Explainable Artificial Intelligence in Movement Sciences

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Chapter 1

General Introduction

Human Movement Sciences and Gait

Human Movement Sciences represents a dynamic, multidisciplinary field dedicated to unraveling the intricate relationship between physical activity, aging, and various health conditions. Gait, the way in which individuals walk, is a fundamental component of daily physical activity. It serves as a window into the delicate control and cooperation of various systems within the human body, including the musculoskeletal, cardiorespiratory, and nervous systems. Outcomes of gait analysis have evolved into biomarkers, disclosing crucial insights into understanding age-related mobility decline and back pain related motor impairments [1, 2]. Gait analysis can be used to diagnose gait abnormalities, inform treatment strategies, guided rehabilitation regimens, and measured the effectiveness of interventions [3, 4]. In broader applications, gait analysis extends its impact by contributing to the understanding of the health among aging populations and monitoring their overall well-being [5]. In summary, Human Movement Sciences, with its focus on gait analysis, offers invaluable insights into the relationships between human movement and health. Through the lens of gait, it paves the way for advanced healthcare, rehabilitation, and health promotion.

Gait Analysis

After decades of evolution, gait analysis has emerged as a critical clinical tool for many medical and healthcare applications [6]. In the past, the focus has been on gait speed. Studies have demonstrated that, in older adults (aged over 65), gait speed is a prime predictor of mortality [7, 8]. Even an 0.1 m/s difference in speed corresponds to statistically significant changes in the expected remaining years of life [8]. Therefore, the accurate[1] estimation of gait outcomes, such as gait speed, is essential.

In current clinical settings, gait analysis is typically conducted using subjective and qualitative approaches. For instance, experts such as well-trained clinicians, can visually evaluate the gait performance of patients and assess their gait disorders. Through the observer-based timing, some qualitative gait outcomes, such as gait speed can be obtained. But the gait speed obtained via this way may lack precision[2].

To achieve more accurate estimations of gait outcomes, standard gait analysis tools such as optical motion capture systems (e.g., Vicon) are utilized in some specialized centers and clinics. Although these systems can provide highly accurate gait outcomes based on high-precision data, they are relatively costly, and involve an intrusive marker setup procedure that is time-

[1] Accuracy refers to the "closeness of agreement between a measured quantity value and the true quantity value of the measurand" [9]

[2] Precision refers to the "closeness of agreement between indications and measured quantity values obtained by replicated measurements on the same or similar objects under specified conditions" [9].

consuming and may interfere with the patient's natural movement [10]. Moreover, these systems are limited to laboratory environments for short-term walking assessment and may not accurately reflect gait in real-world settings [11]. Therefore, these systems are not pervasive enough among clinics.

Advances in wearable sensor technologies [12], particularly inertial measurement units (IMUs) equipped with accelerometers, gyroscopes, and/or magnetometers, have shown significant potential as a replacement. These devices are cost-effective, portable (non-intrusive), and capable of recording precise time-series sensor data (spanning several days or weeks) for gait analysis. Furthermore, they can be used in both clinical settings and daily living environments, and better reflect gait patterns in real-world scenarios.

Based on time-series data, accurate spatial-temporal gait outcomes such as gait speed, step length, and step width can be calculated. Additionally, based on the time information from the sensor data, dynamic gait outcomes have been explored. These gait outcomes may provide insights into how gait evolves over time [13]. Key aspects of these outcomes include gait regularity (e.g., stride regularity and gait symmetry index calculated using autocorrelation coefficients) [14], smoothness (e.g., the index of harmonicity and harmonic ratio derived from power spectral signal frequency analysis) [15], predictability (e.g., sample entropy based on information theory) [16], and stability (e.g., maximal Lyapunov exponent rooted in chaos theory) [17]. Based on these gait outcomes, different populations can be characterized.

Gait Analysis in Aging

Gait speed has been utilized as an indicator of survival rates and life expectancy in older adults and for evaluating geriatric status [7, 8]. However, gait speed alone cannot capture all the changes attributable to aging and disorders. Thus, a broader range of gait outcomes should be included for a comprehensive assessment of aging. It is observed that older adults exhibit a reduced gait speed, shorter step lengths, wider step widths, and decreased gait symmetry and regularity compared to adults [18]. Moreover, gait analysis has revealed that fallers exhibit a lower gait speed [19], lower smoothness (as indicated by harmonic ratio) [20], and lower local stability (measured by Lyapunov exponent) [21] in gait, in contrast to non-fallers.

