, M., Farhangian, M., Habibi, A. H., Tafakhori, A., & Hasson, S. (2022). Reliability and validity of Persian versions of Mini-BESTest and Brief-BESTest in persons with Parkinson's disease. *Physiother Theory Pract*, 38(9), 1264-1272. <https://doi.org/10.1080/09593985.2020.1822967>
- Okita, S., De Lucena, D. S., & Reinkensmeyer, D. (2024). Movement Diversity and Complexity Increase as Arm Impairment Decreases After Stroke: Quality of Movement Experience as a Possible Target for Wearable Feedback. *IEEE Trans Neural Syst Rehabil Eng*, 32, 2961-2970. <https://doi.org/10.1109/TNSRE.2024.3439669>
- Onuma, R., Masuda, T., Hoshi, F., Matsuda, T., Sakai, T., Okawa, A., & Jinno, T. (2021). Measurements of the centre of pressure of individual legs reveal new characteristics of reduced anticipatory postural adjustments during gait initiation in patients with post-stroke hemiplegia. *Journal of Rehabilitation Medicine*, 53, jrm00211. <https://doi.org/10.2340/16501977-2804>
- Ozturk, A., Tartar, A., Ersoz Huseyinsinoglu, B., & Ertas, A. H. (2016). A clinically feasible kinematic assessment method of upper extremity motor function impairment after stroke. *Measurement*, 80, 207-216. <https://doi.org/https://doi.org/10.1016/j.measurement.2015.11.026>
- Phan, T., Nguyen, H., Vermillion, B., Kamper, D., & Lee, S. W. (2022). Abnormal proximal-distal interactions in upper-limb of stroke survivors during object manipulation: A pilot study. *Front Hum Neurosci*, 16, 1022516. <https://doi.org/10.3389/fnhum.2022.1022516>
- Pongmoragot, J., Lee, D. S., Park, T. H., Fang, J., Austin, P. C., & Saposnik, G. (2016). Stroke and Heart Failure: Clinical Features, Access to Care, and Outcomes. *J*

- Stroke Cerebrovasc Dis, 25(5), 1048-1056.
<https://doi.org/10.1016/j.jstrokecerebrovasdis.2016.01.013>
- Potter, K., & Brandfass, K. (2015). The Mini-Balance Evaluation Systems Test (Mini-BESTest). *J Physiother*, 61(4), 225. <https://doi.org/10.1016/j.jphys.2015.04.002>
- Quijoux, F., Nicolăi, A., Chairi, I., Bargiotas, I., Ricard, D., Yelnik, A., Oudre, L., Bertin-Hugault, F., Vidal, P. P., Vayatis, N., Buffat, S., & Audiffren, J. (2021). A review of center of pressure (COP) variables to quantify standing balance in elderly people: Algorithms and open-access code. *Physiological reports*, 9(22), e15067. <https://doi.org/10.14814/phy2.15067>
- Quinn, L., Riley, N., Tyrell, C. M., Judd, D. L., Gill-Body, K. M., Hedman, L. D., Packel, A., Brown, D. A., Nabar, N., & Scheets, P. (2021). A Framework for Movement Analysis of Tasks: Recommendations From the Academy of Neurologic Physical Therapy's Movement System Task Force. *Phys Ther*, 101(9). <https://doi.org/10.1093/ptj/pzab154>
- Rast, F., Graser, J., Meichtry, A., Ernst, M., & Bauer, C. (2017). Reproducibility of a new signal processing technique to assess joint sway during standing. *J Biomech*, 25(51), 133-136. <https://consensus.app/papers/reproducibility-of-a-new-signal-processing-technique-to-rast-graser/f5276f5b23ee5ded8d00e9b215ad33b8/>
- Rejnö, Å., Nasic, S., Bjälkefur, K., Bertholds, E., & Jood, K. (2019). Changes in functional outcome over five years after stroke. *Brain Behav*, 9(6), e01300. <https://doi.org/10.1002/brb3.1300>
- Roerdink, M., De Haart, M., Daffertshofer, A., Donker, S. F., Geurts, A. C., & Beek, P. J. (2006). Dynamical structure of center-of-pressure trajectories in patients recovering from stroke. *Experimental Brain Research*, 174(2), 256–269. <https://doi.org/10.1007/s00221-006-0441-7>
- Rothwell, J. C. (2012). Overview of neurophysiology of movement control. *Clin Neurol Neurosurg*, 114(5), 432-435. <https://doi.org/10.1016/j.clineuro.2011.12.053>
- Sahrmann, S. (2022). Doctors of the Movement System - Identity by Choice or Therapists Providing Treatment - Identity by Default. *Int J Sports Phys Ther*, 17(1), 1-6. <https://doi.org/10.26603/001c.30175>

- Saladin, L., & Voight, M. (2017). Introduction to the movement system as the foundation for physical therapist practice education and research. *Int J Sports Phys Ther*, 12(6), 858-861.
- Schroeder, S., Jaeger, S., Schwer, J., Seitz, A., Hamann, I., Werner, M., Thorwaechter, C., Santos, I., Wendler, T., Nebel, D., & Welke, B. (2022). Accuracy measurement of different marker based motion analysis systems for biomechanical applications: A round robin study. *PLoS One*, 17. <https://doi.org/10.1371/journal.pone.0271349>
- Seo, J. P., & Koo, D. K. (2023). Degeneration of nigrostriatal pathway in patients with middle cerebral infarct: A diffusion tensor imaging study. *Medicine*, 102(14), e33370. <https://doi.org/10.1097/md.00000000000033370>
- Shumway-Cook, A., & Woollacott, M. H. (2017). *Motor Control: Translating Research Into Clinical Practice*. Wolters Kluwer. <https://books.google.pt/books?id=xy3EsgEACAAJ>
- Sibley, K. M., Beauchamp, M. K., Van Ooteghem, K., Straus, S. E., & Jaglal, S. B. (2015). Using the Systems Framework for Postural Control to Analyze the Components of Balance Evaluated in Standardized Balance Measures: A Scoping Review. *Arch Phys Med Rehabil*, 96(1), 122-132. <https://doi.org/https://doi.org/10.1016/j.apmr.2014.06.021>
- Sibley, K. M., Howe, T., Lamb, S. E., Lord, S. R., Maki, B. E., Rose, D. J., Scott, V., Stathokostas, L., Straus, S. E., & Jaglal, S. B. (2015). Recommendations for a Core Outcome Set for Measuring Standing Balance in Adult Populations: A Consensus-Based Approach. *PLoS One*, 10(3), e0120568. <https://doi.org/10.1371/journal.pone.0120568>
- Siciliano, R., Agapito, G., Siciliano, S., & Fimognari, F. (2019). Aging changes complexity of heart rate dynamics assessed by entropy and Lyapunov exponent analysis. *Geriatr Care*. <https://doi.org/10.4081/GC.2019.8038>
- Silva, A., Sousa, A. S., Silva, C., Tavares, J. M., Santos, R., & Sousa, F. (2015). Ankle antagonist coactivation in the double-support phase of walking: Stroke vs. healthy subjects. *Somatosens Mot Res*, 32(3), 153-157. <https://doi.org/10.3109/08990220.2015.1012492>

- Sousa, A. S., Silva, A., & Santos, R. (2015). Reliability of Two Methods for Identifying the Postural Phase of Gait Initiation in Healthy and Poststroke Subjects. *J Appl Biomech*, 31(5), 349-356. <https://doi.org/10.1123/jab.2014-0222>
- Sousa, A. S. P., Silva, A., Santos, R., Sousa, F., & Tavares, J. (2013). Interlimb coordination during the stance phase of gait in subjects with stroke. *Arch Phys Med Rehabil*, 94(12), 2515-2522. <https://doi.org/10.1016/j.apmr.2013.06.032>
- Sousa, A. S. P., Moreira, J., Silva, C., Mesquita, I., Silva, A., Macedo, R., & Santos, R. (2022). Postural control during turn on the light task assisted by functional electrical stimulation in post stroke subjects. *Scientific Reports*, 12, 6999. <https://doi.org/10.1038/s41598-022-10972-y>
- Stamenkovic, A., Stapley, P. J., Robins, R., & Hollands, M. A. (2018). Do postural constraints affect eye, head, and arm coordination? *J Neurophysiol*, 120(4), 2066-2082. <https://doi.org/10.1152/jn.00200.2018>
- Stergiou, N. (2016). *Nonlinear Analysis for Human Movement Variability*. CRC Press. <https://doi.org/10.1201/9781315370651>
- Stergiou, N., & Decker, L. M. (2011). Human movement variability, nonlinear dynamics, and pathology: is there a connection? *Hum Mov Sci*, 30(5), 869-888. <https://doi.org/10.1016/j.humov.2011.06.002>
- Sternad, D. (2018). It's not (only) the mean that matters: variability, noise and exploration in skill learning. *Curr Opin Behav Sci*, 20, 183-195. <https://doi.org/10.1016/j.cobeha.2018.01.004>
- Takahashi, S., Hoshino, M., Ohyama, S., Hori, Y., Yabu, A., Kobayashi, A., Tsujio, T., Kotake, S., & Nakamura, H. (2021). Relationship of back muscle and knee extensors with the compensatory mechanism of sagittal alignment in a community-dwelling elderly population. *Sci Rep*, 11. <https://doi.org/10.1038/s41598-021-82015-8>
- Takakusaki, K. (2017). Functional Neuroanatomy for Posture and Gait Control. *J Mov Disord*, 10(1), 1-17. <https://doi.org/10.14802/jmd.16062>
- Tasseel-Ponche, S., Yelnik, A. P., & Bonan, I. V. (2015). Motor strategies of postural control after hemispheric stroke. *Neurophysiol Clin*, 45(4-5), 327-333. <https://doi.org/10.1016/j.neucli.2015.09.003>

- Thayabaranathan, T., Kim, J., Cadilhac, D. A., Thrift, A. G., Donnan, G. A., Howard, G., Howard, V. J., Rothwell, P. M., Feigin, V., Norrving, B., Owolabi, M., Pandian, J., Liu, L., & Olaiya, M. T. (2022). Global stroke statistics 2022. *Int J Stroke*, 17(9), 946-956. <https://doi.org/10.1177/17474930221123175>
- Tomita, Y., Mullick, A. A., Feldman, A. G., & Levin, M. F. (2024). Altered Anticipatory Postural Adjustments During Whole-Body Reaching in Subjects With Stroke. *Neurorehabilitation and Neural Repair*, 38(3), 176-186. <https://doi.org/10.1177/15459683241231528>
- Tricco, A. C., Lillie, E., Zarin, W., O'Brien, K. K., Colquhoun, H., Levac, D., Moher, D., Peters, M. D. J., Horsley, T., Weeks, L., Hempel, S., Akl, E. A., Chang, C., McGowan, J., Stewart, L., Hartling, L., Aldcroft, A., Wilson, M. G., Garritty, C., . . . Straus, S. E. (2018). PRISMA Extension for Scoping Reviews (PRISMA-ScR): Checklist and Explanation. *Ann Intern Med*, 169(7), 467-473. <https://doi.org/10.7326/m18-0850>
- Tsang, C. S. L., Liao, L.-R., Chung, R. C. K., & Pang, M. Y. C. (2013). Psychometric Properties of the Mini-Balance Evaluation Systems Test (Mini-BESTest) in Community-Dwelling Individuals With Chronic Stroke. *Phys Ther*, 93(8), 1102-1115. <https://doi.org/10.2522/ptj.20120454>
- Ueta, K., Okada, Y., Nakano, H., Osumi, M., & Morioka, S. (2015). Effects of Voluntary and Automatic Control of Center of Pressure Sway During Quiet Standing. *J Mot Behav*, 47, 256-264. <https://doi.org/10.1080/00222895.2014.974496>
- Van Criekinge, T., Saeys, W., Hallemans, A., Velghe, S., Viskens, P.-J., Vereeck, L., De Hertogh, W., & Truijen, S. (2017). Trunk biomechanics during hemiplegic gait after stroke: A systematic review. *Gait & Posture*, 54, 133-143. <https://doi.org/https://doi.org/10.1016/j.gaitpost.2017.03.004>
- Van Criekinge, T., Truijen, S., Schröder, J., Maebe, Z., Blanckaert, K., van der Waal, C., Vink, M., & Saeys, W. (2019). The effectiveness of trunk training on trunk control, sitting and standing balance and mobility post-stroke: a systematic review and meta-analysis. *Clin Rehabil*, 33(6), 992-1002. <https://doi.org/10.1177/0269215519830159>
- van Emmerik, R. E. A., Ducharme, S. W., Amado, A. C., & Hamill, J. (2016). Comparing dynamical systems concepts and techniques for biomechanical

