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EFFECTS OF SPEED ON THE MOVEMENT PATTERNS OF HUMAN GAIT

São Bernardo do Campo - SP
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To Reginaldo,

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Abstract

The most common form of human locomotion is walking, where the speed has been reported as one of the main determinants of the gait biomechanical pattern. Therefore, to understanding how gait speed influences the gait biomechanical pattern, three studies were conducted to address the following goals: (1) to comprehend the effects of speed on gait biomechanics variables of young and older adults; (2) to create a public dataset of walking kinematics and kinetics of young and older adults at different gait speeds; (3) to investigate the influence of the gait speed on the Gait Profile Score index and on the minimum and maximum values of kinematic and kinetic variables. For the first study, based on a systematic review and meta-analysis, the speed demonstrated to affect the gait pattern of different populations with respect to spatiotemporal parameters, joint kinematics, joint kinetics and ground reaction forces, where most of the minimum and maximum values were reduced at slower speeds and increased at faster speeds. The second study was conducted in healthy young and older adults where a public database was created allowing to examine the influences of speed, age, and environment (overground vs. treadmill) on gait biomechanics. Lastly, due to the complex interpretation of the gait analysis and the potential influence of gait speed on gait indices, the effects of the gait speed on Gait Profile Score and on the peak and valley values based on a regression prediction method were examined. For this, a prediction method was proposed which considered the effects of gait speed, and the results demonstrated that the prediction method could be used to generate more unbiased reference data for clinical gait analysis when the effects of gait speed were also considered.

Keywords: gait, walking speed, regression analysis, Gait Profile Score

Resumo

A forma mais comum de locomoção humana é a caminhada, onde a velocidade tem sido relatada como um dos principais determinantes do padrão biomecânico da marcha. Portanto, para entender como a velocidade da marcha influencia o padrão biomecânico, três estudos foram conduzidos para abordar os seguintes objetivos: (1) compreender os efeitos da velocidade nas variáveis biomecânicas da marcha de jovens e idosos; (2) criar um conjunto de dados públicos de cinemática e cinética de andar de jovens e idosos em diferentes velocidades de marcha; (3) investigar a influência da velocidade da marcha no índice Gait Profile Score e nos valores de mínimo e máximo das variáveis cinemáticas e cinéticas. Para o primeiro estudo, baseado em uma revisão sistemática e meta-análise, a velocidade foi demonstrada para afetar o padrão de marcha de diferentes populações em relação aos parâmetros espaço-temporais, cinemática, cinética e forças de reação do solo, onde a maioria dos valores dos mínimos e máximos foram reduzidos em velocidades mais lentas e aumentados em velocidades mais rápidas. O segundo estudo foi realizado em adultos jovens saudáveis e idosos, onde foi criado um banco de dados público que permite examinar as influências de velocidade, idade e ambiente (overground vs. esteira) na biomecânica da marcha. Por fim, devido à interpretação complexa da análise da marcha e a potencial influência da velocidade nos índices da marcha, os efeitos da velocidade da marcha no índice Gait Profile Score e nos valores de picos e vales baseados no método de predição de regressão foram examinados. Para isso, foi proposto um método de predição que considerou os efeitos da velocidade da marcha, e os resultados demonstraram que o método de predição poderia ser usado para gerar dados de referência mais imparciais para a análise clínica da marcha quando os efeitos da velocidade da marcha também fossem considerados.

Palavras-chave: marcha, velocidade, análise de regressão, Gait Profile Score

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List of Abbreviations

3D	Three-dimensional
ASIS	Anterior superior iliac spine
CGA	Clinical gait analysis
CIs	Confidence intervals
ES	Effect size
FAQ	Gillette Functional Assessment Questionnaire Walking Scale
FMS	Functional Mobility Scale
GA	Gait analysis
GDI	Gait Deviation Index
GGI	Gillette Gait Index
GMFCS	Gross Motor Function Classification System
GPS	Gait Profile Score
GRF	Ground reaction forces
GVS	Gait Variable Score
LCS	Laboratory coordinate system
MAP	Movement Analysis Profile
MCID	Minimal clinically important difference
PCA	Principal component analysis
Q	Cochran's heterogeneity statistic
QI	Quality Index
R^2	Coefficient of determination
RMS	Root mean square
RMSE	Root mean square error
SD	Standard-deviation
SEs	Standard errors
X^2_{red}	Reduced chi-squared

Table of Contents

PREFACE

Five chapters of this thesis are based on manuscripts that have been either accepted or submitted to a scientific journal:

Chapter 3	Fukuchi CA, Fukuchi RK, Duarte M. (Submitted). Effects of walking speed on gait in healthy participants: a systematic review and meta-analysis. *BMC Systematic Reviews*.
Chapter 4	Fukuchi CA, Fukuchi RK, Duarte M. A public dataset of overground and treadmill walking kinematics and kinetics in healthy individuals. *PeerJ* 2018, 6:e4640. doi: 10.7717/peerj.4640
Chapter 5	Fukuchi CA, Duarte M. A prediction method of speed-dependent walking patterns for healthy individuals. *Gait & Posture* 2019, 68: 208-284. doi: 10.1016/j.gaitpost.2018
Chapter 6	Fukuchi CA, Duarte M. Gait Profile Score in able-bodied and post-stroke individuals adjusted for the effect of gait speed. *Gait & Posture* 2019, 69: 40-45. doi: 10.1016/j.gaitpost.2019.01.018
Chapter 7	Fukuchi CA, Fukuchi RK, Duarte M. (Submitted). Test of two prediction methods for minimum and maximum values of gait kinematics and kinetics over a range of speeds. *Gait & Posture.* Short Communication.

All chapters were written in a manuscript-based style. Thus, some chapters may contain redundant information, mainly in the introduction and methods sections.

Conferences

The work was presented and discussed on following conferences:

- Progress in Motor Control XI Conference, Miami, United States, July 2017
- 26th Annual Meeting of ESMAC (European Society for Movement Analysis in Adults and Children), Trondheim, Norway, September 2017.
- CMAS Annual Scientific Meeting, Salford, Manchester, April 2017.
- 21st Annual Meeting of GCMAS (Gait and Clinical Movement Analysis Society), Memphis, Tennesse, May 2016.
- XVI Brazilian Congress of Biomechanics & VI Symposium on Applied Neuromechanics, Florianopolis, Brazil, May 2015.

Chapter 1. Overview

1.1 Introduction

The characterization of the human movement during locomotion is commonly performed by biomechanical analysis of gait to enhance the understanding of gait changes related to either ageing or disease (1). The analysis of human gait typically involves the measurements of body kinematics, the measurement and estimation of external forces (kinetics) acting on the body, such as gravitational force on each segment, and ground reaction forces; and also the measurement of electrical activity associated with the muscle contraction (electromyography). Furthermore, the kinematics and kinetics data are commonly combined to estimate the internal forces and moments on the joints through an inverse dynamics approach. This type of gait analysis has become more popular worldwide to assist in the clinical decision making process. In fact, it has been observed a growing number of research laboratories and clinical facilities offering gait analysis services in many countries including Brazil. However, the conduction of a gait analysis and the interpretation of its results may be challenging due to the complex nature of the processes involved in measuring human movement (2).

Gait speed has been reported as the primary determinant of kinematic and kinetic walking changes (3)**.** Spatio-temporal gait parameters, ground reaction forces, joint angles and moments as well as muscle activity have all been reported to be affected by gait speed (8–12). For instance, it is known that ageing and some diseases (e.g. stroke) may impact gait speed (13–15). Hence, any change in gait speed can alter the movement pattern and bias the interpretation of the effect of ageing and pathologies on gait patterns. Therefore, it is important to consider the gait speed when studying walking biomechanics to allow a better interpretation of the results when comparing the gait pattern of different population (e.g. young vs. old). The study of the effects of walking speed on gait patterns is paramount and should be elucidated prior examining the effects of other conditions such as ageing and pathology. In this way, first is necessary to understand the effects of walking speed on the gait pattern of healthy individuals.

For this, the creation of a public dataset of healthy individuals walking at a number of gait speeds would provide information about the typical gait patterns thus allowing compare these data with other datasets to make inferences about the effect of walking speed or diseases. In fact, previous published datasets have been provided where it may be possible to compare the gait pattern of an individual walking at the same speed than the reference dataset (16–18). However, these studies reported only few gait variables and a limited number of subjects, let alone the fact that some of these studies presented an insufficient description of the methodology, which limited their application. Thus, the creation of a public dataset of gait variables of young and older healthy adults walking at a variety of gait speeds is necessary.

Even though the use of clinical gait analysis is growing over the years, many challenges remain that prevent its widespread application within a clinical context (2,19). Due to the high number of biomechanical variables that is employed in the analysis, some gait indices, such as the Gait Profile Score (GPS) (20), have been proposed to enhance the interpretation of the gait analysis results. These indices allow the assessment of the overall quality of the gait movement pattern of subjects. However, it is still unknown how the walking speed would affect these indices. For example, in a typical gait analysis, the gait of pathological individual is usually compared with a reference pattern performed by healthy subjects walking at their comfortable speed. Nevertheless, as it is known that the gait of pathological individuals is usually slower than healthy controls, the direct comparison of the gait of an impaired subject with a database of healthy individuals may not be appropriate because it is not possible to determine whether the observed differences are due to the pathology, the speed, or both. Thus, a reference dataset where gait speed is considered is necessary to perform an unbiased analysis of the gait indices.

Another popular approach to reduce the dimensionality of gait data is to select peak and valley values (maximum and minimum), as dependent variables, to compare the gait patterns between groups of individuals (e.g. healthy vs. pathological). However, as previous studies have suggested that peak and valley values of joint angles may be affected by gait velocity (10,12,21) it is also important to consider the effects of gait speed on these variables when comparing different groups of individuals.

Thus, the aims of this thesis are:

- to study the effects of walking speed on gait biomechanics variables of young and older adults;
- to create a public dataset of the walking pattern of young and older adults in different gait speeds;
- to investigate the influence of the gait speed in gait index, and on the peak and valley values.

1.2 Thesis Outline

This thesis is divided in 8 chapters. A thesis map, which defines the chapters, is presented in Figure 1-1. Chapter 2 provides a definition of gait cycle, presents the main variables examined in clinical gait analysis, approaches the use of gait indices and how gait speed may affect these variables. This body of knowledge is summarized to define the goals and the scope of this thesis.

Chapter 3 presents a systematic review and meta-analysis summarizing the scientific evidence about the effects of walking speed on gait pattern of healthy individuals (children, young adults and older adults) walking both on treadmill and overground surfaces. The results of this review help to understand how gait speed affects the kinematic and kinetic variables. The review is based on a systematic database search and a strict quality assessment scheme to identify relevant articles.

We also conducted an experimental study where the walking kinematics and kinetic data of 24 young adults and 18 older adults were collected in different gait speeds to create a public dataset, which is discussed in Chapter 4. We then examined the influence of gait speed on joint angles, joint moments, and ground reaction forces (GRF).

Chapter 5 presents a prediction method to consider the effects of gait speed on biomechanical variables to yield a more appropriate comparison of gait patterns between pathological and control individuals. For this, the data from the public dataset (24 subjects) were analyzed. The prediction method based on either a linear or quadratic regression model was validated and then its application is further discussed in Chapter 6. In Chapter 6 we applied the Gait Profile Score (GPS) to compare the gait pattern of sixteen post-stroke individuals was compared with fifteen healthy individuals walked at the comfortable speed. The GPS score was then adjusted to consider the speed effects on the prediction model.

Since the maximum and minimum values (peaks and valleys) of the joint angles and moments have been commonly reported in clinical gait analysis, the same prediction method was also applied to assess the ability to predict maximum and minimum values, using our public data set of 24 subjects (Chapter 4), with previously prediction methods available. For this, we also used the data from the dataset for further analysis. The results of the minimum and maximum values are described and further discussed in Chapter 7.