The growing number of older adults highlights the need for monitoring gait degradation, assessing fall risks, and preventing falls for the older adults [22, 23]. To conserve limited medical resources, automatic gait analysis is becoming more and more important [24]. However, gait outcomes are related to each other in a linear way (e.g., gait speed and stride length) or interacted in non-linear ways (e.g., gait speed and gait smoothness) [25]. To handle the complex interplay within gait outcomes and accurately classify gait patterns, alternative statistical approaches may be necessary, differing from traditional approaches.

Conventional Machine Learning in Gait Analysis

Artificial intelligence (AI), including conventional machine learning (CML), is able to take the linear relationship and non-linear interaction into account [26]. Hence, it can automatically learn the gait patterns from gait outcomes and may offer valuable insights into interrelationships and interactions within gait outcomes [27]. CML has been successfully applied to classify different gait patterns related to aging and pathology [28]. For example, artificial neural networks have been used to classify age-related gait patterns with an impressive 90% accuracy [27]. Random forest has accurately distinguished fallers from non-fallers with an accuracy of 98% [29] and has supported the diagnosis of Parkinson's disease with 92.6% accuracy [30] from healthy controls.

However, CML-based gait classification depends on gait outcomes and the dependency may cause challenges of applications in clinical and daily living environments. Firstly, the used gait outcomes in CML-based gait analysis are manually designed and selected by experts, such as clinicians, rehabilitation experts, or human movement scientists. This process requires specialized knowledge and is prone to being labor-intensive [31]. Moreover, if some useful gait outcomes that can reflect the age-related changes are overlooked, it might decrease the performance of the gait classification. Secondly, to obtain stable and accurate gait outcomes such as the maximum Lyapunov exponent, certain requirements must be met, e.g., the specific signal length and sampling frequency [32]. Lastly, the computation of these handcrafted gait outcomes is often performed offline [33], meaning this approach may not be well-suited for real-time applications, such as falls detection in daily-living environments.

Deep Learning in Gait Analysis

In response to the challenges of CML-based gait analysis, deep learning (DL) has been introduced into the gait analysis. DL is an end-to-end approach [34] which means it can use time-series sensor data as input and provide predictions as output. The end-to-end character allows DL to eliminate the need for handcrafted gait outcomes, thereby avoiding the limitations of CML mentioned above. Furthermore, DL has shown superior performance over CML in various fields, such as computer vision [35] thanks to its superior learning capacity. The multi-layered structures of DL facilitate a hierarchical learning process; the initial layers extract fundamental features from sensory data, while subsequent layers progressively build upon these features to learn more abstract and high-level features [36]. This process could enable DL to learn the most suitable features for classification [31], potentially leading to more a more accurate gait classification.

Researchers have started to introduce DL into the field of gait analysis and highlight its promising performance in certain gait classification tasks [37, 38]. For instance, it has demonstrated the ability to classify fallers and non-fallers in adults with an AUC (Area under the receiver operator curve) of 93.3% [39] and is able to classify gait of patients with Parkinson's disease with an accuracy of 89% [40]. Since aging is a continuous process and gait patterns will change gradually, classifying age-related gait patterns may be challenging. Given the growing older adult population, it is vital to explore optimal AI models for classifying age-related gait patterns. Therefore, **Chapter 2** of this thesis presented a comprehensive comparison in classification performance of CML and DL for classifying age-related gait patterns.

Black-Box Nature in AI

AI-driven gait analysis has shown promising performance, but its implementation in clinical practice is still in its infancy. Even in areas like medical imaging, where AI has already a strong tradition in research, and its performance is comparable with trained physicians [41, 42], the use of AI still suffers harsh criticisms [43]. One of the limitations for their clinical implementation arises from the black-box nature of AI models. Although the mathematical principles behind the models are well-established, the inner decision-making process of models is often opaque.

The black-box nature of AI-driven gait analysis results in a lack of interpretability and transparency, which poses challenges for patients and clinicians to trust the AI models [44]. Furthermore, this opacity may fail to meet legal requirements, such as the European General Data Protection Regulation (GDPR, EU 2016/679), which mandates transparent justifications for automated decision-making processes that have a significant impact on individuals [45]. Therefore, addressing the black-box issue in AI is crucial not only for building trust but also for ensuring ethical and legal compliance.