- analysis. *J Sport Health Sci*, 5(1), 3-13.
<https://doi.org/10.1016/j.jshs.2016.01.013>
- Vaughan-Graham, J., & Cott, C. (2016). Defining a Bobath clinical framework - A modified e-Delphi study. *Physiother Theory Pract*, 32(8), 612-627.
<https://doi.org/10.1080/09593985.2016.1228722>
- Vonesch, A., Duhot, C., Lelard, T., Léonard, G., Błażkiewicz, M., & Mouras, H. (2023). Non-Linear Measures of Postural Control in Response to Painful and Non-Painful Visual Stimuli. *Entropy*, 25(11), 1561. <https://www.mdpi.com/1099-4300/25/11/1561>
- Wafa, H. A., Wolfe, C. D. A., Bhalla, A., & Wang, Y. (2020). Long-term trends in death and dependence after ischaemic strokes: A retrospective cohort study using the South London Stroke Register (SLSR). *PLoS Med*, 17(3), e1003048.
<https://doi.org/10.1371/journal.pmed.1003048>
- Walcott, B. P., Miller, J. C., Kwon, C. S., Sheth, S. A., Hiller, M., Cronin, C. A., Schwamm, L. H., Simard, J. M., Kahle, K. T., Kimberly, W. T., & Sheth, K. N. (2014). Outcomes in severe middle cerebral artery ischemic stroke. *Neurocrit Care*, 21(1), 20-26. <https://doi.org/10.1007/s12028-013-9838-x>
- Watanabe, E., Kiyono, K., Hayano, J., Yamamoto, Y., Inamasu, J., Yamamoto, M., Ichikawa, T., Sobue, Y., Harada, M., & Ozaki, Y. (2015). Multiscale Entropy of the Heart Rate Variability for the Prediction of an Ischemic Stroke in Patients with Permanent Atrial Fibrillation. *PLoS One*, 10(9), e0137144.
<https://doi.org/10.1371/journal.pone.0137144>
- Winter, L., Taylor, P., Bellenger, C., Grimshaw, P., & Crowther, R. G. (2023). The application of the Lyapunov Exponent to analyse human performance: A systematic review. *J Sports Sci*, 41(22), 1994-2013.
<https://doi.org/10.1080/02640414.2024.2308441>
- Wong, C. K. (2014). Interrater Reliability of the Berg Balance Scale When Used by Clinicians of Various Experience Levels to Assess People With Lower Limb Amputations. *Phys Ther*, 94(3), 371-378. <https://doi.org/10.2522/ptj.20130182>
- Wu, C.-H., Lee, C.-H., Jiang, B. C., & Sun, T.-L. (2019). Multiscale Entropy Analysis of Postural Stability for Estimating Fall Risk via Domain Knowledge of Timed-

- Up-And-Go Accelerometer Data for Elderly People Living in a Community. *Entropy*, 21(11), 1076. <https://www.mdpi.com/1099-4300/21/11/1076>
- Xu, P., Yu, H., Wang, X., & Song, R. (2022). Characterizing stroke-induced changes in the variability of lower limb kinematics using multifractal detrended fluctuation analysis. *Front Neurol*, 13, 893999. <https://doi.org/10.3389/fneur.2022.893999>
- Yang, C. L., Creath, R. A., Magder, L., Rogers, M. W., & McCombe Waller, S. (2019). Impaired posture, movement preparation, and execution during both paretic and nonparetic reaching following stroke. *J Neurophysiol*, 121(4), 1465-1477. <https://doi.org/10.1152/jn.00694.2018>
- Yentes, J. M., & Raffalt, P. C. (2021). Entropy Analysis in Gait Research: Methodological Considerations and Recommendations. *Ann Biomed Eng*, 49(3), 979-990. <https://doi.org/10.1007/s10439-020-02616-8>
- Yiou, E., Caderby, T., Delafontaine, A., Fourcade, P., & Honeine, J. L. (2017). Balance control during gait initiation: State-of-the-art and research perspectives. *World J Orthop*, 8(11), 815-828. <https://doi.org/10.5312/wjo.v8.i11.815>

APPENDICES

Appendix I - Search strategy for the study I.

Table 1: Initial search for different databases.

Database	Entry Terms
Pubmed®	Stroke AND (measure OR measurement OR evaluation OR analysis OR assessment) AND (non-linear OR nonlinear OR entropy OR Lyapunov OR "nonlinear variables" OR tools OR dynamic OR variability) AND ("human movement" OR motion) NOT (EEG OR Cardiac).
Institute of Electrical and Electronics Engineers®	Stroke AND (nonlinear OR entropy OR Lyapunov OR variability) NOT EEG
Web of Science®	Stroke AND (non-linear OR entropy OR Lyapunov) AND ("human movement")
Science Direct®	Stroke AND (non-linear OR entropy OR Lyapunov) AND ("human movement") NOT (EEG OR Cardiac)
Google Scholar®	Stroke AND "non-linear measure"

Appendix II - Ethics committee's deliberation

CE/IPSN/CESPU-14/23 approved on 17/04/2023



Comissão de Ética

Exma. Senhora Investigadora
Prof. Doutora Marta Sofia Nicolau Gonçalves de Freitas

N/Ref.: CE/IPSN/CESPU-14/23

Data: 2023/abril/17

Assunto: - Parecer relativo ao Projeto de Investigação nº 8/CE-IPSN/2023
- Título do Projeto: "Adaptação Cultural e linguística e validação do Mini-BESTest para a Cultura Portuguesa (Portugal)"
- Investigadora responsável: Prof. Doutora Marta Sofia Nicolau Gonçalves de Freitas

Exma. Senhora,

Informo V. Exa. que o projeto supracitado foi analisado na reunião da Comissão de Ética do IPSN, da CESPU, Crl, no dia 13/04/2023.

A Comissão de Ética é **favorável** à realização do projeto tal como apresentado.

Com os melhores cumprimentos.



Rua Central de Gandra, 1317
4585-116 GANDRA PRD • Portugal
T. +351 224157100 • F. +351 224157101
www.cespu.pt

Maria de Fátima Pinto Ribeiro
Prof. Doutora Maria de Fátima Pinto Ribeiro
Presidente da Comissão de Ética do IPSN



CESPU – COOPERATIVA DE ENSINO SUPERIOR POLITÉCNICO E UNIVERSITÁRIO, CRL
RUA CENTRAL DE GANDRA, 1317 - 4585 116 GANDRA PRD - T. +351 224 157 100 - F. +351 224 157 101
NIF 501 577 840 - CAP. SOCIAL 1.250.000 EUR - MAT. CONS. R. C. PORTO Nº 216 - www.cespu.pt

CE0054D, approved on 24/11/2023

PARECER DA COMISSÃO DE ÉTICA

Número de Registo da Comissão de Ética: CE0054D
Data receção do Documento: 17/11/2023
Existência de entradas anteriores: Sim (25/10/2023 e 02/05/2023)

TÍTULO DO TRABALHO: NEUROBIOMECHANICS CHARACTERIZATION OF STROKE

INVESTIGADOR RESPONSÁVEL: MARTA GONÇALVES

DATA PREVISTA PARA A REALIZAÇÃO DO TRABALHO: Início 28/11/2023 | Fim 30/12/2026

RESUMO DO ESTUDO

OBJETIVOS: Nada a referir.

AMOSTRA: A indicação dos indivíduos, por parte dos responsáveis das entidades, só será realizada, caso o participante concorde previamente em colaborar no estudo e qualquer dado só será registado após assinatura do consentimento informado. Para a amostra de indivíduos saudáveis, quer para o estudo em si quer para o estudo piloto, só será usado o email institucional via secretariado da presidência, contacto presencial ou redes sociais. Os investigadores usarão apenas comunidade da ESS.

FORMULÁRIO DE DADOS A RECOLHER: Questionário apresentado em formato papel e digital, corrigido. Esclarecido que será aplicado a todos os participantes saudáveis e do estudo piloto. Relembra-se que as respostas de participantes com fatores de exclusão deverão ser imediatamente eliminadas do registo.

MATERIAL: Nada a referir.

MÉTODOS: O cronograma foi novamente ajustado. Os dados vão ser armazenados no computador do investigador principal e apenas acessível com password. Dados vão ser destruídos após o término temporal previsto da realização do estudo – entende-se desta frase que seja logo após o fim do projeto. Salienta-se a necessidade de a base de dados ser encriptada.

RISCOS: Refere que são inexistentes.

CONSENTIMENTO INFORMADO: Corrigido.

AUTORIZAÇÃO PELOS RESPONSÁVEIS LOCAIS: MO.313 conforme. Sendo um doutoramento da FADEUP e tendo esta instituição protocolo com a ESS|Porto não existe necessidade de autorização do departamento da instituição, tal como confirmado via email pelo coordenador do Programa Doutoral em Fisioterapia Professor Jorge Mota. Foi esclarecido que a recolha da amostra não será em diferente UO do P.Porto, mas sim apenas na EES, por isso não existe a necessidade de apresentar essas declarações/autorizações das UO.

APRECIACÃO DA COMISSÃO DE ÉTICA: As dúvidas levantadas foram esclarecidas e os documentos retificados. Salienta-se apenas o cumprimento do exposto infra e nos documentos anteriores.

PARECER FINAL DA COMISSÃO DE ÉTICA: De acordo com os dados analisados, o parecer é favorável desde que cumpridas todas as diretrizes submetidas a esta Comissão, recomendando-se que a decisão seja suspensa caso haja algum incumprimento grave.



SSS ESS.004.MO.318.02

24/11/2023

Assinado por: Pedro Manuel Ribeiro da Rocha Monteiro
Num. de Identificação: 09132856
Data: 2023.11.24 15:41:41 +0000

Appendix III - Informed Consents



Declaração de Consentimento Informado

Conforme o RGPD, a Lei n.º 67/98 de 26 de outubro e a “Declaração de Helsínquia” da Associação Médica Mundial (Helsínquia 1964; Tóquio 1975; Veneza 1983; Hong Kong 1989; Somerset West 1996, Edimburgo 2000; Washington 2002, Tóquio 2004, Seul 2008, Fortaleza 2013)

“Adaptação Cultural e Linguística e Validação da Mini-BESTest para a cultura portuguesa em indivíduos com comprometimento sensório-motor.”