The final chapter, the Chapter 8, summarizes the finding of the previous chapters, provides an overall conclusion and suggests areas for future research.

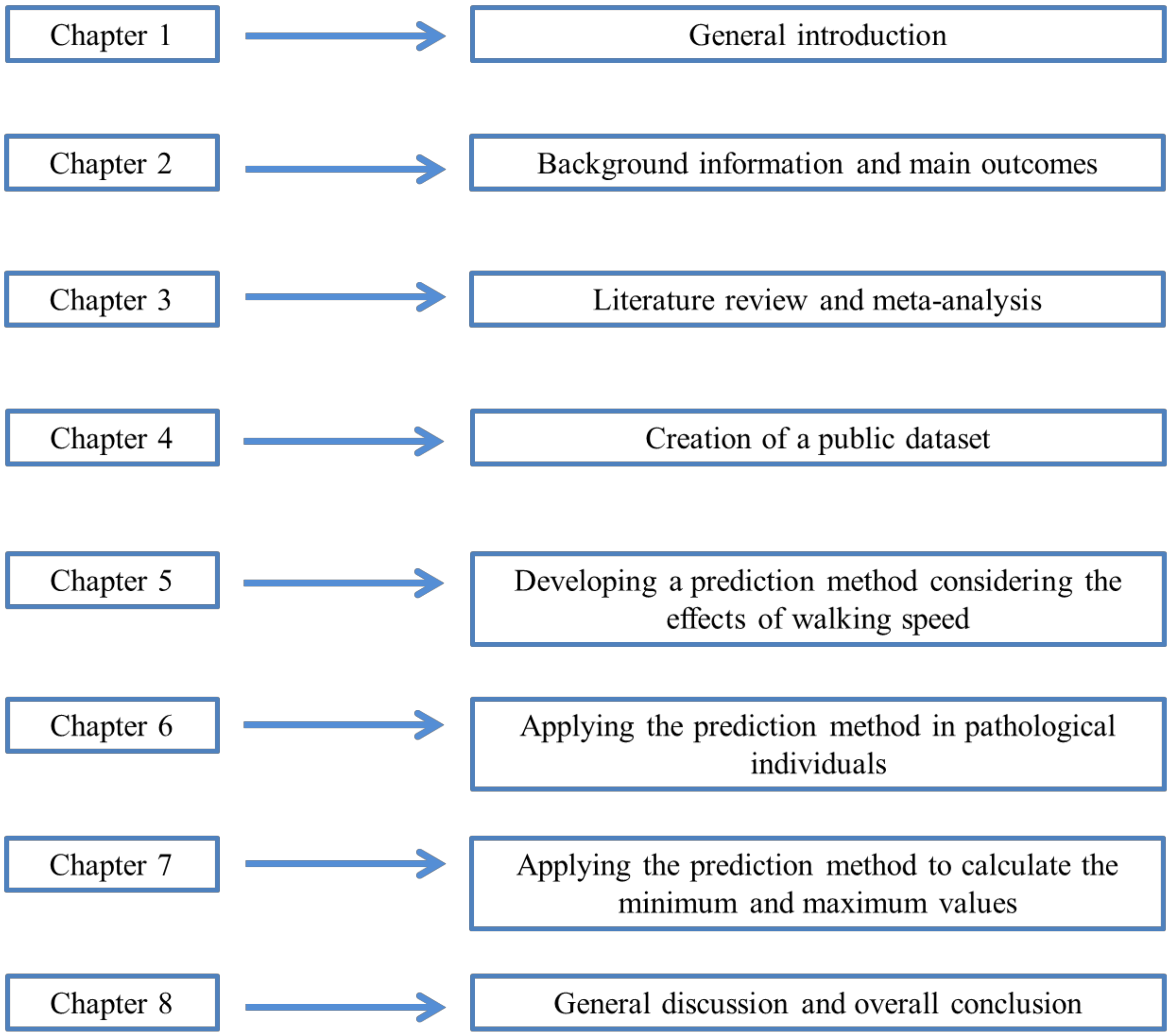

Figure 1-1. A summary of the proposed outline of the thesis.

Chapter 2. Background information and main objectives

2.1 Introduction

Human gait is a form of locomotion characterized as bipedal, where the human body moves as a result of the coordination of different body segments. Among the various ways of human gait, walking is the most common and accessible form of daily and physical activity (22). In simple mechanical terms, walking can be modelled as an inverted pendulum in which after the foot hits the ground, the leg rolls over it in each step (23). Walking is a cyclical task and the gross aspects of the way a person walks can be represented by a gait cycle, characterized by a sequence of movements between two successive events, for example, between two successive strikes of the same foot with the ground. But no two gait cycles are the same and it is well known that there is a variability of their gait pattern across cycles (19). A gait cycle can be divided in different number of phases and the most common approach is to separate it into two phases: stance phase (the time which the foot is in contact with the floor) and swing phase (when the foot is not in contact with the floor) (Figure 2-1). Typically, the stance phase comprises about 60% of the gait cycle while the swing phase is approximately 40% of the gait cycle during walking by healthy people (19). However, as walking speed increases, this proportion can be altered; the duration of the stance phase decreases and the duration of the swing phase increases (24). Although walking has been characterized by a sequence of events, the walking pattern (amplitude and timing of these events) varies across individuals and populations. Thus, it is important to understand the 'normal' gait pattern as a basis of comparison when deciding for the specific intervention to pathological or abnormal gait.

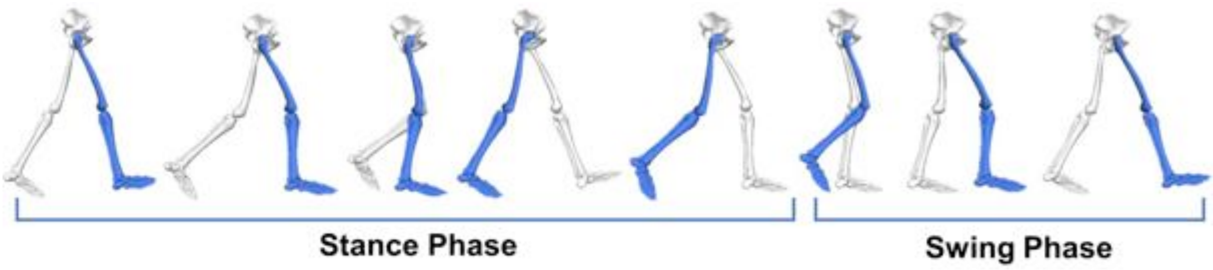

Figure 2-1. Phases of the gait cycle: stance phase and swing phase.

A gait cycle can also be referred as a stride, which is comprised by two steps. A *step* refers when one foot moves forward in front of the other while the *stride* is a step of one foot followed by a step of the other foot. A *step length* is the distance that one part of the foot travels with respect to the same part of the other foot during a step. A *stride length* is the distance travelled between two consecutive placements of the same foot (19,25) (Figure 2-2). The number of steps during a specific period is defined as *cadence* (steps/min). Based on that, the walking speed, the distance covered by the body in a given time can be calculated as:

$$\text{walking speed(m/s)} = \frac{\text{cadence(steps/min) x stride length(m)}}{120}$$

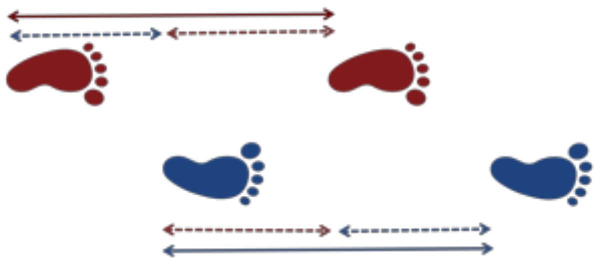

Figure 2-2. Step (dashed line) and stride (solid line) parameters of the right (blue) and left (red) foot. (Adapter from Baker (19)).

In order to assess the gait pattern and to understand whether it deviates from the expected pattern, different scores have been proposed to classify the gait quality of children (26–29). The Gillette Functional Assessment Questionnaire Walking Scale (FAQ) is based on the parent-report walking scale (27); the Edinburgh Gait score is based in observational video analysis schemes (29); the Functional Mobility Scale (FMS) is established by questionnaire rating the children accordingly with their level of sensitive device they might use (28); while the Gross Motor Function Classification System (GMFCS) is a five-level classification system based on self-initiated movement (26). While these functional assessments provided valuable information, particularly for clinicians, they are subjective in nature, unable to quantify the gait pattern, and difficult to perform any comparison with data from healthy subjects.

Contrary to this, the clinical gait analysis (CGA) has been widely used by clinicians to comprehensively examine the gait pattern of humans based on instrumented measures and biomechanical interpretation. These measures are objective and are typically performed using a three-dimensional (3D) motion capture system, force plates and electromyography systems. Although the CGA is comprised by quantitative measures that are desirable to minimize the subjectivity compared to the aforementioned functional measures, it has still been susceptible to errors. For example, a high variability of different gait analysis services was found when 11 patients were evaluated in four different centers, resulting in a distinct treatment recommendations based on a CGA report (30). While the CGA measurement itself is usually based on the knowledge of mechanics, its interpretation is rather subjective and relies on clinical skills and experience (31). In fact, after the CGA interpretation, recommendations for conservative treatment (32) or surgical procedures (33,34) have been adopted by clinicians. Furthermore, the CGA might be helpful to support their clinical decision-making (35), and positive outcomes have been found when evaluating the intervention results from the CGA report in post-surgery treatments (36,37). However, the evidence for the correct diagnosis of a pathology based on the CGA is still limited (1). Additionally, the CGA provides a high volume of data about the human movement patterns that can make the interpretation challenging (2) (Figure 2-3). Therefore, gait indices have been proposed where the gait pattern is reduced to a single score or a composite score thus enhancing the ability to compare gait patterns (20,38–40). The Gillette Gait Index (GGI, originally referred to as the Normalcy Index) (38) uses a multivariate statistical technique (principal component analysis (PCA)) to quantify the difference of the gait cycle for a particular individual and a reference dataset, which is considered the normal gait. The GGI is based on 16 variables including 13 kinematic variables (mean pelvic tilt, range of pelvic tilt, mean pelvic rotation, minimum hip flexion, range of hip flexion, peak abduction in swing, mean hip rotation in stance, knee flexion at initial contact, time of peak knee flexion, range of knee flexion, peak of dorsiflexion in stance, peak of dorsiflexion in swing and mean foot progression angle) and 3 spatio-temporal parameters (percentage of stance phase, normalized velocity and cadence). The Gait Deviation Index (GDI) is also determined by PCA but uses only angular kinematic variables (39). In contrast to the GGI, where only discrete variables are used, the GDI considered the entire gait cycle waveform of each variable, thus minimizing any subjectivity in the selection of variables. GDI calculates the overall distance between patient's data and the average from the reference database on 15 gait features in total. However, the GDI is based on the preliminary analysis of a large number of people (3351 subjects). A newer index similar to GDI based on kinetic variables, the GDI-Kinetic, was proposed by Rozumalski & Schwartz (41). The GDI-Kinetic determines the first 20 gait features of the gait kinetic data using singular value decomposition to define the gait index of each subject in comparison to a normal reference dataset. Lastly, the Gait Profile Score (GPS) has been proposed as an alternative method to quantify the gait pattern based on a root-mean-square difference of a particular individual from the average normal population along the entire gait cycle using the same 15 variables from the GDI (20,42). The advantage of the GPS is that it has a simpler clinical interpretation, summarizing the influence of each kinematic variable by first calculating the Gait Variable Score (GVS), creating the Movement Analysis Profile (MAP), which enables the understanding of how each variable is influences the gait pattern and consequently the GPS (Figure 2-4). The disadvantage of both GDI and GGI indices is that they depend on the preliminary analysis of a large dataset (38,39). Additionally, while the variables analyzed in the GGI were chosen based on children with cerebral palsy, potentially limiting the application to other pathologies; the analysis of the GDI depends on the decomposition into eigenvectors and eigenvalues, making the interpretation more cumbersome within the clinical context. For a more detailed description of GGI, GDI and GPS indices please refer to the original study (40).