Explainable AI in Gait Analysis

To bridge this gap between AI and the need for interpretability and transparency, explainable AI (XAI) [46] has gained attention in the medical field. XAI focuses on revealing the underlying reasoning behind the predictions and decisions made by AI models. XAI can be broadly categorized into two main categories based on the usage stage: 1) ante-hoc explainability; and 2) post-hoc explainability [47]. Ante-hoc explainability refers to AI models that are interpretable by design, including simple CML models (such as linear regression, decision trees, and k-nearest neighbor), as well as a big part of unsupervised CML models (such as K-means, hierarchical clustering, and self-organization map) [48]. Post-hoc explainability approaches, such as SHapley Additive exPlanations (SHAP) [49], are employed to explain previously trained AI models and have thus attracted considerable interest.

Post-hoc explainability approaches have been employed in the realm of medical imaging. The explanations provided by XAI in the form of heat maps can visually highlight the salient or important parts within an image that influence the model's decision-making process [41, 42, 50]. By comparing these salient or important parts with the assessments of medical experts, like radiologists [50], the trustworthiness of the AI model can be visually evaluated. Additionally, it is important to note that XAI explanations may not always align with domain expertise, potentially leading to discrepancies that offer fresh insights and contribute to the generation of new knowledge.

In the context of gait analysis, visualizing the important parts of time-series sensor data may not be intuitive, since it is difficult to correlate a segment of sensor signal with the domain expertise of movement scientists or clinicians. Consequently, based on the DL models discussed in chapter 2**,** the study described in **Chapter 3** of this thesis aimed to explore what AI models have learned from the accelerometer signal data for distinguishing gait patterns between adults and older adults by using post-hoc XAI, and to connect these findings with the domain expertise in movement sciences.

Gait in Back Pain

The knowledge and the methodologies of gait analysis obtained in Chapters 2 and 3 from older adults can also be applied to other populations, such as patients with back pain.

Low back pain (LBP) is the leading cause of disability [51], with the potential to progress into chronic low back pain (CLBP) when the pain persists beyond a 3-month duration. Notably, within the CLBP population, approximately 85% to 90% of patients are non-specific CLBP, as the link between known pathoanatomical factors and clinical presentations is absent [52, 53]. The CLBP population is heterogeneous [54], and the presence of central sensitization (CS) may contribute to this heterogeneity [55]. CS refers to an increased responsiveness of nociceptive neurons in the central nervous system to their normal or subthreshold afferent input [56]. Given the current limitations in directly measuring mechanisms related to CS in individual humans, the term “Human Assumed Central Sensitization” (HACS) has been introduced to describe CS. HACS is considered to play a role in the development and maintenance of CLBP [57].

Gait analysis has reported conflicting evidence in gait outcomes of patients with CLBP, including the preferred walking speed [58, 59], stride length [60, 61], and stride-to-stride variability [62, 63] when compared to healthy controls. Since movement may be changed due to pain, HACS may be a factor relating to the observed inconsistent gait patterns. To investigate the relationship between gait, CLBP, and HACS, AI-driven gait analysis could offer valuable insights. In **Chapter 4**, it was assumed that if HACS relates to changes in gait, AI-driven gait analysis could accurately classify patients with CLBP into different HACS-related groups. In this chapter, CML was selected for gait pattern classification instead of DL. Although

DL demonstrates superior performance, it comes with greater opacity [48]. Considering the trade-off between a model's performance and its transparency, CML was used. After the classification, a post-hoc XAI was employed to explain the differences in gait patterns among the HACS-related groups.

Physical Activity in Back Pain

CLBP poses substantial socioeconomic burdens and causes great individual suffering. In the Netherlands, the direct and indirect costs of back pain amount to around 0.6% to 0.9% of the gross national product [64]. Although the overall efficacy of CLBP rehabilitation programs is positive, the effect sizes are modest [65]. In the treatment of CLBP, physical exercise is often recommended [66]. However, the relationship between CLBP and physical activity is still unclear and inconsistent evidence has been shown. Some studies observed that people with CLBP exhibit lower overall physical activity intensity (PAI) during the day [67, 68], while others report no differences between patients with CLBP and healthy controls [69, 70].

Similar to Chapter 4, which assumed that gait alterations could be related to HACS, **Chapter 5** of this thesis proposed that inconsistencies in PAI evidence might also be associated with HACS. Therefore, the study described in this chapter aimed to explore PAI patterns of HACS-related subgroups in patients with CLBP using 24-hour accelerometer signal data. In this analysis, unsupervised CML with ante-hoc explainability [71] was utilized to explore and explain the differences in PAI patterns among HACS-related groups.