Eu, _____
_____ (NOME COMPLETO) declaro que compreendi a explicação que me foi fornecida acerca do estudo em que estou a ser incluído.

Sei que neste estudo está prevista a validação de uma escala, tendo-me sido explicado em que consiste e quais os seus objetivos. Sei que neste estudo está prevista a realização de um momento de avaliação. Primeiramente, serei submetido a uma avaliação clínica onde serão retirados dados relativos ao sexo, idade, peso e altura e aplicadas as escalas de avaliação (*Mini-BESTest* e *MMSE*).

Na avaliação, as escalas serão aplicadas pelos investigadores responsáveis, de forma individual e num ambiente controlado, após os comandos verbais do investigador do estudo. Será permitido um período de descanso sempre que necessário minutos entre a realização dos testes. No final da avaliação, será também serão esclarecidas as dúvidas que poderão surgir durante a realização dos testes.

Foi-me garantido que todos os dados relativos à identificação dos Participantes neste estudo são confidenciais e que será mantido o anonimato. Sei que posso recusar-me a participar ou interromper a qualquer momento a participação no estudo, sem nenhum tipo de penalização por este facto.

Compreendi a informação que me foi dada, tive oportunidade de fazer perguntas e as minhas dúvidas foram esclarecidas. Aceito participar de livre vontade no estudo acima mencionado. Também autorizo a divulgação dos resultados obtidos no meio científico, garantindo o anonimato.

Nome do Investigador e Contacto: Marta Freitas (916143447)

Data e Assinatura Participante:

____/____/____, _____

TERMO DE
CONSENTIMENTO INFORMADO

DESIGNAÇÃO DO ESTUDO: “*Neurobiomechanics Characterization of Chronic Stroke*”.

Declaração de Consentimento Informado

Conforme o RGPD, a Lei n.º 67/98 de 26 de outubro e a “Declaração de Helsínquia” da Associação Médica Mundial (Helsínquia 1964; Tóquio 1975; Veneza 1983; Hong Kong 1989; Somerset West 1996, Edimburgo 2000; Washington 2002, Tóquio 2004, Seul 2008, Fortaleza 2013)

Eu, abaixo-assinado

(

)
Fui informado de que o Estudo de Investigação, acima mencionado, se destina a um projeto de investigação que visa a caracterização das variáveis biomecânicas com impacto no desempenho das atividades funcionais, em indivíduos pós-AVC.

Sei que neste estudo está prevista a realização de uma avaliação clínica e recolha de dados durante as tarefas: posição de sentado, passagem de sentado para de pé, passagem de pé para sentado, posição de pé, marcha e subir um degrau. As medidas antropométricas massa corporal (Kg) e altura (m) serão avaliadas através de uma balança Tanita® BC-601 (Tanita – Body Composition Monitor®, Tokyo, Japão) e uma análise cinemática através do sistema optoeletrónico Qualisys Motion Capture System.

Foi-me garantido que todos os dados relativos à identificação dos Participantes neste estudo são confidenciais e que será mantido o anonimato. Sei que posso recusar-me a participar ou interromper a qualquer momento a participação no estudo, sem nenhum tipo de penalização por este facto.

Compreendi a informação que me foi dada, tive oportunidade de fazer perguntas e as minhas dúvidas foram esclarecidas. Aceito participar de livre vontade no estudo acima mencionado.

Também autorizo a divulgação dos resultados obtidos no meio científico, garantindo o anonimato.

Nome do Investigador e Contacto: Marta Freitas (916143447)

Data e Assinatura Participante:

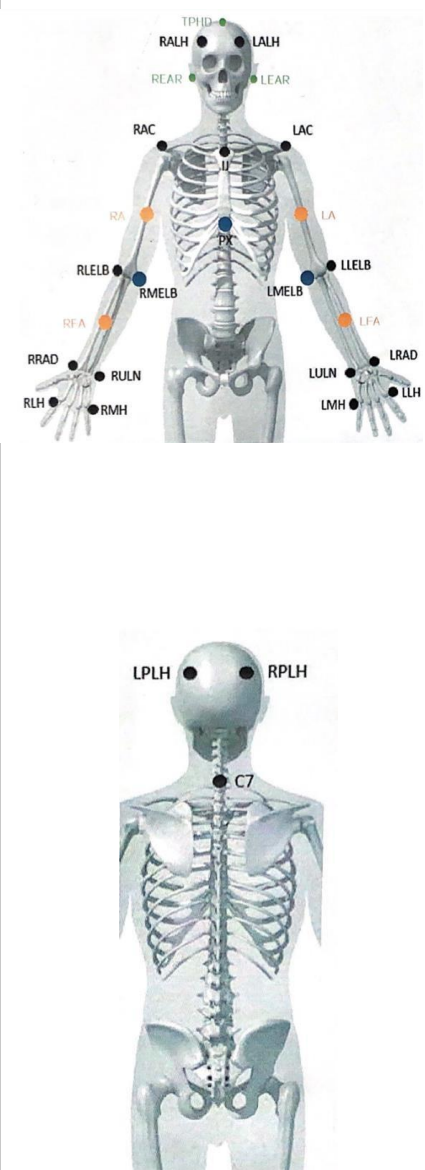


SGS ESS.0004.MO.317.02

_____/_____/_____, _____
1 | 1

Appendix IV – Supplementary data from study III

Table 1: Anatomical Reference Points for Marker Placement.

Table IV: Anatomical Reference Points for Marker Placement			
	Reflective Markers		
	Name	Side	Location
	RALH	Right	Anterolateral Portion of the Head
	LALH	Left	
	RPLH	Right	Posterolateral Portion of the Head
	LPLH	Left	
	REAR	Right	Earlobe
	LEAR	Left	
	RACJ	Right	Acromion
	LACJ	Left	
	C7	-	Cervical Vertebra C7
	TV2	-	Thoracic Vertebra T2
	TV7	-	Thoracic Vertebra T7
	LV1	-	Lumbar Vertebra L1
	LV3	-	Lumbar Vertebra L3
	LV5	-	Lumbar Vertebra L5
	SJN	-	Jugular Notch
	SXS	-	Xiphoid Process
	RLELB	Right	Lateral Epicondyle of the Humerus
	LLELB	Left	
	RMELB	Right	Medial Epicondyle of the Humerus
	LMELB	Left	
	RFA	Right	Forearm (tracking)
	LFA	Left	
	RRAD	Right	Styloid Process of the Radius
	LRAD	Left	
	RULN	Right	Styloid Process of the Ulna
	LULN	Left	
	RLH	Right	Medial Aspect of the 2 nd Metacarpal Head
	LLH	Left	
RMH	Right	Medial Aspect of the 5 th Metacarpal Head	
LMH	Left		
Clusters			
RUA1 RUA2 RUA3	Right	Upper Extremity	
LUA1 LUA2 LUA3	Left		
Lower Extremity			
	Name	Side	Location
	RIAS	Right	Anterior Superior Iliac Spine

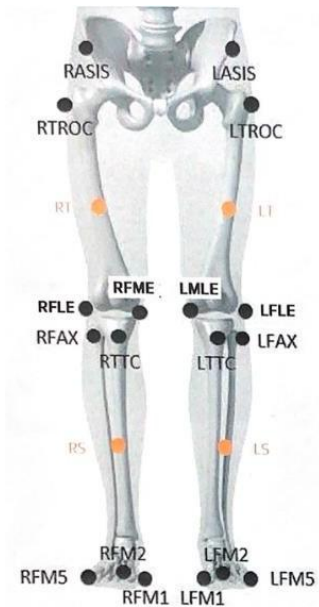
	LIAS	Left	Posterior Superior Iliac Spine
	RIPS	Right	
	LIPS	Left	
	RFTC	Right	Greater Trochanter of the Femur
	LFTC	Left	
	RFLE	Right	Lateral Epicondyle of the Femur
	LFLE	Left	
	RFME	Right	Medial Epicondyle of the Femur
	LFME	Left	
	RFAX	Right	Head of the Fibula
	LFAX	Left	
	RTTC	Right	Anterior Tibial Tuberosity
	LTTC	Left	
	RFAL	Right	Lateral Malleolus
	LFAL	Left	
	RTAM	Right	Medial Malleolus
	LTAM	Left	
	RFCC	Right	Posterior Aspect of the Calcaneus
LFCC	Left		
RFM1	Right	Dorsal Aspect of the 1 st Metatarsal Head	
LFM1	Left		
RFM2	Right	Dorsal Aspect of the 2 nd Metatarsal Head	
LFM2	Left		
RFM5	Right	Dorsal Aspect of the 5 nd Metatarsal Head	
LFM5	Left		
Clusters			
RTH1	Right	Lower Limb (Thigh)	
RTH2			
RTH3			
RTH4			
LTH1	Left		
LTH2			
LTH3			
LTH4			
RSK	Right	Lower Limb (Leg)	
LSK	Left		
			

Table 2: Interpretation table to the meaning of the positive and negative values of joint angles.

Joint Signal	Positive Value (+)	Negative Value (-)
Head (X)	Extension	Flexion
Head (Y)	Tilt to the right	Tilt to the left
Head (Z)	Rotation to the left	Rotation to the right
Thorax (X)	Extension	Flexion
Thorax (Y)	Tilt to the right	Tilt to the left
Thorax (Z)	Rotation to the left	Rotation to the right
Pelvis (X)	Retroversion	Anteversion
Pelvis (Y)	Tilt to the right	Tilt to the left
Pelvis (Z)	Rotation to the left	Rotation to the right
Shoulder (X)	Flexion	Extension
Shoulder (Y)	Adduction	Abduction
Shoulder (Z)	Internal rotation	External rotation
Elbow (X)	Flexion	Extension
Elbow (Y)	Adduction	Abduction
Elbow (Z)	Internal rotation ¹	External rotation ¹
Wrist (X)	Flexion	Extension
Wrist (Y)	Ulnar deviation	Radial deviation
Wrist (Z)	Internal rotation ²	External rotation ²
Hip (X)	Flexion	Extension
Hip (Y)	Adduction	Abduction
Hip (Z)	Internal rotation	External rotation
Knee (X)	Flexion ³	Extension ³
Knee (Y)	Tibial adduction (knee varus)	Tibial abduction (knee valgus)
Knee (Z)	Internal rotation	External rotation
Ankle (X)	Dorsiflexion	Plantar flexion
Ankle (Y)	Inversion	Eversion
Ankle (Z)	Internal rotation	External rotation

¹The rotation of the forearm is related to the pronation/supination of the hand. This movement creates the opposition of the radius and ulna markers, which will generate a 180° rotation in relation to the shoulder.

²Considering the anatomical position. This is empirically related to the pronation/supination movement. However, to perform such a movement, the forearm also must rotate over itself. As such, this hand rotation should be considered as the hand rotation is a fully immobile forearm.

³This is negated in relation to the right-hand rule (it should be extension (+)/flexion (-)) due to the fact there will be minimal extension, and the conventions have set the flexion has a positive signal.

Table 3. Median (MED), 25th (P25) and 75th (P75) percentiles of position (POS), total displacement (TDISP), mean displacement (MDISP) and amplitude (AMP) values of linear outcome of the head, trunk, and pelvis.