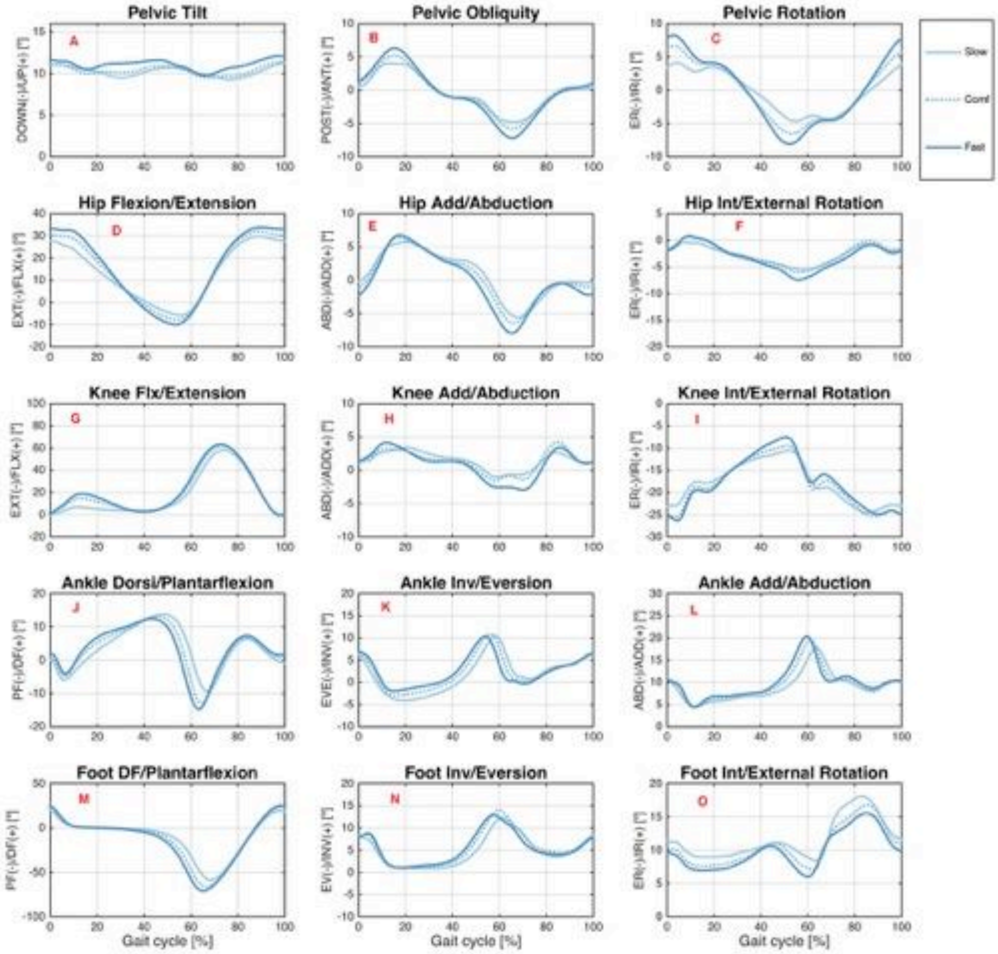

Figure 2-3. Example of a typical gait analysis of the lower extremity in the three planes (sagittal, frontal and transverse). (Fukuchi et al 2018)

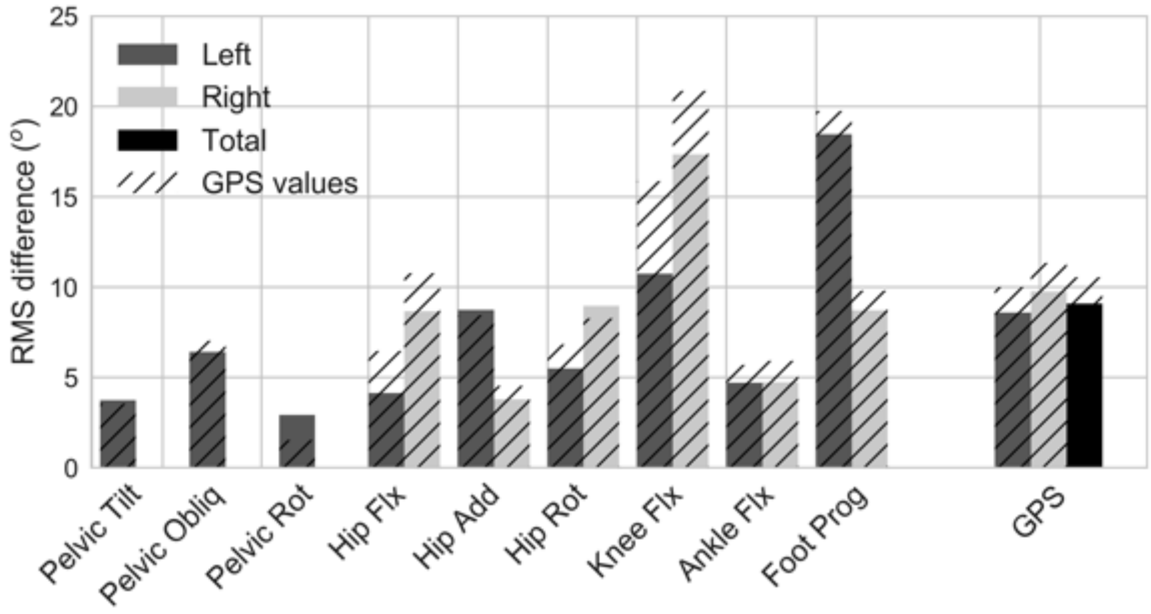

Figure 2-4. Example of a typical gait analysis of the lower extremity in the three planes (sagittal, frontal and transverse). (Fukuchi et al 2018)

In CGA, the gait data from an individual are commonly compared with gait data from a population without any gait pathology (43). However, patients with neurological disorders (e.g. stroke (44,45) or Parkinson's disease (46), knee disabilities (47) and elderly people (13–15) tend to walk slower than healthy controls, not to mention children with disabilities. Additionally, when individuals of different sizes are compared, a 'normalization' procedure of the walking speed can be performed, e.g., dividing the walking speed by the height or leg length of the individual(48), in an attempt to make the analysis more comparable. In fact, walking speed has been reported to alter the average gait pattern in healthy children (49). Stansfield et al. (3) found that speed affected kinematics and kinetics in children at a greater extent than age. Additionally, previous studies reported that spatio-temporal gait parameters, ground reaction forces, joint angles, joint moments, muscle activity, and plantar pressure are affected by gait speed (8–12,50). Despite these evidences, to date, the effect of gait speed on these commonly used gait indices, employed to compare the gait pattern between pathological and healthy individuals, has not been investigated.

One solution to this problem would be to collect many individuals walking at a variety of gait speeds; however, the involved costs would be prohibitive. Instead, the use of public datasets (16) would allow the comparison of the gait pattern of different population considering various walking speeds. Although the existent datasets allow the comparison of the gait pattern in various aspects, they present limitations such as reporting a single type of data (e.g. only kinematics data), one walking surface (either overground or treadmill), and a limited number of gait speeds. To overcome this issue, there is a need to create a public dataset of the 3D walking kinematics and kinetics data of healthy individuals walking at a range of gait speeds and different surfaces. Even though a new gait dataset addressing some of the previous limitations is useful, it would unlikely contain all possible gait speeds within the range of speeds humans typically adopt. Therefore, regression methods have been proposed as a feasible alternative for predicting the gait parameters at any desired gait speed (10,12). Nevertheless, since these prediction methods are based only on specific event (e.g., peak values), or solely in a few gait speeds; prediction methods that consider the full gait cycle and in a wider range of gait speeds are needed.

Thus, the objective of this study was to address the following purposes:

- To understand the effects of the speed on the gait kinematic and kinetic patterns in healthy individuals;
- To create a public gait dataset of young and older healthy adults walking on both treadmill and overground over a variety of speeds;
- To present a prediction method to analyze the gait pattern considering the effects of gait speed;
- To apply the prediction method to analyze the GPS index in people who present any gait impairment;
- To compare the peak and valley values by the prediction method proposed with standard prediction models.

Chapter 3. Literature Review and Meta-Analysis

Submitted as:

Effects of walking speed on gait in healthy participants: a systematic review and meta-analysis

Claudiane Arakaki Fukuchi, Reginaldo Kisho Fukuchi, Marcos Duarte

BMC Systematic Review, March 2018.

Student contributions

In this study, the student conceived and designed the protocol, research and analyzed the data, prepared figures and/or tables, wrote the paper, approved the final draft.

Abbreviations

CIs: confidence intervals; ES: effect size; GRF: ground reaction forces; QI: Quality Index; SEs: standard errors; Q: Cochran's heterogeneity statistic; 3D: three-dimensional

3.1 Abstract

Background: Understanding the effects of gait speed on biomechanical variables is fundamental for a proper evaluation of alterations in gait, since pathological individuals tend to walk slower than healthy controls. Therefore, the aim of the study was to perform a systematic review of the effects of gait speed on spatiotemporal parameters, joint kinematics, joint kinetics and ground reaction forces in healthy children, young adults and older adults.

Methods: A systematic electronic search was performed on PubMed, Embase and Web of Science databases to identify studies published between 1980 and 2019. A modified Quality Index was applied to assess methodological quality, and effect sizes with 95% confidence intervals were calculated as the standardized mean differences. For the meta-analyses, a fixed or random effect models and the statistical heterogeneity were calculated using the I^2 index.

Results: Twenty original full-length studies were included in the final analyses with a total of 587 healthy individuals evaluated, of whom four studies analyzed the gait pattern of 227 children, 16 studies of 310 young adults, and three studies of 59 older adults. In general, gait speed affected the amplitude of spatiotemporal gait parameters, joint kinematics, joint kinetics and ground reaction forces with a decrease at slow speeds and increase at fast speeds in relation to the comfortable speed. Specifically, moderate-to-large effect sizes were found for each age group and speed: children (slow: -3.61 to 0.59; fast: -1.05 to 2.97), young adults (slow: -3.56 to 4.06; fast: -4.28 to 4.38), and older adults (slow: -1.76 to 0.52; fast: -0.29 to 1.43).

Conclusions: This review identified that speed affected the gait patterns of different populations with respect to the amplitude of spatiotemporal parameters, joint kinematics, joint kinetics and ground reaction forces. Specifically, most of the values analyzed decreased at slower speeds, and increased at faster speeds. Therefore, the effects of speed on gait patterns should also be considered when comparing the gait analysis of pathological individuals with normal or control ones.

Keywords: walking speed, kinematics, kinetics, ground reaction forces, gait analysis

3.2 Background

The quantification of the biomechanical characteristics of a person's gait is an important clinical tool for evaluating normal and pathological patterns of locomotion (1, 2), and has been used in the decision process to prescribe treatment as well as to evaluate the intervention outcomes (3–5). For example, the walking speed and not age has been considered the primary determinant of the kinematic and kinetic changes in children (6). In fact, the speed at which a person walks influences biomechanical variables such as joint kinematics, ground reaction forces (GRF), joint moments of force (moments) and powers, muscle activity and spatiotemporal gait parameters in children (6–9), young adults (10–14) and older adults (15, 16). However, none of these studies considered all these variables together nor examined different age groups in the same study.