In Chapters 4 and 5, the HACS-related groups were determined by the central sensitization inventory (CSI) with a cut-off value of 40 [72]. However, it has been reported that the cut-off values for CSI may vary depending on different types of musculoskeletal pain [73, 74], as well as different cultural and national contexts [75]. It should be noted that the gold standard to assess HACS is currently unavailable and CSI is an indirect evaluation of the presence and severity of HACS [76]. Therefore, the study described in **Chapter 6** aimed to establish an optimal cut-off value for the Dutch-speaking population with CLBP. This chapter used unsupervised CML models with ante-hoc explainability to explore the HACS-related subgroups based on clinical outcomes, which include questionnaire data reflecting pain, physical functioning, psychological factors, and CSI values. Then, based on the found subgroups, an optimal CSI cut-off value could be established.

Aim and Outline

This thesis aims to enhance the comprehension of movement, especially gait, in healthy older adults and patients with back pain through insights from XAI. The architectural framework of the thesis is visually represented in Figure 1.

In **Chapter 2,** it was aimed to compare the performance of CML and DL in age-related gait pattern classification. Building upon the results of Chapter 2, the study described in **Chapter 3** aimed to enhance the interpretability and transparency of DL-based gait analysis in the classification of adults and older adults by using XAI. The insights gained from gait analysis in Chapters 2 and 3 could be applied to study the gait of patients with CLBP. **Chapter 4** focused on using CML to classify HACS-related subgroups based on gait outcomes collected in daily living environments, with XAI facilitating the explanation of differences in gait patterns among these subgroups. Extending the analysis beyond gait, the study described in **Chapter 5** aimed to explore and explain PAI patterns of HACS-related subgroups of patients with CLBP based on ante-hoc XAI. Additionally, the study described in **Chapter 6** aimed to establish an optimal CSI cut-off value for the Dutch-speaking population with CLBP by investigating HACS-related subgroups through clinical outcomes by using unsupervised CML with ante-hoc XAI. Lastly, **Chapter 7** provided a comprehensive discussion and conclusion, summarizing the findings and implications of this thesis.

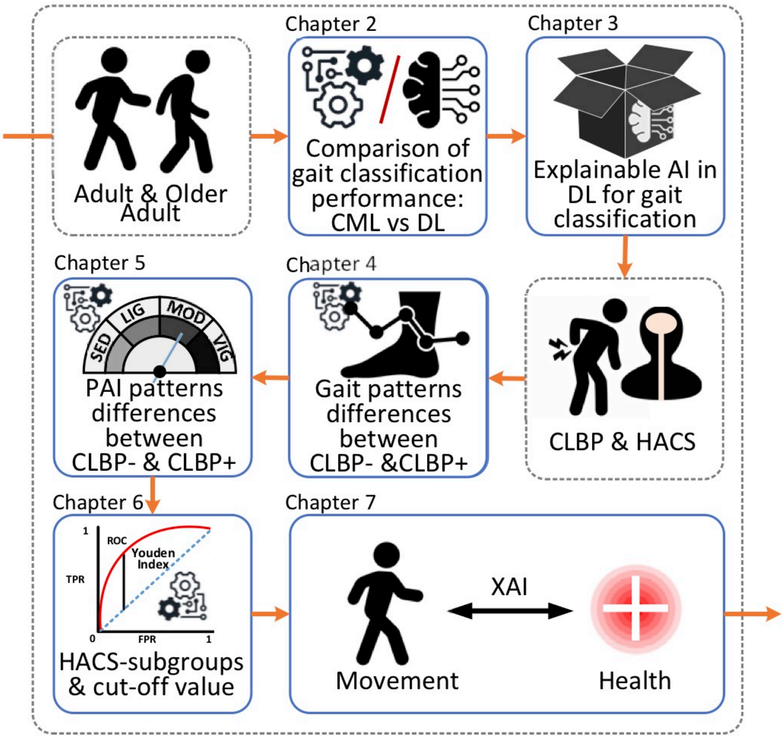

Figure 1. The architecture of this thesis. CML: conventional machine learning; DL: deep learning; AI: artificial intelligence; CLBP: chronic low back pain; HACS: human assumed central sensitization; CLBP+: chronic low back pain with high central sensitization; CLBP-: chronic low back pain with low central sensitization; PAI: physical activity intensity; XAI: explainable artificial intelligence.

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