		MED (P25; P75)		p value [#]
		Healthy	Stroke	
Head (Extension +/Flexion -)	POS (°)	0.281 (-6.856; 14.368)	-2.867 (-10.286; 4.014)	0.296
	TDISP (°)	0.438 (0.334; 0.693)	1.609 (0.416; 5.396)	0.019
	MDISP (°)	0.007 (0.005; 0.011)	0.025 (0.006; 0.083)	0.019
	AMP (°)	0.279 (0.219; 0.472)	0.855 (0.303; 5.096)	0.009
Trunk (Extension+/Flexion-)	POS (°)	-4.592 (-14.212; -0.396)	-4.087 (-10.013; 1.808)	0.387
	TDISP (°)	0.209 (0.170; 0.257)	0.339 (0.232; 0.708)	0.004
	MDISP (°)	0.005 (0.004; 0.007)	0.009 (0.006; 0.016)	0.004
	AMP (°)	0.267 (0.169; 0.357)	0.481 (0.291; 0.704)	0.002
Pelvis (Retroversion+/Anteversion-)	POS (°)	-9.547 (-12.656; -5.283)	-9.117 (-13.354; -5.334)	0.857
	TDISP (°)	0.318 (0.239; 0.447)	0.576 (0.369; 1.024)	0.017
	DISP (°)	0.003 (0.003; 0.004)	0.005 (0.004; 0.011)	0.014
	AMP (°)	0.173 (0.141; 0.203)	0.269 (0.187; 0.604)	0.009
Head (Right Tilt +/Left Tilt-)	POS (°)	-0.668 (-3.744; 0.308)	-0.297 (-2.790; 1.325)	0.564
	TDISP (°)	0.221 (0.181; 0.257)	0.583 (0.237; 1.086)	0.006
	MDISP (°)	0.003 (0.003; 0.004)	0.009 (0.004; 0.017)	0.005
	AMP (°)	0.120 (0.077; 0.178)	0.355 (0.121; 0.894)	0.006
Trunk (Right Tilt+/Left Tilt-)	POS (°)	1.137 (-0.038; 3.171)	2.394 (0.810; 5.191)	0.160
	TDISP (°)	0.112 (0.096; 0.178)	0.218 (0.100; 0.416)	0.016
	MDISP (°)	0.004 (0.002; 0.004)	0.007 (0.004; 0.010)	0.016
	AMP (°)	0.164 (0.099; 0.207)	0.303 (0.171; 0.450)	0.012
Pelvis (Right Tilt+/Left Tilt-)	POS (°)	0.714 (-1.164; 2.264)	0.207 (-1.570; 2.386)	0.829
	TDISP (°)	0.227 (0.161; 0.290)	0.441 (0.229; 0.637)	0.130
	DISP (°)	0.002 (0.001; 0.003)	0.003 (0.002; 0.006)	0.121
	AMP (°)	0.076 (0.064; 0.124)	0.141 (0.063; 0.328)	0.171

Head (Left Rotation +/Right Rotation-)	POS (°)	0.207 (-2.121; 3.085)	-1.059 (-3.888; 3.076)	0.540
	TDISP (°)	0.265 (0.171; 0.371)	0.917 (0.268; 1.518)	0.009
	DISP (°)	0.004 (0.003; 0.006)	0.014 (0.004; 0.023)	0.009
	AMP (°)	0.129 (0.090; 0.230)	0.704 (0.155; 1.162)	0.004
Trunk (Left Rotation+/Right Rotation-)	POS (°)	-1.090 (-3.927; 0.676)	-0.606 (-3.156; 1.943)	0.494
	TDISP (°)	0.165 (0.124; 0.375)	0.387 (0.215; 0.733)	0.037
	MDISP (°)	0.003 (0.002; 0.004)	0.004 (0.003; 0.009)	0.040
	AMP (°)	0.105 (0.073; 0.151)	0.177 (0.123; 0.406)	0.008
Pelvis (Left Rotation+/Right Rotation-)	POS (°)	0.887 (-0.796; 3.509)	-0.820 (-6.393; 1.408)	0.078
	TDISP (°)	0.169 (0.129; 0.285)	0.292 (0.190; 0.584)	0.011
	DISP (°)	0.003 (0.002; 0.006)	0.006 (0.003; 0.011)	0.009
	AMP (°)	0.103 (0.085; 0.252)	0.326 (0.150; 0.653)	0.002

Mann–Whitney Test; Significant differences in bold.

Table 4. Median (MED), 25th (P25) and 75th (P75) percentiles of position (POS), total displacement (TDISP), mean displacement (MDISP) and amplitude (AMP) values of linear outcome of lower limb joints.

		MED (P25; P75)		P value[#]	MED (P25; P75)		P value[#]
		Swing Healthy	Swing Stroke		Stance Healthy	Stance Stroke	
Hip (Flexion+/Extension-)	POS (°)	-3.673 (-9.233; 1.192)	0.371 (-4.445; 11.872)	0.121	-3.731 (-9.285; 0.623)	-0.570 (-3.390; 10.826)	0.098
	TDISP (°)	0.194 (0.144; 0.294)	0.362 (0.159; 0.968)	0.048	0.201 (0.162; 0.304)	0.358 (0.181; 1.143)	0.052
	MDISP (°)	0.003 (0.002; 0.004)	0.011 (0.003; 0.017)	0.019	0.003 (0.003; 0.005)	0.006 (0.002; 0.013)	0.098
	AMP (°)	0.128 (0.09; 0.188)	0.276 (0.099; 0.794)	0.044	0.141 (0.104; 0.2)	0.263 (0.108; 1.0)	0.061
Knee (Flexion+/Extension-)	POS (°)	-7.635 (-11.981; 2.328)	1.969 (-9.309; 7.228)	0.207	-4.565 (-11.045; 1.011)	1.681 (-7.104; 9.862)	0.113
	TDISP (°)	0.222 (0.153; 0.345)	0.268 (0.192; 0.973)	0.121	0.260 (0.155; 0.300)	0.387 (0.222; 1.380)	0.061
	MDISP (°)	0.003 (0.002; 0.005)	0.01 (0.003; 0.023)	0.019	0.004 (0.002; 0.005)	0.004 (0.003; 0.01)	0.280
	AMP (°)	0.147 (0.092; 0.256)	0.245 (0.133; 0.775)	0.072	0.17 (0.09; 0.192)	0.281 (0.15; 1.272)	0.021
Ankle (Dorsiflexion +/ Plantar)	POS (°)	6.381 (3.309; 9.172)	4.983 (3.052; 8.227)	0.666	6.137 (3.555; 9.534)	7.404 (4.206; 9.605)	0.746
	TDISP (°)	0.162 (0.117; 0.252)	0.277 (0.160; 0.567)	0.034	0.172 (0.113; 0.250)	0.216 (0.156; 0.650)	0.078

Flexion-)	MDISP (°)	0.002 (0.002; 0.004)	0.005 (0.002; 0.01)	0.037	0.003 (0.002; 0.004)	0.004 (0.003; 0.006)	0.052
	AMP (°)	0.137 (0.091; 0.198)	0.227 (0.128; 0.512)	0.028	0.131 (0.085; 0.214)	0.168 (0.114; 0.536)	0.072
Hip (Adduction+/Abduction-)	POS (°)	0.501 (-3.007; 4.642)	1.326 (-1.455; 5.508)	0.719	0.528 (-2.341; 2.572)	1.427 (-1.817; 2.917)	0.692
	TDISP (°)	0.156 (0.116; 0.270)	0.265 (0.138; 0.486)	0.130	0.154 (0.113; 0.219)	0.259 (0.136; 0.523)	0.113
	MDISP (°)	0.002 (0.002; 0.004)	0.004 (0.002; 0.008)	0.084	0.002 (0.002; 0.003)	0.004 (0.002; 0.007)	0.113
	AMP (°)	0.102 (0.071; 0.149)	0.167 (0.091; 0.344)	0.072	0.093 (0.07; 0.139)	0.177 (0.083; 0.358)	0.072
Knee (Tibial Adduction+/Tibial Abduction-)	POS (°)	1.714 (-3.895; 4.003)	-0.816 (-4.687; 3.195)	0.428	1.472 (-4.837; 4.344)	-0.369 (-1.780; 1.416)	0.589
	TDISP (°)	0.083 (0.055; 0.138)	0.104 (0.087; 0.142)	0.183	0.084 (0.062; 0.138)	0.100 (0.079; 0.312)	0.090
	MDISP (°)	0.001 (0.001; 0.002)	0.002 (0.001; 0.005)	0.056	0.001 (0.001; 0.002)	0.001 (0.001; 0.002)	0.235
	AMP (°)	0.048 (0.03; 0.089)	0.064 (0.05; 0.117)	0.150	0.053 (0.036; 0.076)	0.066 (0.048; 0.252)	0.098
Ankle (Inversion +/- Eversion-)	POS (°)	-0.084 (-2.123; 1.244)	1.478 (-0.681; 3.120)	0.130	1.167 (-1.374; 2.503)	2.030 (-0.685; 3.330)	0.494
	TDISP (°)	0.137 (0.105; 0.173)	0.224 (0.124; 0.455)	0.009	0.110 (0.098; 0.172)	0.270 (0.122; 0.449)	0.007
	MDISP (°)	0.002 (0.002; 0.003)	0.004 (0.002; 0.007)	0.026	0.002 (0.002; 0.003)	0.003 (0.002; 0.007)	0.002
	AMP (°)	0.102 (0.066; 0.121)	0.196 (0.093; 0.408)	0.006	0.073 (0.062; 0.12)	0.213 (0.096; 0.4)	0.002
Hip (Internal Rotation+/External Rotation-)	POS (°)	-1.331 (-6.808; 4.386)	-1.916 (-8.346; 2.944)	0.449	-1.014 (-5.119; 5.396)	-4.873 (-9.086; 4.898)	0.517
	TDISP (°)	0.233 (0.159; 0.308)	0.365 (0.275; 0.457)	0.011	0.240 (0.164; 0.373)	0.442 (0.217; 0.862)	0.031
	MDISP (°)	0.004 (0.002; 0.005)	0.007 (0.004; 0.013)	0.011	0.004 (0.002; 0.005)	0.006 (0.004; 0.007)	0.056
	AMP (°)	0.13 (0.097; 0.21)	0.223 (0.158; 0.326)	0.014	0.147 (0.1; 0.231)	0.298 (0.132; 0.631)	0.026
Knee (Internal Rotation+/External Rotation-)	POS (°)	-13.583 (-20.113; -7.516)	-10.794 (-16.714; -4.173)	0.387	-9.494 (-18.908; -5.159)	-10.395 (-20.890; -6.658)	0.471
	TDISP (°)	0.261 (0.190; 0.376)	0.329 (0.275; 0.607)	0.066	0.314 (0.197; 0.425)	0.434 (0.275; 0.747)	0.028
	MDISP (°)	0.004 (0.003; 0.006)	0.007 (0.005; 0.013)	0.017	0.005 (0.003; 0.007)	0.005 (0.004; 0.009)	0.150
	AMP (°)	0.149 (0.099; 0.242)	0.186 (0.166; 0.453)	0.037	0.179 (0.096; 0.248)	0.307 (0.188; 0.474)	0.006
Ankle (Internal Rotation +/External Rotation-)	POS (°)	9.620 (4.694; 13.222)	8.671 (5.734; 12.081)	0.719	9.709 (7.616; 11.588)	8.982 (5.151; 13.392)	0.589
	TDISP (°)	0.143 (0.110; 0.246)	0.171 (0.122; 0.264)	0.517	0.178 (0.101; 0.233)	0.218 (0.133; 0.475)	0.130
	MDISP (°)	0.002 (0.002; 0.004)	0.003 (0.002; 0.006)	0.090	0.003 (0.001; 0.004)	0.003 (0.002; 0.005)	0.589
	AMP (°)	0.086 (0.066; 0.147)	0.116 (0.078; 0.197)	0.235	0.117 (0.055; 0.151)	0.132 (0.081; 0.383)	0.066

Mann–Whitney Test; Significant differences in bold.