In a typical gait analysis, the gait patterns of pathological individuals are compared with a cohort of healthy individuals walking at their comfortable pace. However, as pathological individuals tend to walk slower and considering different age groups, without knowing which biomechanical variables are likely more affected by gait speed, this comparison may not be appropriate. Thus, to improve the knowledge about the effects of gait speed on biomechanical variables is paramount for benefitting clinicians who commonly rely on the outcomes of gait analysis to optimize patient care (17).

Although there are a handful of studies, including some reviews (18, 19) that examined the influence of walking speed on gait biomechanics, to our knowledge, no study has systematically reviewed the effects of speed on gait over a more comprehensive set of biomechanical variables and across different ages. For example, Telfer and collaborators (18) reported that walking speed has the largest effect on knee abduction moment in individuals over 18 years old, which is related to the development of the medial knee osteoarthritis (20). Additionally, a systematic review by Herssens and collaborators (19) reported changes in the spatiotemporal parameters in healthy adults between 18 and 98 years old, but only at the self-selected walking speed.

Hence, the aim of the present study was to perform a systematic review of studies that have investigated the effects of gait speed on spatiotemporal parameters, joint kinematics, joint kinetics and GRF variables in healthy individuals of various ages.

3.3 Methods

3.3.1 Search strategy

This systematic review was conducted according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement (21) (Table 3-1), and was registered in PROSPERO (ID122769). All studies were identified by three electronic databases (PubMed, Embase, and Web of Science) which comprise the most topics within the Biomedical and Health Sciences area (22). The specific search strategy is described in Table 3-2.

Table 3-1. Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement.

Section/topic	#	Checklist item	Reported on page #
TITLE			
Title	1	Identify the report as a systematic review, meta-analysis, or both.	1
ABSTRACT			
Structured summary	2	Provide a structured summary including, as applicable: background; objectives; data sources; study eligibility criteria, participants, and interventions; study appraisal and synthesis methods; results; limitations; conclusions and implications of key findings; systematic review registration number.	2
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of what is already known.	3
Objectives	4	Provide an explicit statement of questions being addressed with reference to participants, interventions, comparisons, outcomes, and study design (PICOS).	3-4
METHODS			
Protocol and registration	5	Indicate if a review protocol exists, if and where it can be accessed (e.g., Web address), and, if available, provide registration information including registration number.	4
Eligibility criteria	6	Specify study characteristics (e.g., PICOS, length of follow-up) and report characteristics (e.g., years considered, language, publication status) used as criteria for eligibility, giving rationale.	4-5
Information sources	7	Describe all information sources (e.g., databases with dates of coverage, contact with study authors to identify additional studies) in the search and date last searched.	4
Search	8	Present full electronic search strategy for at least one database, including any limits used, such that it could be repeated.	Table 3-2

Study selection	9	State the process for selecting studies (i.e., screening, eligibility, included in systematic review, and, if applicable, included in the meta-analysis).	4-5
Data collection process	10	Describe method of data extraction from reports (e.g., piloted forms, independently, in duplicate) and any processes for obtaining and confirming data from investigators.	5
Data items	11	List and define all variables for which data were sought (e.g., PICOS, funding sources) and any assumptions and simplifications made.	5
Risk of bias in individual studies	12	Describe methods used for assessing risk of bias of individual studies (including specification of whether this was done at the study or outcome level), and how this information is to be used in any data synthesis.	5
Summary measures	13	State the principal summary measures (e.g., risk ratio, difference in means).	6-7
Synthesis of results	14	Describe the methods of handling data and combining results of studies, if done, including measures of consistency (e.g., I^2) for each meta-analysis.	6-7
Section/topic	#	Checklist item	Reported on page #
Risk of bias across studies	15	Specify any assessment of risk of bias that may affect the cumulative evidence (e.g., publication bias, selective reporting within studies).	5
Additional analyses	16	Describe methods of additional analyses (e.g., sensitivity or subgroup analyses, meta-regression), if done, indicating which were pre-specified.	n/a
RESULTS			
Study selection	17	Give numbers of studies screened, assessed for eligibility, and included in the review, with reasons for exclusions at each stage, ideally with a flow diagram.	8, Figure 3-1
Study characteristics	18	For each study, present characteristics for which data were extracted (e.g., study size, PICOS, follow-up period) and provide the citations.	8, Table 3-3
Risk of bias within	19	Present data on risk of bias of each study and, if available, any outcome level assessment (see item 12).	8, Table 3-4

studies			
Results of individual studies	20	For all outcomes considered (benefits or harms), present, for each study: (a) simple summary data for each intervention group (b) effect estimates and confidence intervals, ideally with a forest plot.	8-11
Synthesis of results	21	Present results of each meta-analysis done, including confidence intervals and measures of consistency.	8-11
Risk of bias across studies	22	Present results of any assessment of risk of bias across studies (see Item 15).	8, Table 3-4
Additional analysis	23	Give results of additional analyses, if done (e.g., sensitivity or subgroup analyses, meta-regression [see Item 16]).	n/a
DISCUSSION			
Summary of evidence	24	Summarize the main findings including the strength of evidence for each main outcome; consider their relevance to key groups (e.g., healthcare providers, users, and policy makers).	12-14
Limitations	25	Discuss limitations at study and outcome level (e.g., risk of bias), and at review-level (e.g., incomplete retrieval of identified research, reporting bias).	14
Conclusions	26	Provide a general interpretation of the results in the context of other evidence, and implications for future research.	14-15
FUNDING			
Funding	27	Describe sources of funding for the systematic review and other support (e.g., supply of data); role of funders for the systematic review.	15

From: Moher D, Liberati A, Tetzlaff J, Altman DG, The PRISMA Group (2009). Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement. PLoS Med 6(7): e1000097. doi:10.1371/journal.pmed1000097. For more information, visit: **www.prisma-statement.org**.

Table 3-2. Search strategy

1	Keywords	gait [or] walk*
2	Keywords	speed [or] velocit*
3	Keywords	kinematic* [or] kinetic* [or] biomech* [or] spatiotemporal [or] spatio-temporal [or] basic parameter$ [or] angle* [or] torque* [or] moment* [or] grf [or] ground reaction force*
4	Combine	1 [and] 2
5	Combine	4 [and] 5

3.3.2 Selection criteria

The initial search was completed on December 2017, and on March 2019 a final search using the same terms was performed to verify potential newly published articles. Only original full-length studies published between 1980 and 2019 were included, with the specific inclusion criteria determined a priori: (1) walking as opposed to running; (2) normal (or equivalent), and slow and/or fast speeds measured quantitatively or qualitatively; (3) walking either on a ground or treadmill surface; (4) healthy participants with no orthopedic or neurological disease; (5) gait analysis on a level surface; (6) gait analysis using a three-dimensional (3D) motion capture system or 3D force platforms or both; and (7) article published in English. Reviews, conference papers, abstracts and letters, cases series and pilot studies were excluded.

Inclusion criteria for the participants will be healthy individuals with the age range based on the specific age group: children (4-17 years of age), young adults (18-59 years of age), and older adults (60-85 years of age). Studies that presented individuals with any musculoskeletal or neurological impairment will be excluded. Since the aim of this systematic review was not to examine the effect of any intervention, only observational studies (e.g. cohort, case-control and cross-sectional design) were included in this systematic review.

To ensure identification of all relevant studies, the reference lists of relevant systematic reviews were hand-searched (18, 19, 22).

3.3.3 Data extraction

All titles returned based on the search terms were first scanned by one of the co-authors, CAF. From the results of the original search, articles were excluded based on the inclusion criteria (e.g., animal study, non-English language, running task etc.). Following this, all titles and abstracts were reviewed by two reviewers, CAF and RKF (co-authors of this article), to determine their eligibility for the study. Whenever there was a disagreement between the two reviewers, the third author was consulted.

Characteristics of studies (authors, year), participants (sample size, age), surface types (treadmill or overground), and gait speed were extracted and reported in Table 3-3.

3.3.4 Methodological quality

All evaluated studies had their quality rated, based on a modified version of the Quality Index (QI) tool originally described by Downs and Black (23). From the original checklist, only item 27 was removed due to its ambiguity (24). Twenty-six items, comprising the reporting and the external and internal (bias and confounding) validity assessment, were considered in the final analyses, with the maximum score being 27. The following cut-off adopted in this review was based on a previous study that also analyzed the gait kinetics, kinematics, and spatiotemporal parameters but during long-distance running (25): high quality (≥ 80%); moderate (< 80% and ≥ 47%), and poor quality (< 40%).

3.3.5 Variables of interest

The following variables were considered in the present study to address the research question: spatiotemporal gait parameters such as step length, stride length, stride time, and cadence; sagittal kinematic and kinetic variables such as hip, knee and ankle joint angles and joint moments (when available); and horizontal and vertical GRF (for a general description of these variables see (26)). Since knee abduction moment (in the frontal plane) has been reported to be related to the incidence of knee injuries (27,28), this variable was also analyzed. For consistency, all joint moments are reported as internal ones. For this review, we considered the maximum or minimum peak values of the hip, knee, and ankle joint angles in the sagittal plane during the stance and swing phases of the gait cycle. For the joint moments, the peak values in the sagittal plane and also the peak value of the knee joint in the frontal plane were considered. For the GRF, the first and second peaks of vertical GRF (vertical1 and vertical2, respectively) and the braking and propulsive forces in the anterior-posterior direction, were evaluated. Peak values of the joint moments and GRF variables were analyzed only during the stance phase. All these variables were included because they have been reported in previous studies within the context of gait analysis (29,30). In this review, only studies that provided graphical or numerical data over the gait cycle were considered for further analysis. If a study was initially included in the final list but presented insufficient information, the authors were contacted and asked to provide the data. If they refused, were unable to, or did not respond to the requests, the study was removed from the list.

The effects of gait speed during walking were analyzed separately for children, young adults, and older adults. In cases where the study included sub-groups (i.e., 4-6 years, 6-8 years, 8-10 years), the results of these sub-groups were combined into one group according to the age groups examined in this review (children (4-17 years of age), young adults (18-59 years of age), and older adults (60-85 years of age)). Males and females were also combined. In this review, only the slow, comfortable and fast speeds were considered for analysis. If any study presented more than three gait speeds (i.e., very slow, slow, comfortable and fast), the very slow and slow speeds were combined. When the authors did not specify the speed for the comfortable condition, ranges from 1.07 to 1.32 m/s in children (6,31), 1.05 to 1.43 m/s in young adults

(31,32), and 0.94 to 1.34 m/s in older adults (33) were adopted. Gait speeds below or above the range of each group were considered as slow and fast, respectively.

To account for the effect of gait speed, the effect size (ES) was calculated based on the ratio of the difference between group means of gait speeds and the pooled standard deviation. We compared the comfortable speed with the slow and fast speeds separately where the specific convention was adopted: for the comparison between slow and comfortable speed (slow < comfortable), and for the fast and comfortable speed (fast > comfortable). Additionally, when numerical data were not available but graphs were presented, we manually digitized the graph using the *WebPlotDigitizer* application (https://automeris.io/WebPlotDigitizer/) to obtain the values. The following guidelines were used to interpret the Cohen's *d* ES (34,35): small (0.2-0.5), moderate (0.5-0.8), and large (> 0.8). To calculate the standardized effects across studies, a fixed or random (heterogeneity) effects model was applied based on the following criteria: if the heterogeneity is high ($I^2 > 50\%$), a random-model effect will be chosen; contrarily, a fixed-effect model will then be considered (36). The 95% confidence intervals (CIs) were calculated to evaluate the heterogeneity of the standardized effects. The results for all variables are summarized as a Table including effect sizes, lower and upper CIs, standard errors (SEs), Cochran's heterogeneity statistic (Q), I^2 statistic, and *p*-values for the children and older-adult groups.