Table 5. Median (MED), 25th (P25) and 75th (P75) percentiles of position (POS), total displacement (TDISP), mean displacement (MDISP) and amplitude (AMP) values of linear outcome of upper limb joints.

		MED (P25; P75)		p value [#]	MED (P25; P75)		p value [#]
		Swing Healthy	Swing Stroke		Stance Healthy	Stance Stroke	
Shoulder (Flexion+/Extension-)	POS (°)	14.146 (8.153; 18.882)	14.483 (8.342; 22.519)	0.801	12.251 (9.047; 15.077)	12.768 (8.858; 18.603)	0.692
	TDISP (°)	0.267 (0.203; 0.334)	0.407 (0.232; 0.712)	0.026	0.266 (0.206; 0.353)	0.473 (0.261; 0.837)	0.019
	MDISP (°)	0.004 (0.003; 0.005)	0.007 (0.004; 0.013)	0.013	0.004 (0.003; 0.005)	0.006 (0.004; 0.011)	0.048
	AMP (°)	0.165 (0.111; 0.225)	0.299 (0.175; 0.562)	0.004	0.15 (0.11; 0.215)	0.282 (0.188; 0.625)	0.003
Elbow (Flexion+/Extension-)	POS (°)	19.325 (8.002; 29.015)	28.919 (15.248; 43.259)	0.098	23.010 (13.212; 26.439)	20.988 (7.137; 32.821)	0.692
	TDISP (°)	0.197 (0.174; 0.305)	0.337 (0.171; 0.536)	0.264	0.244 (0.215; 0.317)	0.421 (0.192; 0.882)	0.113
	MDISP (°)	0.003 (0.003; 0.005)	0.007 (0.003; 0.013)	0.034	0.004 (0.003; 0.005)	0.005 (0.003; 0.008)	0.313
	AMP (°)	0.117 (0.095; 0.151)	0.234 (0.114; 0.483)	0.044	0.138 (0.116; 0.174)	0.312 (0.11; 0.712)	0.031
Wrist (Flexion+/Extension-)	POS (°)	1.092 (-3.185; 4.199)	2.559 (-0.983; 5.300)	0.801	1.148 (-1.496; 6.255)	0.729 (-1.343; 6.798)	0.746
	TDISP (°)	0.354 (0.221; 0.520)	0.417 (0.351; 0.864)	0.066	0.337 (0.234; 0.840)	0.605 (0.365; 0.974)	0.105
	MDISP (°)	0.005 (0.003; 0.008)	0.009 (0.006; 0.013)	0.016	0.005 (0.004; 0.013)	0.006 (0.005; 0.017)	0.121
	AMP (°)	0.149 (0.098; 0.238)	0.233 (0.196; 0.557)	0.008	0.145 (0.123; 0.437)	0.306 (0.194; 0.678)	0.072
Shoulder (Adduction+/Abduction-)	POS (°)	-12.337 (-16.113; -9.282)	-11.705 (-16.633; -6.673)	0.494	-13.971 (-18.146; -9.497)	-10.662 (-14.144; -6.095)	0.121
	TDISP (°)	0.217 (0.176; 0.306)	0.259 (0.174; 0.419)	0.313	0.230 (0.150; 0.293)	0.331 (0.186; 0.541)	0.090
	MDISP (°)	0.003 (0.003; 0.005)	0.004 (0.003; 0.007)	0.090	0.004 (0.002; 0.004)	0.004 (0.003; 0.006)	0.249
	AMP (°)	0.146 (0.117; 0.17)	0.206 (0.111; 0.285)	0.264	0.158 (0.103; 0.21)	0.201 (0.104; 0.376)	0.121
Elbow (Adduction+/Abduction-)	POS (°)	13.967 (4.640; 20.301)	1.254 (-1.241; 8.400)	0.056	15.175 (6.397; 19.363)	5.577 (-1.725; 14.782)	0.130
	TDISP (°)	0.211 (0.172; 0.359)	0.306 (0.207; 0.509)	0.056	0.277 (0.178; 0.368)	0.401 (0.232; 0.725)	0.113
	MDISP (°)	0.003 (0.003; 0.006)	0.006 (0.004; 0.011)	0.031	0.004 (0.003; 0.005)	0.004 (0.003; 0.009)	0.264
	AMP (°)	0.117 (0.085; 0.165)	0.233 (0.138; 0.359)	0.004	0.139 (0.102; 0.18)	0.230 (0.138; 0.431)	0.026
Wrist (Ulnar Deviation+/Radial Deviation-)	POS (°)	2.899 (0.334; 5.321)	0.119 (-1.092; 5.889)	0.235	3.021 (1.153; 7.276)	1.677 (0.231; 6.123)	0.387
		0.246 (0.170; 0.294)	0.295 (0.216; 0.520)	0.113	0.249 (0.177; 0.343)	0.335 (0.206; 0.722)	0.387
	DISP (°)	0.004 (0.003; 0.004)	0.005 (0.003; 0.009)	0.040	0.004 (0.003; 0.005)	0.004 (0.003; 0.011)	0.494
	AMP (°)	0.107 (0.079; 0.145)	0.146 (0.126; 0.297)	0.021	0.137 (0.099; 0.166)	0.157 (0.104; 0.377)	0.296
Shoulder	POS (°)	-17.120 (-36.353; 7.499)	12.811 (-9.952; 34.121)	0.019	-9.655 (-34.033; 12.475)	-5.645 (-41.230; 27.128)	0.943

(Internal Rotation+/ External Rotation-)	TDISP (°)	0.488 (0.413; 0.751)	0.626 (0.384; 1.081)	0.349	0.526 (0.440; 0.861)	0.740 (0.435; 1.210)	0.113
	MDISP (°)	0.007 (0.006; 0.012)	0.014 (0.006; 0.018)	0.105	0.008 (0.007; 0.013)	0.009 (0.007; 0.018)	0.494
	AMP (°)	0.282 (0.222; 0.381)	0.308 (0.223; 0.766)	0.280	0.283 (0.241; 0.464)	0.379 (0.227; 0.762)	0.150
Elbow (Internal Rotation +/ External Rotation-)	POS (°)	125.492 (91.457; 145.071)	127.845 (70.402; 142.806)	0.943	125.947 (102.469; 135.530)	126.945 (92.484; 145.429)	0.666
	TDISP (°)	0.464 (0.366; 0.796)	0.579 (0.386; 1.218)	0.105	0.657 (0.422; 0.846)	0.758 (0.497; 1.483)	0.113
	MDISP (°)	0.007 (0.006; 0.012)	0.012 (0.008; 0.022)	0.019	0.01 (0.007; 0.012)	0.009(0.006; 0.02)	0.589
	AMP (°)	0.229 (0.179; 0.388)	0.425 (0.236; 0.768)	0.026	0.305 (0.239; 0.406)	0.443 (0.331; 0.799)	0.028
Wrist (Internal Rotation+/ External Rotation-)	POS (°)	16.925 (12.795; 19.396)	0.506 (-0.647; 14.965)	0.009	20.094 (16.696; 31.567)	0.605 (-1.297; 16.873)	<.001
	TDISP (°)	0.212 (0.155; 0.242)	0.269 (0.183; 0.512)	0.021	0.236 (0.172; 0.332)	0.280 (0.192; 0.693)	0.349
	MDISP (°)	0.003 (0.002; 0.004)	0.005 (0.003; 0.01)	0.021	0.004 (0.003; 0.005)	0.004 (0.003; 0.009)	0.387
	AMP (°)	0.108 (0.084; 0.134)	0.155 (0.084; 0.359)	0.044	0.126 (0.083; 0.196)	0.157 (0.094; 0.403)	0.249

Mann–Whitney Test; Significant differences in bold.

Table 6. Median (MED). 25th (P25) and 75th (P75) percentiles of position (POS) and displacement (DISP) values of non- linear outcome of head. trunk and pelvis.

		POSITION MED (P25; P75)			MEAN DISPLACMENT MED (P25; P75)		
		Healthy	Post-Stroke	P value #	Healthy	Post-Stroke	P value #
Head (Extension +/ Flexion -)	Ly	-5.691 (-8.247; -4.555)	-2.776 (-5.384; -0.077)	0.004	-12.220 (-16.973; 2.905)	-4.314 (-10.222; 6.252)	0.130
	MSE S1	0.234 (0.209; 0.270)	0.169 (0.087; 0.208)	0.002	0.533 (0.466; 0.572)	0.470 (0.258; 0.505)	0.009
	MSE S2	0.409 (0.352; 0.481)	0.322 (0.167; 0.375)	0.009	1.069 (0.800; 1.187)	0.833 (0.418; 1.077)	0.034
	CI	0.641 (0.561; 0.748)	0.503 (0.254; 0.583)	0.006	1.581 (1.215; 1.777)	1.375 (0.645; 1.558)	0.021
Trunk (Extension+/ Flexion-)	Ly	-3.567 (-4.910; -2.793)	-2.917 (-3.493; -1.413)	0.056	-14.268 (-18.386; -10.263)	-10.775 (-15.369; -6.928)	0.130
	MSE S1	0.171 (0.152; 0.204)	0.162 (0.107; 0.190)	0.195	0.525(0.476; 0.582)	0.479 (0.431; 0.538)	0.078
	MSE S2	0.319 (0.281; 0.414)	0.304 (0.204; 0.337)	0.160	1.057 (0.871; 1.141)	0.915 (0.830; 1.002)	0.121
	CI	0.493 (0.434; 0.613)	0.463 (0.309; 0.518)	0.160	1.598(1.329; 1.680)	1.413 (1.232; 1.501)	0.061
Pelvis	Ly	-11.396 (-14.178; -9.298)	-5.251 (-8.179; -1.043)	<.001	-11.216 (-14.525; -6.332)	-10.913 (-13.536; -8.351)	0.943