3.4 Results

The search returned 19791 articles that were first screened and considered for inclusion in the review. Based on the inclusion criteria, the full texts of 218 articles were then reviewed, and 18 studies were retained. Two additional studies were included because they were cited by the included studies and considered relevant for this review. Twenty studies were therefore used in the final analyses (Figure 3-1 and Table 3-3). The methodological quality of the assessed studies was considered moderate, with a mean score of 15 (55%), ranging between 12 (44%) and 18 (67%) (Table 3-4). Overall, data from 587 healthy individuals were analyzed: 227 children (4 studies), 310 young adults (16 adults), and 59 older adults (3 studies), in both treadmill (6 studies) and ground (14 studies) surfaces with a range of walking speeds. The mean ages of the participants per group were: children 10.3 years, young adults 27.1 years, and older adults 69.2 years. For consistency when available, gait speeds were reported in meters per second. However, as this information was not reported in two studies (7,37), the specific speeds (m/s) were adopted based on previous studies that applied similar methods (12,38).

Forest plots for all gait parameters are shown in Figure 3-2 to Figure 3-6. Due to the small number of studies of children and older adults, their results were presented as a table instead of a forest plot in the supplemental material (Supplementary material). Specific changes in gait pattern due to walking speed were reported separately for each age group.

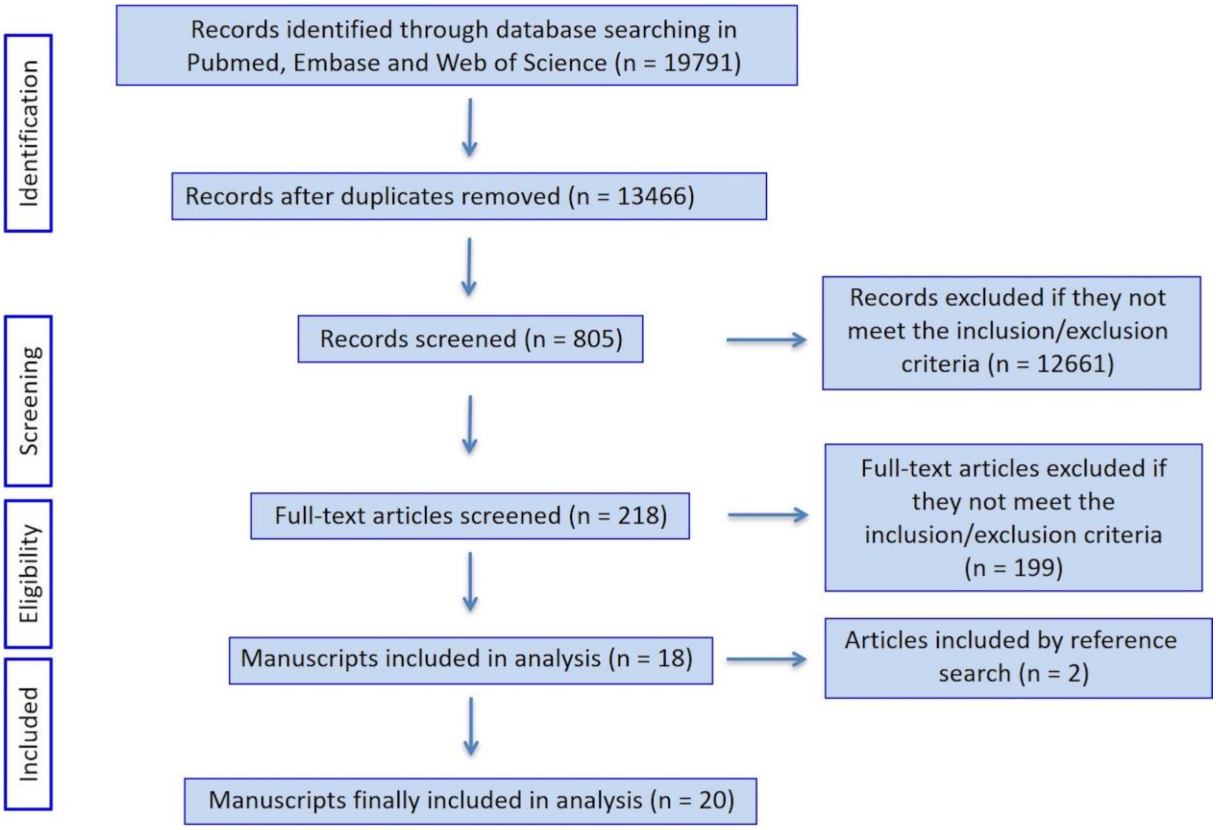

Figure 3-1. PRISMA flow diagram of the article search and screening for data extraction.

Table 3-3. Details of the manuscripts used in the final analysis.

Author, year (ref)	**Sample size**			**Age mean (SD)**			**Surface**	**Gait speed (m/s)**
	Children	**Young adults**	**Older adults**	**Children**	**Young adults**	**Older adults**		
de David et al.2015 (62)		11			21.2 (1.8)		Overground	1.61, 2.09
Diop et al. 2005 (40)	94			7.3 (0.6)			Treadmill	0.75, 1.0, 1.25
Dubbeldam et al. 2010 (63)		14			43 (8)		Overground	0.81, 1.28
Giarmatzis et al. 2015 (64)		20			22.2 (1.6)		Treadmill	0.83, 1.25, 1.67
Hsiao et al. 2015 (65)		20			33.5 (20.1)		Treadmill	1.08, 1.30
Kerrigan et al. 1998 (66)		31	31		28.5 (4.9)	72.5 (5.5)	Overground	1.37, 1.19, 1.55
Khan et al. 2017 (67)		20			29 (4.1)		Overground	0.85, 1.18, 1.43
Kwon et al. 2015 (37)		40			23.2 (3.8)		Overground	1.00, 1.50, 2.00
Lewek 2011 (68)		15			27 (9)		Treadmill	0.60, 1.20, 1.60
Linden et al. 2002 (69)	36			9 (0.6)			Overground	0.75, 1.21
Monaco et al. 2009 (70)		9	8		26.4 (2.3)	70.4 (5.3)	Treadmill	0.77, 1.13
Ridge et al. 2016 (71)	14			14.4 (2.1)			Overground	1.23, 1.87
Riley et al. 2001 (72)		24			23.9 (4.4)		Overground	0.87, 1.19, 1.74
Robbins et al. 2009 (73)		32			32 (8)		Overground	1.19, 1.39, 1.60
Schwartz et al. 2008 (7)	83			10.5 (3.5)			Overground	0.65, 1.15, 1.56
Silder et al. 2008 (74)		20	20		26 (3.5)	72.5 (5)	Overground	1.06, 1.33, 1.59
Wang et al. 2017 (75)		15			24.7 (1.2)		Overground	1.1, 1.4, 1.7
Weinhandl et al. 2017 (76)		10			25.8 (6.2)		Overground	1.21, 1.34, 1.48
Winiarski et al. 2019 (77)		20			20.1 (1.2)		Overground	1.04, 1.32, 1.62
Yang et al. 2013 (78)		9			26.4 (2.4)		Treadmill	0.40, 0.93, 1.47

Table 3-4. Quality index assessment of the manuscripts used in the final analysis.

	Reporting (0-11)	**External validity (0-3)**	**Internal validity - bias (0-7)**	**Internal validity – confounding (0-6)**	**Quality Index Score (0-27) (%)**
de David et al. 2015 (62)	8	1	5	0	14 (52)
Diop et al. 2005 (40)	9	1	5	2	17 (63)
Dubbeldam et al. 2010 (63)	8	1	5	1	15 (56)
Giarmatzis et al. 2015 (64)	9	1	5	2	17 (63)
Hsiao et al. 2015 (65)	6	1	5	0	12 (44)
Kerrigan et al. 1998 (66)	8	1	5	1	15 (56)
Khan et al. 2017 (67)	7	1	5	2	15 (56)
Kwon et al. 2015 (37)	6	1	4	1	12 (44)
Lewek 2011 (68)	8	1	5	1	15 (56)
Linden et al. 2002 (69)	5	1	5	1	12 (44)
Monaco et al. 2009 (70)	8	2	5	1	16 (59)
Ridge et al. 2016 (71)	9	1	5	2	17 (63)
Riley et al. 2001 (72)	7	1	5	0	13 (48)
Robbins et al. 2009 (73)	9	1	5	3	18 (67)
Schwartz et al. 2008 (7)	7	1	5	1	14 (52)
Silder et al. 2008 (74)	9	1	5	2	17 (63)
Wang et al. 2017 (75)	6	1	5	0	12 (44)
Weinhandl et al. 2017 (76)	8	1	5	2	16 (59)
Winiarski et al. 2019 (77)	9	3	5	1	18 (67)
Yang et al. 2013 (78)	7	1	5	1	14 (52)
				Mean	**15 (55)**

3.4.1 Children

Gait speed influenced the spatiotemporal parameters in the child population. More specifically, large effects for cadence (ES = -3.61, $p < 0.001$), step length (ES = -3.29, $p < 0.001$), and stride length (ES = -3.22, $p < 0.001$) were found during slower speeds, with a reduction in these variables when children walked slower. On the other hand, the stance duration (ES = 0.59, $p < 0.001$) presented a moderate effect, indicating an increase during slower speeds. At faster speeds, both cadence (ES = 2.97, $p < 0.001$) and step length (ES = 2.35, $p < 0.001$) presented large effect sizes, with higher values as the speed increased. Contrary to this, although there was also a large effect size for stance duration (ES = -1.05, $p < 0.001$), its value decreased as the speed increased.

The joint kinematics showed large effect sizes for hip flexion (ES = -0.80, $p < 0.001$), knee flexion (ES = -1.34, $p < 0.001$), and ankle plantarflexion (ES = -1.14, $p < 0.001$) angles, with decreases in their values as the speed decreased. There was a moderate effect for dorsiflexion angle (ES = 0.34, $p = 0.031$), but this increased at slower speeds. Regarding the fast speeds, a moderate effect was also found for ankle dorsiflexion angle (ES = -0.63, $p < 0.001$), with a decrease in this at higher speeds.

For the joint kinetics, large effect sizes were found for the hip flexion (ES = -1.70, $p < 0.001$) and knee extension (ES = -1.52, $p < 0.001$) moments, and a moderate effect for the ankle plantarflexion moments (ES = -0.60, $p < 0.001$). The results indicated that these variables decreased as walking speed decreased. In contrast, at faster speeds the hip flexion, knee extension and knee abduction moments increased as speed increased, with a moderate effect size for knee abduction (ES = 0.59, $p < 0.001$) and large effect sizes for hip flexion (ES = 1.84, $p < 0.001$) and knee extension (ES = 1.17, $p = 0.024$).

With regard to ground reaction forces, there were large effect sizes for the vertical1 (ES = -1.21, $p < 0.001$), braking (ES = -2.00, $p < 0.001$) and propulsive (ES = -2.98, $p < 0.001$) forces, with lower values as the speed decreased. At faster speeds these variables increased, with larger effect sizes for vertical1 (ES = 1.39, $p < 0.001$), braking (ES = 1.36, $p < 0.001$) and propulsive (ES = 1.50, $p < 0.001$) forces.

Table 3-5. Meta-analysis for the comparison between slow x comfortable speeds for the children.

Outcome Measures	**# studies**	**ES**	**CI lower**	**CI upper**	**SE**	**Q**	**I^2**	***p*-value**
Gait parameters								
Cadence	2	-3.61	-4.02	-3.20	0.21	0.03	0.0%	<0.001*
Step Length	2	-3.29	-3.68	-2.90	0.20	0.54	0.0%	<0.001*
Stride Length	1	-3.22	-3.92	-2.52	0.36	0.00	0.0%	<0.001*
Stance Duration	1	0.59	0.29	0.88	0.15	0.00	0.0%	<0.001*
Joint angles								
Hip Flexion	1	-0.80	-1.11	-0.48	0.16	0.00	0.0%	<0.001*
Knee Flexion	1	-1.34	-1.68	-1.00	0.17	0.00	0.0%	<0.001*
Ankle Dorsiflexion	1	0.34	0.03	0.64	0.16	0.00	0.0%	0.031*
Ankle Plantarflexion	1	-1.14	-1.46	-0.81	0.17	0.00	0.0%	<0.001*
Joint moments								
Hip Flexion	1	-1.70	-2.06	-1.35	0.18	0.00	0.0%	<0.001*
Knee Extension	1	-1.52	-1.87	-1.18	0.18	0.00	0.0%	<0.001*
Knee Abduction	1	-0.16	-0.47	0.14	0.16	0.00	0.0%	0.289
Ankle Plantarflexion	1	-0.60	-0.91	-0.29	0.16	0.00	0.0%	<0.001*
Ground reaction forces								
Vertical1 Force	2	-1.21	-1.44	-0.99	0.12	0.00	0.0%	<0.001*
Vertical2 Force	2	-0.42	-0.98	0.13	0.28	6.88	85.5%	0.137
Braking Force	2	-2.00	-2.47	-1.52	0.24	3.37	70.3%	<0.001*
Propulsive Force	2	-2.98	-4.10	-1.86	0.57	13.08	92.4%	<0.001*

Table 3-6. Meta-analysis for the comparison between comfortable x fast speeds for the children.

Outcome Measures	**# studies**	**ES**	**CI lower**	**CI upper**	**SE**	**Q**	**I^2**	***p*-value**
Gait parameters								
Cadence	1	2.97	2.53	3.41	0.22	0.00	0.0%	<0.001*
Step Length	2	2.33	1.97	2.70	0.19	1.10	9.0%	<0.001*
Stance Duration	1	-1.05	-1.36	-0.75	0.16	0.00	0.0%	<0.001*
Joint angles								
Hip Flexion	2	0.60	-0.07	1.27	0.34	2.69	62.9%	0.079
Knee Flexion	2	0.90	-0.42	2.23	0.67	8.52	88.3%	0.180
Ankle Dorsiflexion	1	-0.63	-0.94	-0.32	0.16	0.00	0.0%	<0.001*
Ankle Plantarflexion	1	0.05	-0.26	0.35	0.16	0.00	0.0%	0.764
Joint moments								
Hip Flexion	2	1.84	0.92	2.76	0.47	3.35	70.1%	<0.001*
Knee Extension	2	1.17	0.15	2.19	0.52	4.91	79.6%	0.024*
Knee Abduction	1	0.59	0.28	0.90	0.16	0.00	0.0%	<0.001*
Ankle Plantarflexion	2	0.56	-0.19	1.31	0.38	3.32	69.9%	0.142
Ground reaction forces								
Vertical1 Force	2	1.39	1.15	1.62	0.12	0.01	0.0%	<0.001*
Vertical2 Force	2	0.36	-0.01	0.72	0.18	2.95	66.1%	0.054
Braking Force	2	1.36	0.99	1.73	0.19	2.58	61.3%	<0.001*
Propulsive Force	2	1.50	1.27	1.74	0.12	0.00	0.0%	<0.001*

3.4.2 Young adults

At slower speeds, the gait parameters showed large effect sizes for cadence (ES =-1.96, $p < 0.001$), step length (ES = -1.53, $p = 0.001$), and stride length (ES = -3.56, $p = 0.009$), indicating a decrease when individuals walked slower. At faster speeds, there were large effect sizes for both cadence (ES = 1.67, $p < 0.001$) and step length (ES = 0.83, $p < 0.001$), indicating increases in these variables as the speed increased (Figure 3-2).

For the joint kinematics at slow speeds, the effect sizes were small for the hip flexion (ES = -0.34, $p = 0.028$) and extension angles (ES = -0.45, $p = 0.004$), moderate for the ankle plantarflexion angle (ES = -0.54, $p < 0.001$) and large for the knee flexion angle (ES = -0.90, $p = 0.012$), indicating decreases in these variables as the speed decreased. Regarding the faster speeds, small effect sizes were found for the hip flexion (ES = 0.41, $p = 0.013$) and ankle plantarflexion (ES = 0.32, $p = 0.044$) angles, indicating an increase in these variables with faster speeds (Figure 3-4).

The joint kinetics showed large effect sizes for the hip flexion (ES = -0.88, $p = 0.003$) and ankle plantarflexion moments (ES = -1.37, $p = 0.008$), and a moderate effect size for the knee extension moment (ES = -0.69, $p = 0.018$), indicating that these values decreased as the speed decreased. In contrast, at faster speeds there were large effects for the hip flexion (ES = 1.82, $p < 0.001$), knee extension moments (ES = 1.27, $p < 0.001$), and ankle plantarflexion moments (ES = 1.03, $p < 0.001$) indicating higher values at faster speeds (Figure 3-5).

For the ground reaction forces, there was a large effect size for vertical1 (ES = -0.93, $p = 0.017$), indicating a decrease at slower speeds. At faster speeds, the propulsive force showed a moderate effect size (ES = 0.57, $p = 0.019$), indicating an increase as the speed increased (Figure 3-6).

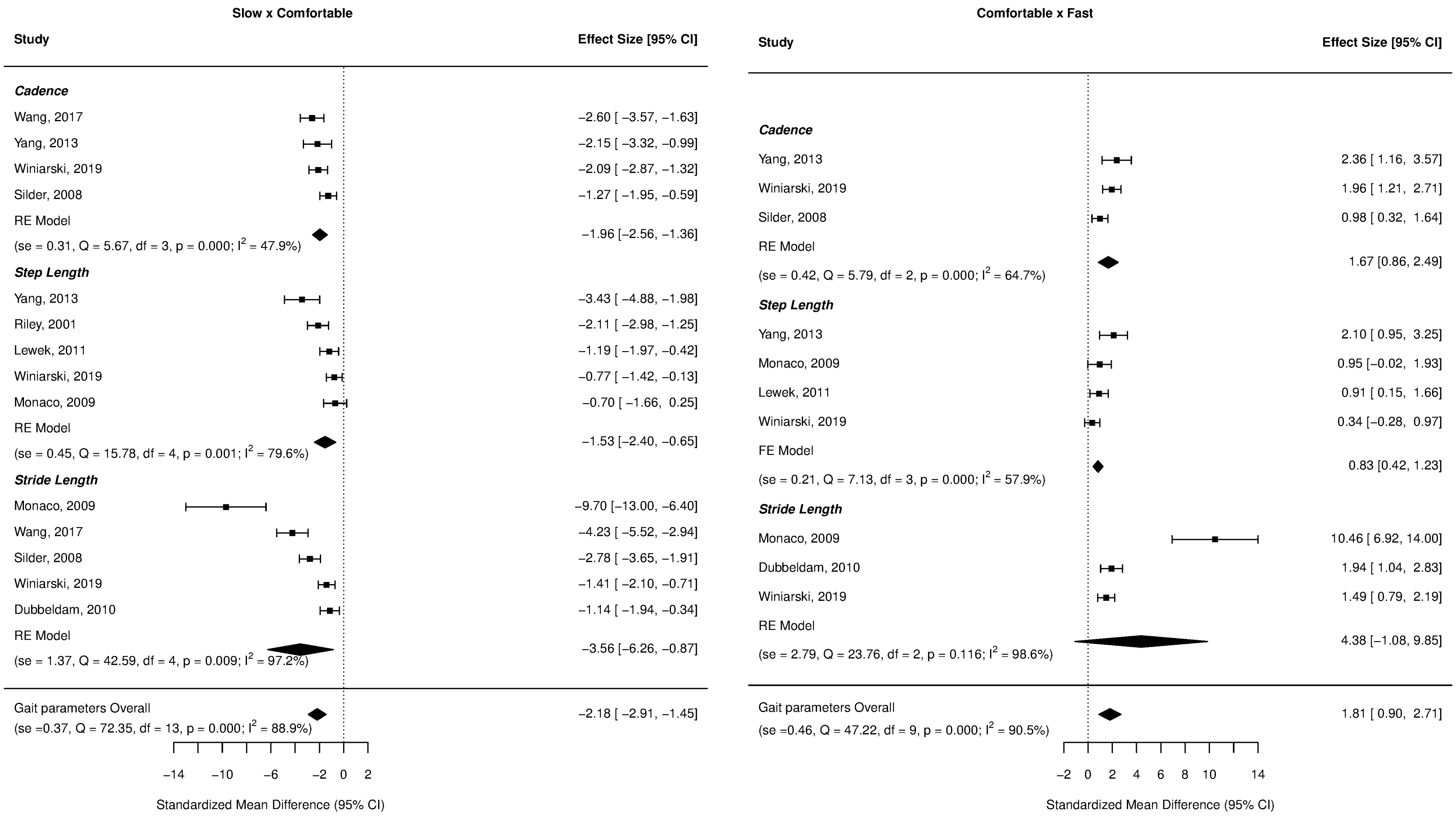

Figure 3-2. Forest plot of the gait parameters comparing the comfortable speed to the slow and fast speeds for the young adults.