(Retroversion+ /Anteversio-)	MSE S1	0.143 (0.114; 0.162)	0.145 (0.119; 0.156)	0.857	0.480 (0.440; 0.529)	0.480 (0.417; 0.508)	0.666
	MSE S2	0.250 (0.212; 0.321)	0.243 (0.220; 0.303)	0.943	0.940 (0.857; 1.064)	0.848 (0.786; 1.003)	0.195
	CI	0.397 (0.329; 0.485)	0.379 (0.336; 0.458)	0.971	1.412 (1.315; 1.532)	1.270 (1.222; 1.456)	0.150
Head (Right Tilt +/Left Tilt-)	Ly	-9.011 (-12.178; -6.777)	-4.583 (-8.552; -3.008)	0.006	-7.096 (-14.706; 1.694)	-8.421 (-12.539; -1.563)	0.885
	MSE S1	0.310 (0.249; 0.349)	0.193(0.158; 0.316)	0.023	0.665 (0.596; 0.730)	0.522 (0.453; 0.582)	< 0.001
	MSE S2	0.564 (0.435; 0.689)	0.376 (0.281; 0.565)	0.021	1.167 (0.997; 1.372)	0.946 (0.777; 1.125)	0.007
	CI	0.870 (0.665; 1.038)	0.558 (0.446; 0.870)	0.013	1.798 (1.615; 2.092)	1.464 (1.219; 1.709)	0.006
Trunk (Right Tilt+ /Left Tilt-)	Ly	-4.327 (-5.609; -2.845)	-3.361 (-5.702; -2.092)	0.368	-9.668 (-14.084; 1.769)	-12.286 (-14.639; -4.436)	0.387
	MSE S1	0.193 (0.165; 0.231)	0.148 (0.127; 0.176)	0.007	0.540 (0.464; 0.572)	0.492 (0.420; 0.543)	0.150
	MSE S2	0.339 (0.299; 0.404)	0.268 (0.242; 0.294)	0.002	0.988 (0.907; 1.142)	0.942 (0.857; 1.153)	0.885
	CI	0.548(0.453; 0.616)	0.434 (0.369; 0.468)	0.003	1.502 (1.373; 1.699)	1.455 (1.283; 1.635)	0.614
Pelvis (Right Tilt+ /Left Tilt-)	Ly	-11.206 (-14.113; -9.469)	-7.997(-11.055; -3.938)	0.011	3.581 (-6.017; 6.079)	3.241 (-9.452; 6.761)	0.564
	MSE S1	0.220 (0.182; 0.271)	0.172 (0.127; 0.240)	0.051	0.558 (0.510; 0.602)	0.513 (0.445; 0.597)	0.235
	MSE S2	0.379 (0.327; 0.467)	0.349 (0.251; 0.439)	0.207	1.161 (0.943; 1.205)	1.018 (0.852; 1.148)	0.235
	CI	0.613 (0.512; 0.736)	0.518 (0.379; 0.674)	0.105	1.721(1.434; 1.790)	1.531 (1.275; 1.704)	0.207
Head (Left Rotation +/Right Rotation-)	Ly	-9.072 (-12.134; -6.875)	-7.472 (-11.683; -1.293)	0.130	-2.532 (-8.539; 4.605)	-5.688 (-10.120; 1.614)	0.296
	MSE S1	0.314 (0.268; 0.362)	0.244 (0.157; 0.313)	0.009	0.691 (0.572; 0.754)	0.538 (0.399; 0.612)	0.002
	MSE S2	0.591 (0.505; 0.690)	0.466 (0.275; 0.567)	0.006	1.236 (1.108; 1.445)	0.957 (0.762; 1.160)	0.006
	CI	0.903 (0.798; 1.056)	0.700 (0.443; 0.856)	0.005	1.970 (1.704; 2.078)	1.502 (1.141; 1.738)	0.005
Trunk (Left Rotation+ /Right Rotation-)	Ly	-6.592 (-7.767; -4.999)	-5.723 (-7.473; -2.846)	0.221	-11.008 (-14.720; -0.753)	-7.469 (-16.431; -3.228)	0.719
	MSE S1	0.247 (0.224; 0.274)	0.226 (0.177; 0.245)	0.021	0.599 (0.503; 0.710)	0.532 (0.497; 0.616)	0.160
	MSE S2	0.460 (0.379; 0.503)	0.397 (0.332; 0.433)	0.052	1.149 (0.922; 1.284)	0.930 (0.845; 1.106)	0.052
	CI	0.696 (0.603; 0.782)	0.629 (0.518; 0.677)	0.040	1.756(1.396; 1.971)	1.477 (1.312; 1.677)	0.048
Pelvis (Left Rotation+ /Right Rotation-)	Ly	-11.027(-13.406; -8.215)	-7.008 (-9.626; -1.944)	0.011	-13.785 (-17.085; -11.108)	-13.581 (-17.568; -9.212)	1.000
	MSE S1	0.225 (0.188; 0.269)	0.160 (0.128; 0.196)	0.002	0.514 (0.476; 0.571)	0.469 (0.401; 0.499)	0.021
	MSE S2	0.383 (0.349; 0.440)	0.302 (0.262; 0.379)	0.019	1.011 (0.840; 1.039)	0.883 (0.708; 1.008)	0.105
	CI	0.593 (0.543; 0.713)	0.480 (0.388; 0.561)	0.004	1.523(1.260; 1.571)	1.333 (1.093; 1.478)	0.044

Mann–Whitney Test; Significant differences in bold; LyE: Lyapunov Exponent; MSE: Multiscale Entropy; S1: Scale 1; S2: Scale 2; CI: Complexity Index.

Table 7. Median (MED), 25th (P25) and 75th (P75) percentiles of position (POS) values of non-linear outcome of lower limb joints.

		POSITION MED (P25; P75)					
		Swing Healthy	Swing Stroke	P value [#]	Stance Healthy	Stance Stroke	P value [#]
Hip (Flexion+/Extension-)	Ly	-8.589 (-10.509; -6.026)	-4.520 (-6.745; -3.151)	0.021	-5.372 (-8.269; -3.385)	-5.195 (-7.357; -3.582)	0.006
	MSE S1	0.201 (0.173; 0.258)	0.198 (0.160; 0.238)	0.048	0.215 (0.178; 0.256)	0.191 (0.174; 0.252)	0.053
	MSE S2	0.368 (0.310; 0.481)	0.365 (0.285; 0.414)	0.026	0.403 (0.331; 0.519)	0.354 (0.287; 0.477)	0.060
	CI	0.569 (0.489; 0.735)	0.566 (0.447; 0.624)	0.040	0.625 (0.515; 0.743)	0.545 (0.461; 0.736)	0.428
Knee (Flexion+/Extension-)	Ly	-6.216 (-7.962; -3.008)	-3.865 (-5.662; -1.208)	0.564	-5.383 (-8.579; -2.934)	-4.359 (-6.628; 1.526)	0.971
	MSE S1	0.230 (0.187; 0.268)	0.206 (0.154; 0.234)	0.471	0.217 (0.197; 0.268)	0.189 (0.133; 0.237)	0.943
	MSE S2	0.425 (0.319; 0.505)	0.343 (0.281; 0.415)	0.471	0.385 (0.359; 0.459)	0.348 (0.243; 0.458)	0.885
	CI	0.667 (0.508; 0.757)	0.566 (0.427; 0.645)	0.026	0.592 (0.557; 0.713)	0.536 (0.386; 0.696)	0.666
Ankle (Dorsiflexion +/ Plantar Flexion-)	Ly	-2.538 (-3.582; -1.734)	-1.982 (-3.511; -1.465)	0.589	-2.388 (-3.438; -0.495)	-2.395 (-4.532; -0.461)	0.016
	MSE S1	0.176 (0.131; 0.196)	0.133 (0.117; 0.172)	0.280	0.160 (0.132; 0.189)	0.167 (0.146; 0.195)	0,057
	MSE S2	0.334 (0.246; 0.381)	0.258 (0.212; 0.288)	0.313	0.287 (0.247; 0.355)	0.286 (0.257; 0.365)	0,062
	CI	0.510 (0.392; 0.570)	0.391 (0.337; 0.470)	0.773	0.447 (0.372; 0.539)	0.464 (0.403; 0.552)	0.280
Hip (Adduction+/Abduction-)	Ly	-10.303 (-12.835; -8.672)	-6.209 (-7.474; -4.529)	0.052	-6.774 (-7.971; -4.657)	-5.603 (-6.773; -3.707)	0.746
	MSE S1	0.232 (0.181; 0.279)	0.170 (0.133; 0.210)	0.023	0.246 (0.225; 0.275)	0.185 (0.139; 0.245)	0.494
	MSE S2	0.416 (0.346; 0.566)	0.318 (0.262; 0.455)	0.009	0.430 (0.405; 0.475)	0.325(0.270; 0.449)	0.057
	CI	0.653 (0.509; 0.838)	0.488 (0.394; 0.656)	0.004	0.680 (0.643; 0.730)	0.512 (0.411; 0.688)	0.564
Knee (Tibial Adduction+/Tibial Abduction-)	Ly	-6.167 (-8.560; -1.446)	-5.338 (-6.781; -3.438)	0.090	-7.593 (-9.534; -5.351)	-5.535 (-8.462; -3.460)	0.971
	MSE S1	0.216 (0.205; 0.291)	0.247 (0.216; 0.282)	0.061	0.253 (0.204; 0.278)	0.238 (0.167; 0.284)	0.885
	MSE S2	0.398 (0.347; 0.488)	0.430 (0.397; 0.497)	0.313	0.421 (0.372; 0.539)	0.419 (0.306; 0.548)	0.130
	CI	0.626 (0.546; 0.787)	0.689 (0.611; 0.792)	0.105	0.670 (0.577; 0.828)	0.631 (0.478; 0.839)	0.264
Ankle (Inversion +/Eversion-)	Ly	-4.844 (-5.759; -3.433)	-3.933 (-5.292; -2.829)	0.368	-6.005 (-7.544; -3.643)	-2.467 (-4.306; -1.426)	0.048
	MSE S1	0.212 (0.169; 0.267)	0.161 (0.134; 0.193)	0.914	0.212(0.192; 0.258)	0.181 (0.128; 0.204)	0.387
	MSE S2	0.438 (0.287; 0.509)	0.306 (0.248; 0.394)	0.001	0.445 (0.397; 0.528)	0.373 (0.273; 0.407)	0.008
	CI	0.650 (0.454; 0.780)	0.467 (0.379; 0.595)	<.001	0.658 (0.595; 0.779)	0.536 (0.402; 0.608)	<.001

Hip (Internal Rotation+/External Rotation-)	Ly	-10.472 (-11.189; -8.557)	-7.350 (-9.785; -4.882)	0.006	-7.377 (-9.433; -5.627)	-7.424 (-9.547; -3.959)	0.296
	MSE S1	0.254 (0.222; 0.299)	0.248 (0.193; 0.267)	0.098	0.265 (0.195; 0.305)	0.208 (0.178; 0.252)	0.407
	MSE S2	0.498 (0.425; 0.545)	0.438 (0.370; 0.491)	0.061	0.485 (0.372; 0.522)	0.396 (0.334; 0.445)	0.719
	CI	0.742 (0.645; 0.826)	0.667 (0.571; 0.756)	0.040	0.754 (0.565; 0.822)	0.618 (0.511; 0.679)	0.773
Knee (Internal Rotation+/External Rotation-)	Ly	-8.514 (-9.483; -6.228)	-6.367 (-9.501; -4.112)	0.207	-7.265 (-9.084; -5.767)	-5.801 (-9.063; -5.332)	0.140
	MSE S1	0.256 (0.225; 0.278)	0.222 (0.203; 0.261)	0.084	0.273 (0.200; 0.316)	0.206 (0.186; 0.263)	0.130
	MSE S2	0.472 (0.394; 0.545)	0.418 (0.368; 0.478)	0.061	0.518 (0.370; 0.563)	0.398 (0.345; 0.459)	0.331
	CI	0.736 (0.610; 0.826)	0.631 (0.574; 0.743)	0.066	0.784 (0.568; 0.879)	0.625 (0.548; 0.697)	0.296
Ankle (Internal Rotation +/External Rotation-)	Ly	-5.123 (-6.817; -3.350)	-3.774 (-5.675; -2.362)	0.013	-5.454 (-8.203; -3.499)	-4.022 (-5.941; -2.539)	<.001
	MSE S1	0.261 (0.237; 0.309)	0.213 (0.176; 0.256)	0.098	0.252 (0.215; 0.305)	0.204 (0.168; 0.255)	0.016
	MSE S2	0.487 (0.456; 0.522)	0.410 (0.341; 0.499)	0.640	0.456 (0.403; 0.543)	0.373(0.334; 0.494)	<.001
	CI	0.740 (0.702; 0.841)	0.653 (0.516; 0.755)	0.221	0.708 (0.631; 0.841)	0.572 (0.508; 0.743)	<.001

Mann–Whitney Test; Significant differences in bold; LyE: Lyapunov Exponent; MSE: Multiscale Entropy; S1: Scale 1; S2: Scale 2; CI: Complexity Index.

Table 8. Median (MED), 25th (P25) and 75th (P75) percentiles of displacement (DISP) values of non-linear outcome of lower limb joints.

		DISPLACMENT MED (P25; P75)					
		Swing Healthy	Swing Stroke	P value #	Stance Healthy	Stance Stroke	P value #
Hip (Flexion+/Extension-)	Ly	6.144 (-5.855; 10.499)	-6.558 (-10.687; -1.985)	0.801	0.185 (-5.981; 8.766)	-2.536 (-9.129; 7.298)	0.494
	MSE S1	0.524 (0.447; 0.569)	0.502 (0.440; 0.601)	0.387	0.524 (0.480; 0.585)	0.490 (0.426; 0.599)	0.296
	MSE S2	0.974 (0.871; 1.105)	0.986 (0.842; 1.105)	0.195	1.021 (0.891; 1.080)	0.888 (0.720; 1.080)	0.105
	CI	1.490 (1.327; 1.643)	1.488 (1.308; 1.715)	0.195	1.534 (1.406; 1.586)	1.355 (1.167; 1.617)	0.098
Knee (Flexion+/Extension-)	Ly	6.064 (-3.393; 10.437)	-4.541 (-8.172; -0.283)	0.160	4.963 (-9.906; 11.420)	3.271 (-9.769; 8.492)	0.449
	MSE S1	0.554 (0.505; 0.600)	0.480 (0.431; 0.571)	0.105	0.517 (0.476; 0.574)	0.491 (0.356; 0.556)	0.264
	MSE S2	1.007 (0.912; 1.196)	0.953 (0.812; 1.075)	0.195	1.001 (0.905; 1.118)	0.883 (0.626; 1.005)	0.121
	CI	1.507 (1.353; 1.802)	1.456 (1.236; 1.606)	0.171	1.500 (1.359; 1.675)	1.317 (0.967; 1.547)	0.171
Ankle (Dorsiflexion +/-)	Ly	-5.881 (-8.706; 9.055)	-9.501 (-11.620; -7.167)	0.614	-3.687 (-9.756; 1.077)	-3.284 (-11.747; 0.602)	0.885

Plantar Flexion-)	MSE S1	0.491 (0.394; 0.603)	0.485 (0.412; 0.551)	0.517	0.515 (0.379; 0.612)	0.525 (0.391; 0.576)	0.857
	MSE S2	0.997 (0.789; 1.260)	0.907 (0.828; 1.001)	0.801	0.933 (0.811; 1.200)	0.873 (0.695; 1.163)	0.564
	CI	1.506 (1.183; 1.838)	1.389 (1.269; 1.512)	0.746	1.462 (1.191; 1.778)	1.347 (1.052; 1.776)	0.692
Hip (Adduction+/Abduction-)	Ly	9.991 (5.590; 17.894)	-2.493 (-9.438; 2.174)	0.130	2.440 (-2.841; 10.292)	-0.436 (-7.928; 3.191)	0.171
	MSE S1	0.535 (0.437; 0.597)	0.531 (0.436; 0.637)	0.034	0.565 (0.496; 0.579)	0.546 (0.454; 0.603)	0.746
	MSE S2	1.021 (0.843; 1.143)	0.984 (0.822; 1.235)	0.040	1.008 (0.970; 1.080)	0.997 (0.870; 1.163)	0.746
	CI	1.522 (1.251; 1.726)	1.489 (1.295; 1.796)	0.034	1.548 (1.448; 1.612)	1.517 (1.336; 1.738)	0.692
Knee (Tibial Adduction+/Tibial Abduction-)	Ly	11.390 (6.114; 16.888)	-1.094 (-7.806; 2.243)	0.235	4.032 (-2.721; 12.353)	3.892 (-4.617; 16.476)	0.801
	MSE S1	0.574 (0.478; 0.645)	0.614 (0.546; 0.645)	0.428	0.582 (0.542; 0.646)	0.603 (0.499; 0.642)	0.746
	MSE S2	1.080 (0.934; 1.279)	1.062 (0.909; 1.212)	0.517	1.138 (0.939; 1.309)	1.121 (0.943; 1.292)	0.746
	CI	1.626 (1.439; 1.893)	1.628 (1.399; 1.838)	0.449	1.679 (1.436; 1.919)	1.682 (1.449; 1.925)	0.773
Ankle (Inversion +/Eversion-)	Ly	7.223 (2.367; 13.489)	-5.404 (-7.078; -0.805)	0.021	4.797 (-0.009; 9.825)	-2.401 (-7.719; 0.319)	0.002
	MSE S1	0.595 (0.558; 0.800)	0.572 (0.517; 0.731)	0.012	0.668 (0.616; 0.785)	0.664 (0.548; 0.760)	0.280
	MSE S2	1.263 (1.027; 1.367)	1.160 (0.940; 1.401)	0.021	1.189 (1.094; 1.333)	1.181 (0.924; 1.260)	0.331
	CI	1.824 (1.536; 2.152)	1.675 (1.437; 2.145)	0.011	1.821 (1.706; 2.098)	1.749 (1.468; 2.048)	0.368
Hip (Internal Rotation+/External Rotation-)	Ly	13.433 (7.142; 23.623)	-2.590(-7.263; 5.460)	0.614	6.727 (-0.553; 11.447)	0.889 (-7.309; 7.304)	0.098
	MSE S1	0.560 (0.487; 0.622)	0.610 (0.551; 0.653)	0.056	0.581(0.483; 0.650)	0.573 (0.499; 0.617)	0.589
	MSE S2	1.027 (0.856; 1.158)	1.164(0.900; 1.287)	0.048	1.069 (1.003; 1.220)	1.095 (0.909; 1.200)	0.719
	CI	1.555 (1.328; 1.688)	1.763 (1.401; 1.890)	0.034	1.607 (1.490; 1.846)	1.677 (1.345; 1.763)	0.801
Knee (Internal Rotation+/External Rotation-)	Ly	9.503 (1.055; 13.929)	-2.750 (-9.590; -0.457)	0.313	5.826 (-1.703; 9.294)	-1.890 (-7.183; 0.748)	0.009
	MSE S1	0.557 (0.522; 0.669)	0.635 (0.567; 0.678)	0.066	0.631 (0.506; 0.738)	0.630 (0.547; 0.708)	0.719
	MSE S2	1.074 (0.945; 1.196)	1.086 (0.991; 1.249)	0.078	1.261(0.989; 1.422)	1.147 (0.986; 1.249)	0.296
	CI	1.580 (1.485; 1.835)	1.652 (1.568; 1.888)	0.066	1.941 (1.480; 2.084)	1.698 (1.568; 1.913)	0.221
Ankle (Internal Rotation +/External Rotation-)	Ly	11.460 (7.820; 23.949)	-3.888 (-9.980; 6.453)	0.090	12.979 (-0.632; 14.881)	-1.132 (-5.547; 3.494)	0.031
	MSE S1	0.530 (0.436; 0.624)	0.645 (0.562; 0.668)	0.023	0.669 (0.535; 0.731)	0.565 (0.525; 0.694)	0.471
	MSE S2	0.969 (0.870; 1.070)	1.143 (1.009; 1.334)	0.072	1.140 (0.932; 1.367)	1.079 (1.03; 1.223)	0.857
	CI	1.488 (1.255; 1.598)	1.778 (1.569; 1.938)	0.040	1.669 (1.495; 2.049)	1.610 (1.535; 1.894)	0.494

Mann–Whitney Test; Significant differences in bold; LyE: Lyapunov Exponent; MSE: Multiscale Entropy; S1: Scale 1; S2: Scale 2; CI: Complexity Index.

Table 9. Median (MED), 25th (P25) and 75th (P75) percentiles of position (POS) values of non-linear outcome of upper limbs joints.

		POSITION MED (P25; P75)					
		Swing Healthy	Swing Stroke	P value [#]	Stance Healthy	Stance Stroke	p value [#]
Shoulder (Flexion+/Extension-)	Ly	-5.795 (-7.331; -3.144)	-2.460 (-5.935; -1.272)	0.540	-6.055 (-7.120; -4.855)	-4.424 (-5.908; -2.048)	0.449
	MSE S1	0.253 (0.204; 0.269)	0.187 (0.119; 0.217)	0.368	0.260 (0.214; 0.279)	0.196 (0.143; 0.236)	0.719
	MSE S2	0.432 (0.386; 0.466)	0.313 (0.244; 0.390)	0.331	0.463 (0.356; 0.501)	0.364 (0.283; 0.391)	0.885
	CI	0.669 (0.599; 0.718)	0.490 (0.359; 0.603)	0.105	0.722 (0.566; 0.764)	0.566 (0.434; 0.626)	0.207
Elbow (Flexion+/Extension-)	Ly	-2.305 (-4.041; -0.327)	-2.146 (-4.431; -1.059)	0.078	-8.921 (-11.699; -7.464)	-6.679 (-9.207; -5.719)	0.471
	MSE S1	0.270 (0.216; 0.299)	0.218 (0.179; 0.266)	0.719	0.279 (0.242; 0.333)	0.248 (0.199; 0.284)	0.084
	MSE S2	0.481 (0.382; 0.550)	0.383 (0.300; 0.482)	0.195	0.522 (0.414; 0.586)	0.426 (0.348; 0.574)	0.313
	CI	0.758 (0.591; 0.873)	0.644 (0.473; 0.733)	0.517	0.801 (0.661; 0.905)	0.672 (0.537; 0.865)	0.195
Wrist (Flexion+/Extension-)	Ly	-5.270 (-6.850; -3.456)	-5.562 (-8.454; -3.574)	0.150	-11.944 (-14.108; -11.196)	-8.801 (-11.303; -7.434)	0.540
	MSE S1	0.303 (0.284; 0.361)	0.263 (0.237; 0.317)	0.171	0.323(0.290; 0.367)	0.279 (0.253; 0.335)	0.160
	MSE S2	0.591 (0.523; 0.716)	0.500 (0.430; 0.557)	0.140	0.588(0.495; 0.655)	0.542 (0.457; 0.607)	0.105
	CI	0.928 (0.799; 1.081)	0.758 (0.668; 0.877)	0.014	0.913 (0.807; 1.013)	0.824 (0.721; 0.938)	0.249
Shoulder (Adduction+/Abduction-)	Ly	-5.939 (-9.583; -4.297)	-5.327 (-9.444; -2.820)	0.090	-3.850 (-6.071; -1.803)	-5.926 (-9.042; -3.380)	0.517
	MSE S1	0.227 (0.181; 0.255)	0.210 (0.184; 0.237)	0.084	0.196 (0.170; 0.209)	0.230 (0.190; 0.262)	0.249
	MSE S2	0.374(0.340; 0.435)	0.365 (0.335; 0.445)	<.001	0.352(0.310; 0.389)	0.404 (0.349; 0.480)	0.016
	CI	0.580 (0.540; 0.690)	0.580 (0.523; 0.663)	<.001	0.555 (0.487; 0.594)	0.638 (0.536; 0.748)	0.028
Elbow (Adduction+/Abduction-)	Ly	-5.189 (-6.939; -2.957)	-3.442 (-7.106; -0.706)	0.160	-10.223 (-12.142; -7.658)	-7.857 (-10.686; -6.555)	0.014
	MSE S1	0.292 (0.247; 0.314)	0.230 (0.176; 0.283)	0.614	0.296 (0.260; 0.357)	0.275 (0.233; 0.320)	0.614
	MSE S2	0.518 (0.433; 0.610)	0.371 (0.312; 0.506)	0.105	0.533 (0.492; 0.686)	0.491 (0.395; 0.604)	0.614
	CI	0.813 (0.696; 0.912)	0.591 (0.488; 0.806)	0.026	0.824 (0.767; 1.052)	0.749 (0.627; 0.921)	0.264