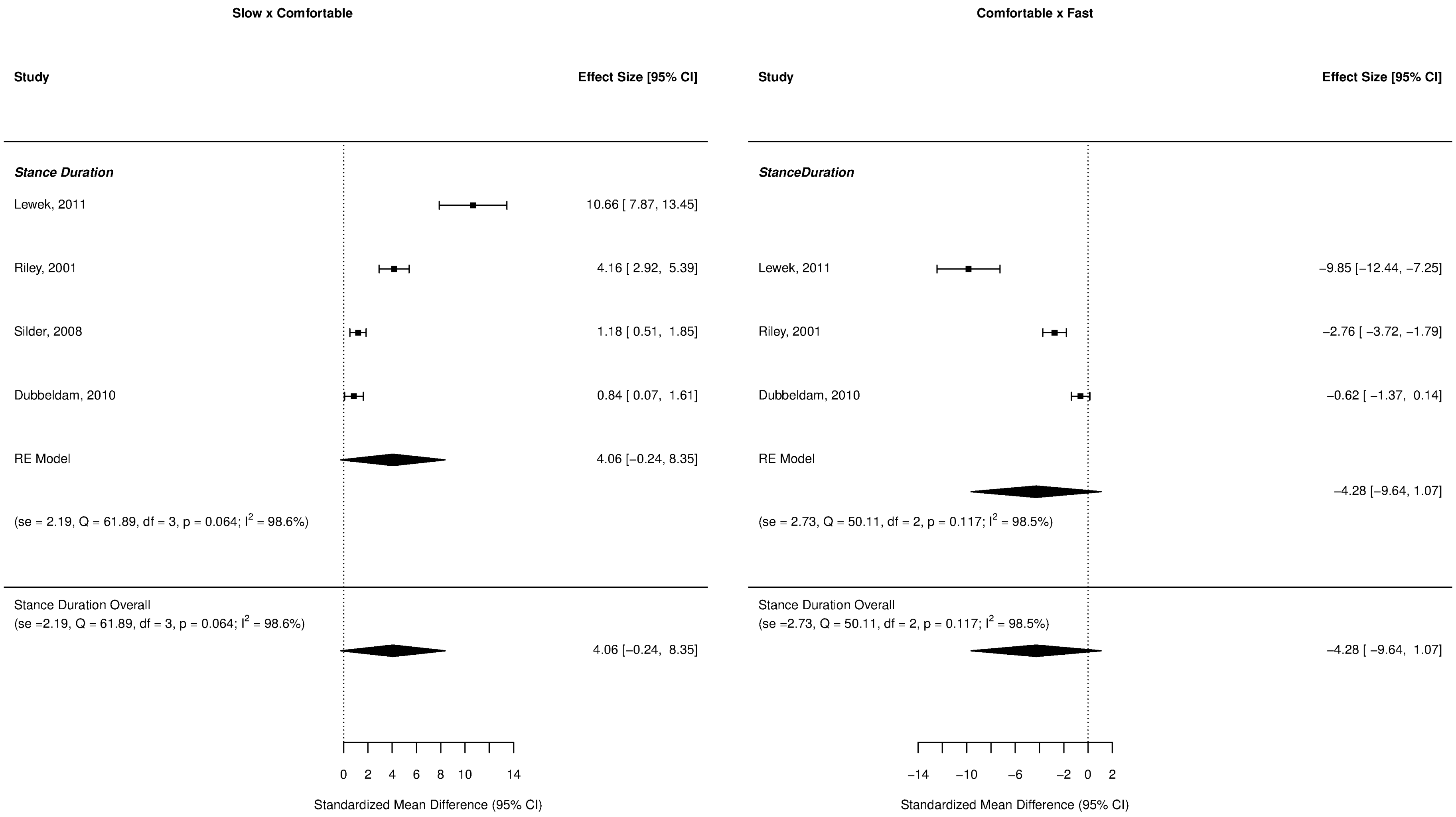

Figure 3-3. Forest plot of the stance duration comparing the comfortable speed to the slow and fast speeds for the young adults.

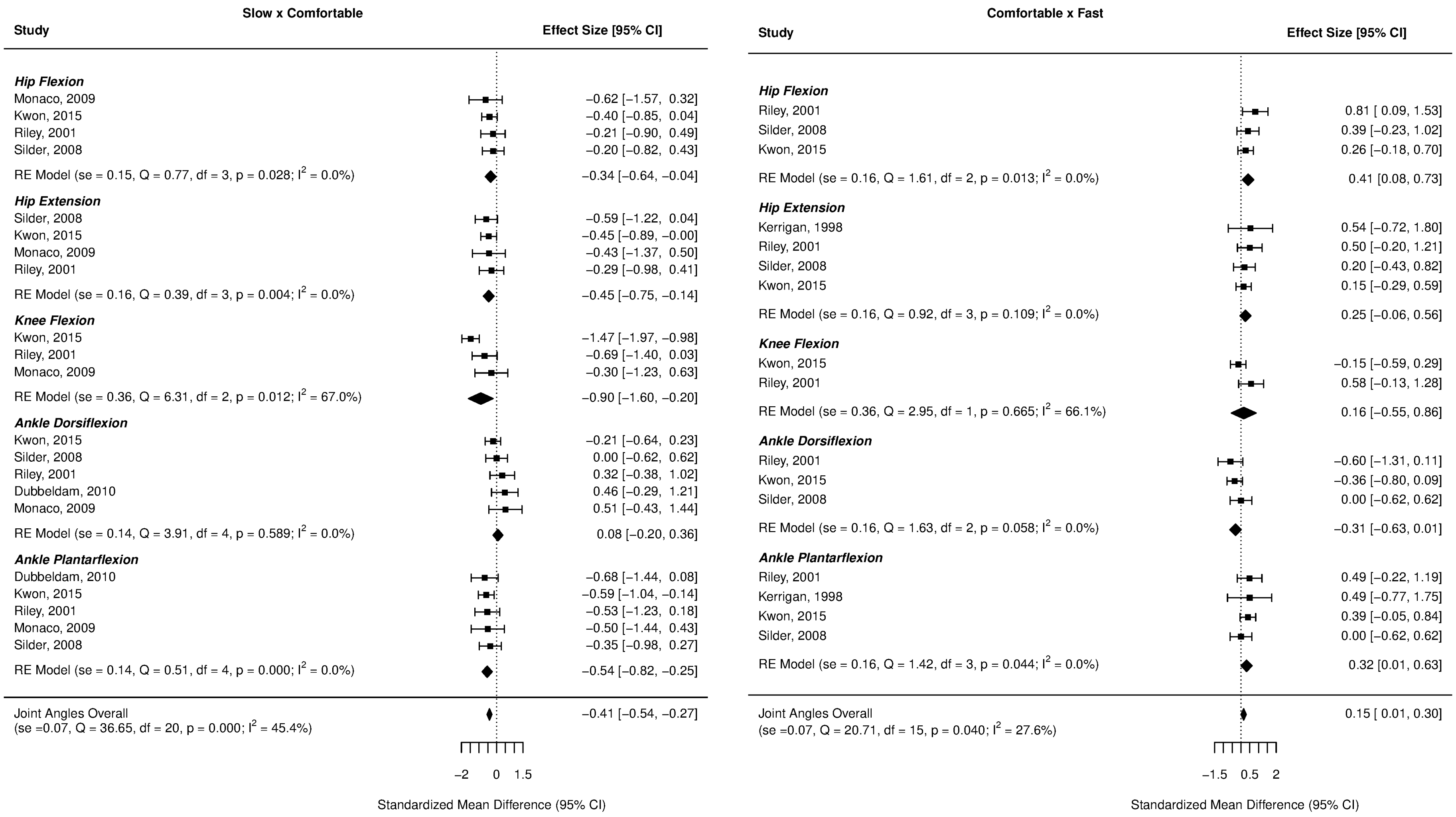

Figure 3-4. Forest plot of the joint angles comparing the comfortable speed to the slow and fast speeds for the young adults.

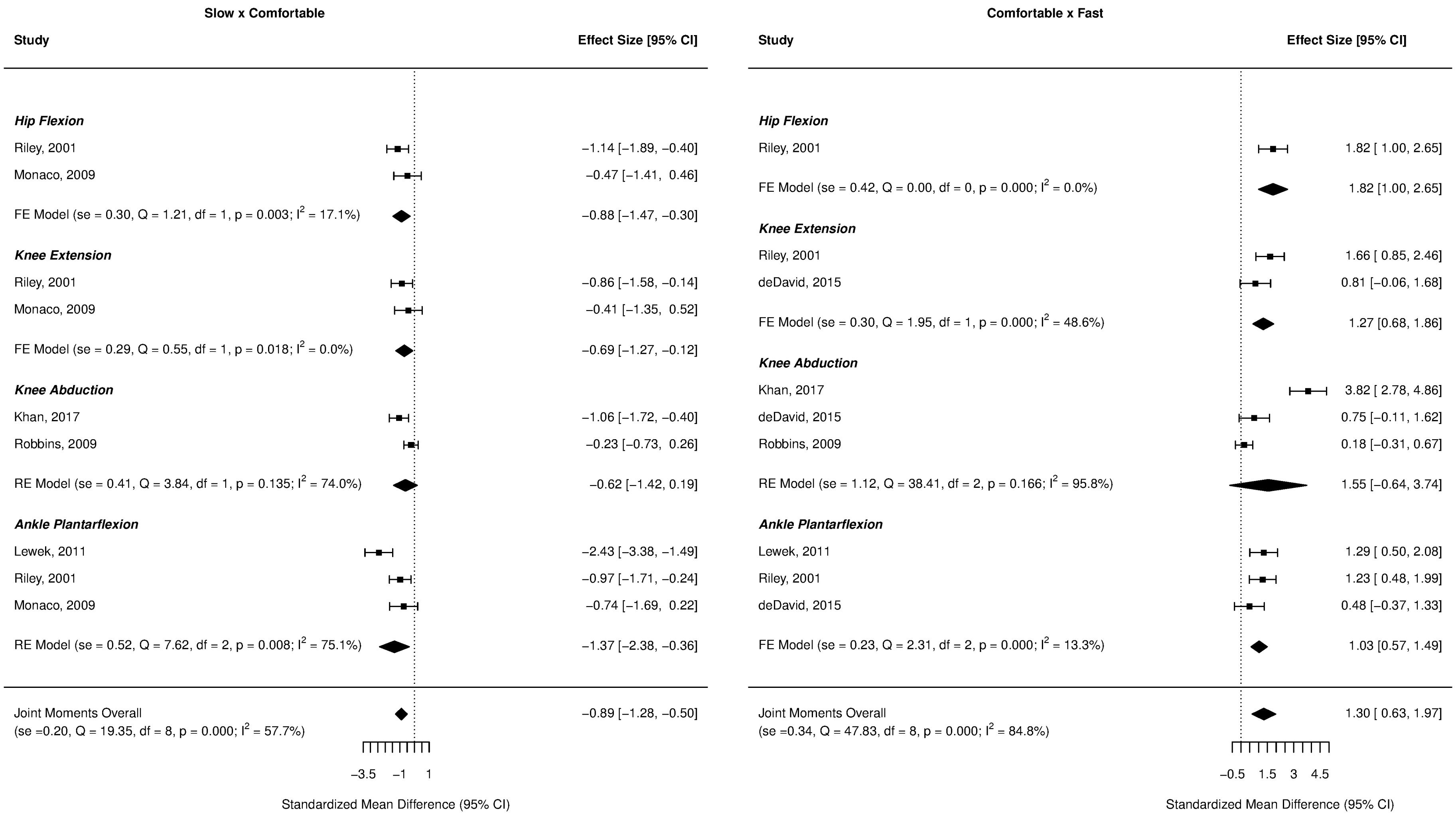

Figure 3-5. Forest plot of the joint moments comparing the comfortable speed to the slow and fast speeds for the young adults.