Wrist (Ulnar Deviation+/Radial Deviation-)	Ly	-4.814 (-6.092; -3.892)	-5.822 (-9.397; -3.422)	0.005	-11.549 (-12.706; -10.382)	-11.560 (-12.595; -7.699)	0.207
	MSE S1	0.316 (0.279; 0.344)	0.273 (0.258; 0.308)	0.059	0.292 (0.256; 0.311)	0.283 (0.253; 0.325)	0.195
	MSE S2	0.534 (0.492; 0.666)	0.494 (0.460; 0.536)	0.066	0.536 (0.435; 0.587)	0.530 (0.451; 0.606)	0.056
	CI	0.856 (0.791; 1.006)	0.789 (0.714; 0.844)	0.066	0.824 (0.685; 0.893)	0.829 (0.711; 0.924)	0.449
Shoulder (Internal Rotation+/External Rotation-)	Ly	-7.817 (-10.206; -5.204)	-6.432 (-9.031; -4.952)	<.001	-9.916 (-11.515; -7.329)	-10.164 (-12.055; -9.124)	0.011
	MSE S1	0.300 (0.256; 0.355)	0.266 (0.236; 0.305)	0.719	0.272 (0.237; 0.303)	0.299 (0.268; 0.311)	0.407
	MSE S2	0.542 (0.469; 0.613)	0.483 (0.395; 0.562)	0.719	0.490 (0.421; 0.593)	0.538 (0.440; 0.582)	0.829
	CI	0.842 (0.738; 0.986)	0.730 (0.637; 0.865)	0.666	0.759 (0.650; 0.897)	0.839 (0.716; 0.874)	0.885
Elbow (Internal Rotation +/External Rotation-)	Ly	-5.962 (-8.261; -2.508)	-4.506 (-8.665; -2.219)	0.034	-9.404 (-12.356; -7.221)	-8.605 (-11.270; -7.150)	0.313
	MSE S1	0.305 (0.247; 0.344)	0.274 (0.238; 0.294)	0.017	0.281 (0.251; 0.342)	0.265 (0.224; 0.305)	0.517
	MSE S2	0.552 (0.515; 0.644)	0.482 (0.398; 0.587)	0.026	0.470 (0.438; 0.585)	0.486 (0.437; 0.544)	0.471
	CI	0.839 (0.794; 0.996)	0.762 (0.639; 0.873)	0.019	0.743 (0.698; 0.903)	0.769 (0.684; 0.844)	0.494
Wrist (Internal Rotation+/External Rotation-)	Ly	-8.149 (-13.682; -6.357)	-9.981 (-13.592; -7.375)	0.048	-10.875 (-13.276; -10.112)	-9.254 (-12.684; -7.779)	0.296
	MSE S1	0.315 (0.228; 0.362)	0.301 (0.271; 0.334)	0.666	0.313 (0.262; 0.337)	0.301 (0.241; 0.338)	0.885
	MSE S2	0.560 (0.408; 0.642)	0.526 (0.478; 0.605)	0.914	0.590 (0.458; 0.656)	0.510 (0.460; 0.586)	0.349
	CI	0.866 (0.645; 1.000)	0.825 (0.749; 0.937)	0.773	0.903 (0.729; 1.014)	0.794 (0.715; 0.920)	0.517

Mann–Whitney Test; Significant differences in bold; LyE: Lyapunov Exponent; MSE: Multiscale Entropy; S1: Scale 1; S2: Scale 2; CI: Complexity Index.

Table 10. Median (MED), 25th (P25) and 75th (P75) percentiles of displacement (DISP) values of non-linear outcome of upper limbs joints.

		DISPLACEMENT MED (P25; P75)					
		Swing Healthy	Swing Stroke	P value[#]	Stance Healthy	Stance Stroke	P value[#]
Shoulder	Ly	-13.520 (-20.576; -10.817)	-13.097 (-16.623; -7.615)	0.011	-16.413 (-17.900; -8.797)	-12.050	0.140

(Flexion+/Extension-)						(-16.493; -8.836)	
	MSE S1	0.548 (0.502; 0.588)	0.480 (0.469; 0.530)	0.002	0.535 (0.501; 0.589)	0.494 (0.456; 0.562)	0.113
	MSE S2	1.022 (0.916; 1.157)	0.899 (0.826; 1.041)	0.003	1.036 (0.894; 1.092)	0.937 (0.779; 1.105)	0.349
	CI	1.550 (1.406; 1.704)	1.369 (1.269; 1.550)	0.002	1.565 (1.396; 1.671)	1.402 (1.199; 1.636)	0.195
Elbow (Flexion+/Extension-)	Ly	-10.949 (-16.001; -6.085)	-9.166 (-12.876; 1.231)	0.034	-5.001 (-10.000; -2.532)	-4.625 (-13.403; 2.421)	0.801
	MSE S1	0.613 (0.577; 0.713)	0.616 (0.526; 0.688)	0.084	0.624 (0.571; 0.726)	0.603 (0.524; 0.645)	0.150
	MSE S2	1.194 (1.013; 1.341)	1.111 (0.963; 1.374)	0.160	1.250 (1.050; 1.458)	1.168 (0.968; 1.302)	0.221
	CI	1.788 (1.565; 2.049)	1.674 (1.488; 2.023)	0.121	1.870 (1.617; 2.101)	1.768 (1.490; 1.944)	0.150
Wrist (Flexion+/Extension-)	Ly	-2.327 (-11.645; 4.203)	0.410 (-4.239; 3.529)	0.012	0.583 (-3.982; 4.141)	1.588 (-8.235; 4.257)	0.692
	MSE S1	0.719 (0.640; 0.788)	0.660 (0.585; 0.759)	0.066	0.712 (0.574; 0.769)	0.663 (0.555; 0.699)	0.171
	MSE S2	1.295 (1.184; 1.489)	1.215 (1.083; 1.434)	0.160	1.221 (1.053; 1.276)	1.102 (0.953; 1.355)	0.471
	CI	1.976 (1.810; 2.269)	1.861 (1.647; 2.065)	0.140	1.839 (1.672; 1.945)	1.732 (1.533; 2.004)	0.614
Shoulder (Adduction+/Abducti on-)	Ly	-15.645 (-17.480; -11.778)	-11.789 (-15.474; -4.944)	0.113	-14.728 (-18.873; -11.923)	-8.718 (-14.409; -4.775)	0.017
	MSE S1	0.523 (0.466; 0.599)	0.555 (0.495; 0.605)	0.113	0.512 (0.487; 0.660)	0.530 (0.473; 0.605)	0.943
	MSE S2	1.030 (0.852; 1.223)	1.021 (0.900; 1.162)	0.171	0.972 (0.897; 1.156)	0.980 (0.868; 1.155)	0.971
	CI	1.550 (1.316; 1.765)	1.524 (1.416; 1.711)	0.130	1.479 (1.343; 1.787)	1.499 (1.338; 1.689)	0.971
Elbow (Adduction+/Abducti on-)	Ly	1.642 (-9.666; 6.207)	-9.901 (-12.718; -0.428)	0.195	-2.691 (-11.759; 2.346)	-4.829 (-11.698; 1.640)	0.666
	MSE S1	0.708 (0.600; 0.772)	0.617 (0.561; 0.656)	0.207	0.715 (0.611; 0.764)	0.661 (0.566; 0.703)	0.084
	MSE S2	1.242 (1.045; 1.394)	1.191 (1.067; 1.326)	0.130	1.310 (1.258; 1.491)	1.283 (1.003; 1.381)	0.296
	CI	1.918(1.600; 2.140)	1.775 (1.617; 1.963)	0.171	2.023 (1.839; 2.281)	1.851 (1.563; 2.098)	0.090
Wrist (Ulnar Deviation+/Radial Deviation-)	Ly	-4.161 (-7.105; -1.483)	0.354 (-3.162; 3.080)	1.000	-1.912 (-6.448; 3.437)	-0.372 (-3.225; 3.329)	0.666
	MSE S1	0.714 (0.637; 0.772)	0.633 (0.569; 0.684)	0.971	0.662 (0.610; 0.752)	0.665 (0.547; 0.700)	0.540
	MSE S2	1.172 (1.089; 1.257)	1.129 (0.971; 1.315)	0.614	1.240 (1.111; 1.338)	1.135 (1.079; 1.317)	0.249
	CI	1.837 (1.693; 1.954)	1.726 (1.521; 1.937)	0.801	1.886 (1.737; 2.004)	1.781 (1.611; 1.961)	0.264

Shoulder (Internal Rotation+/External Rotation-)	Ly	-6.981 (-14.078; 3.783)	-3.434 (-7.556; 2.417)	0.494	-5.090 (-11.934; 2.830)	-2.781 (-5.971; 2.290)	0.449
	MSE S1	0.659 (0.605; 0.700)	0.650 (0.597; 0.681)	0.313	0.639 (0.599; 0.727)	0.648 (0.565; 0.699)	0.589
	MSE S2	1.302 (1.056; 1.389)	1.162 (1.030; 1.249)	0.857	1.256 (1.015; 1.449)	1.104 (0.942; 1.275)	0.098
	CI	1.948 (1.745; 2.077)	1.765 (1.589; 1.884)	0.666	1.859 (1.589; 2.135)	1.754 (1.478; 1.887)	0.061
Elbow (Internal Rotation +/External Rotation-)	Ly	-5.860 (-12.011; 1.537)	-4.790(-8.299; 2.152)	0.280	-6.460 (-8.267; -3.545)	-5.345 (-7.940; -0.013)	0.387
	MSE S1	0.659 (0.629; 0.756)	0.649 (0.586; 0.741)	0.368	0.645 (0.596; 0.696)	0.620 (0.585; 0.680)	0.494
	MSE S2	1.301 (1.101; 1.455)	1.255 (1.122; 1.409)	0.914	1.161 (0.951; 1.352)	1.183 (1.021; 1.303)	0.614
	CI	1.945 (1.736; 2.162)	1.957 (1.669; 2.180)	0.692	1.769 (1.517; 2.014)	1.801 (1.590; 1.960)	0.943
Wrist (Internal Rotation+/External Rotation-)	Ly	1.446 (-3.914; 7.626)	0.117 (-4.343; 5.779)	0.207	1.403 (-1.697; 2.731)	0.519 (-4.047; 4.987)	0.692
	MSE S1	0.678 (0.609; 0.805)	0.695 (0.615; 0.771)	0.614	0.704 (0.648; 0.762)	0.678 (0.613; 0.801)	0.719
	MSE S2	1.272 (1.141; 1.376)	1.235 (1.037; 1.346)	0.296	1.284 (1.137; 1.365)	1.179 (1.069; 1.485)	0.971
	CI	1.954 (1.728; 2.144)	1.889 (1.622; 2.036)	0.280	1.937 (1.724; 2.079)	1.901 (1.648; 2.158)	0.914

Mann–Whitney Test; Significant differences in bold; LyE: Lyapunov Exponent; MSE: Multiscale Entropy; S1: Scale 1; S2: Scale 2; CI: Complexity Index.