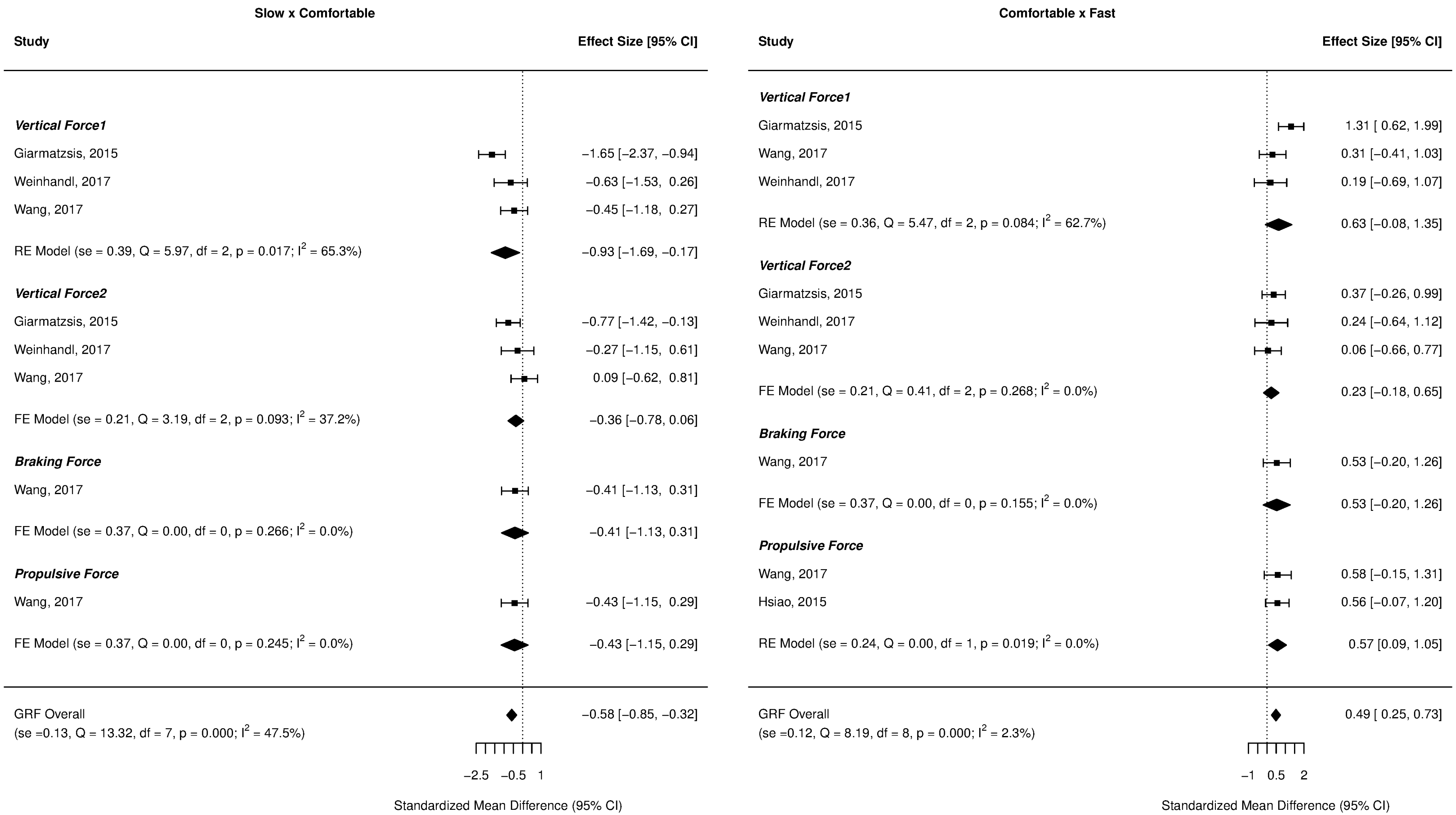

Figure 3-6. Forest plot of the ground reaction forces comparing the comfortable speed to the slow and fast speeds for the young adults.

3.4.3 Older adults

For the older-adult population, large effect sizes were found for the cadence (ES = -1.86, $p < 0.001$), and step length (ES = -1.14, $p = 0.001$) variables, indicating that both cadence and step length decreased when these individuals walked slower. When the individuals walked faster, there were large effect sizes for cadence (ES = 1.43, $p < 0.001$), step length (ES = 1.11, $p = 0.001$), and stride length (ES = 0.98, $p < 0.001$), indicating that these variables increased as the speed increased.

Regarding the joint angles and joint moments, significant effect sizes were found only at faster speeds. A moderate effect size was found for the hip flexion angle (ES = 0.57, $p = 0.005$), indicating an increase during faster speeds. For the joint moments, there were large effect sizes for both the hip flexion (ES = 1.01, $p < 0.001$) and knee extension (ES = 1.26, $p < 0.001$) moments, with these variables increasing as the speed increased.

Table 3-7. Meta-analysis for the comparison between slow x comfortable speeds for the older adults.

Outcome Measures	# studies	ES	CI lower	CI upper	SE	Q	I^2	*p*-value
Gait parameters								
Cadence	2	-1.76	-2.84	-0.69	0.55	2.66	62.4%	0.001*
Step Length	1	-1.14	-1.81	-0.47	0.34	0.00	0.0%	0.001*
Stride Length	1	-1.06	-2.10	-0.01	0.53	0.00	0.0%	0.048*
Stance Duration	1	0.52	-0.48	1.52	0.51	0.00	0.0%	0.307
Joint angles								
Hip Flexion	2	-0.26	-0.79	0.26	0.27	0.16	0.0%	0.327
Hip Extension	2	-0.33	-0.86	0.20	0.27	0.14	0.0%	0.224
Knee Flexion	1	-0.66	-1.67	0.35	0.51	0.00	0.0%	0.198
Ankle Dorsiflexion	2	0.12	-0.41	0.64	0.27	0.21	0.0%	0.659
Ankle Plantarflexion	2	-0.10	-0.63	0.42	0.27	0.02	0.0%	0.704
Joint moments								
Hip Flexion	**1**	-0.52	-1.51	0.48	0.51	0.00	0.0%	0.310
Knee Extension	1	0.13	-0.85	1.11	0.50	0.00	0.0%	0.789
Ankle Plantarflexion	1	-0.86	-1.88	0.17	0.52	0.00	0.0%	0.100

Table 3-8. Meta-analysis for the comparison between comfortable x fast speeds for the older adults.

Outcome Measures	# studies	ES	CI lower	CI upper	SE	Q	I^2	*p*-value
Gait parameters								
Cadence	2	1.43	1.00	1.87	0.22	0.24	0.0%	<0.001*
Step Length	1	1.11	0.44	1.77	0.34	0.00	0.0%	0.001*
Stride Length	1	0.98	0.46	1.51	0.27	0.00	0.0%	<0.001*
Joint angles								
Hip Flexion	2	0.57	0.17	0.96	0.20	0.75	0.0%	0.005*
Hip Extension	2	0.11	-0.28	0.49	0.20	0.13	0.0%	0.594
Knee Flexion	1	0.47	-0.04	0.97	0.26	0.00	0.0%	0.070
Ankle Dorsiflexion	2	-0.29	-0.68	0.10	0.20	1.39	27.9%	0.148
Ankle Plantarflexion	2	0.12	-0.27	0.51	0.20	0.00	0.0%	0.548
Joint moments								
Hip Flexion	1	1.01	0.48	1.54	0.27	0.00	0.0%	<0.001*
Knee Extension	1	1.26	0.71	1.80	0.28	0.00	0.0%	<0.001*
Ankle Plantarflexion	1	-0.13	-0.63	0.37	0.25	0.00	0.0%	0.612

3.5 Discussion

The purpose of this systematic review and meta-analysis was to analyze the effects of walking speed on gait spatiotemporal parameters, joint kinematics, joint kinetics and ground reaction forces in children, young adults and older adults. We compared these variables during walking at either slow or fast speeds with walking at comfortable speeds. In total, 20 studies were included in this review; most of the variables were significantly affected by gait speed, with moderate-to-large effect sizes. Overall, the investigated variables presented smaller absolute amplitudes of the minimum and maximum values at slower speeds and larger absolute amplitudes at faster speeds. However, the effects of speed on gait biomechanics were not similar across the three analyzed groups.

The spatiotemporal gait parameters were generally affected by walking speed in all three age groups, with large effect sizes. Cadence and stride length have been reported as key determinants of walking speed in human locomotion (39). The results found in this study are in agreement with previous studies where they reported a decrease in the duration of the stance phase with increased walking speed in children (10, 40). Additionally, as speed increased, step length in both young adults and older adults, and stride length in older adults, also increased, corroborating the findings of a previous study (10).

In general, differences in joint kinematics, joint kinetics and ground reaction forces due to changes in gait speed showed moderate to large effect sizes. Previous studies have reported the walking-speed dependencies for these variables (6, 7, 11, 12, 31, 41, 42). More specifically, for the child population, we observed that fast walking speeds were related to increased values in knee joint moments, in agreement with previous studies (7, 42). In young adults, the effects of gait speed on the minimum and maximum values of joint angles have also been reported, including increases in hip flexion, hip extension, knee flexion, and ankle plantarflexion angles with higher speeds (31, 41, 43–45). Applying a prediction method, a study by Lelas et al. (12) reported that even though most parameters changed with increasing gait speed, the predictability was better for the kinetic parameters compared to kinematics. For the older adults, the kinematic and kinetic variables were affected to a lesser extent than in either young adults or children because the differences were observed only at fast speeds, while the ground reaction forces did not change in any speed comparisons. Specifically, increases in the hip and knee flexion moments were found when older adults walked faster, which has also been reported in a previous study (44). That the observed changes only occurred at faster speeds in this age group might be explained by the fact that aging itself slows gait, and therefore the impact on slow walking would be smaller (46). Additionally, when compared with the young adults walking at similar speeds, the older adults were less affected by the gait speed, presenting less knee extension at heel-strike and lower knee flexion during the swing phase (47). Regarding the differences in the GRF, this variable was also affected by the gait speed but only in the children's and young adults' groups. Comparing these two groups, changes were more pronounced in the children's group, where the vertical1, braking and propulsive forces decreased at slower speeds and increased at faster speeds. This pattern at faster speeds is in agreement with a previous study (40). In young adults, only the vertical1 force decreased at slow speeds, while the propulsive force increased at fast speeds, as per the findings of previous studies (48, 49).

Comparing the different age groups, while in the child population the gait pattern has not matured yet and the speed seems to affect it to a greater extent (42), in older adults, as the rate of decline in walking speed is typically about 0.7% per year (50), the gait pattern suggests to be less affected by the speed. Therefore, the gait speed should also be considered when studying the effects of age in children and older adults. Moreover, as the minimum and maximum values of these specific biomechanical variables have been used to compare the gait patterns of pathological individuals who tend to walk slower than the control group (5, 51, 52), this comparison may be doable only after collecting data from a number of individuals walking at a variety of gait speeds, which is time-consuming and expensive. Rather, the use of public gait datasets (53–56) when available or the use of prediction methods are more appropriate alternatives to enable the establishment of reference gait patterns at different walking speeds (12, 41, 43, 45, 57, 58). In fact, when a prediction method was applied to predict the gait pattern adjusting for a difference in gait speeds between groups, it has reduced the impact of gait speed on the calculation of gait indices such as the Gait Profile Score in post-stroke individuals (59).

This systematic review included the search of only three electronic databases (PubMed, Embase and Web of Science) and this may be considered a limitation. However, these databases were selected for search because of their broad inclusion of multidisciplinary topics within the Biomedical and Health Sciences domain and because they have been particularly adopted in gait research reviews (18, 22, 60, 61). In addition, only studies that employed 3D gait analysis instrumentation were included in this review and meta-analysis, which resulted in the majority of included studies being observational in nature. Therefore, while we acknowledge its risk, the risk publication bias solely was likely not as important as the overall quality of studies which was assessed through a quality index tool (23).

3.6 Conclusion

The results of this systematic review and meta-analysis show that speed affects the gait patterns of distinct age populations. Broader than previous reviews, where either only the knee moment or the spatiotemporal parameters was reported, this study analyzed the effects of speed on the gait pattern with respect to several gait parameters, including joint kinematics, kinetics, and ground reaction forces. In general, we observed that most of the absolute amplitude of the minimum and maximum values of the variables analyzed decreased at slower speeds, and increased at faster speeds. The results of this study provide a stronger indication for the importance of also taking into account the effects of walking speed when comparing gait data of pathological individuals with normal or control individuals. Future studies involving such type of comparisons must control for the effects of different gait speeds, for example employing prediction methods in order to estimate the gait data of a normative group at the same speed of the pathological individual (58,59).

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Chapter 4. Creation of a public dataset

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A public dataset of overground and treadmill walking kinematics and kinetics in healthy individuals

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Student contributions:

In this study, the student conceived and designed the experiments, performed the experiments, analyzed the data, prepared figures and/or tables, wrote the paper, approved the final draft.

Abbreviations:

3D: three-dimensional; GA: gait analysis; ASIS: anterior superior iliac spine; LCS: laboratory coordinate system; GRF: ground reaction forces

4.1 Abstract

In a typical clinical gait analysis, the gait patterns of pathological individuals are commonly compared with the typically faster, comfortable pace of healthy subjects. However, due to potential bias related to gait speed, this comparison may not be valid. Publicly available gait datasets have failed to address this issue. Therefore, the goal of this study was to present a publicly available dataset of 42 healthy volunteers (24 young adults and 18 older adults) who walked both overground and on a treadmill at a range of gait speeds. Their lower-extremity and pelvis kinematics were measured using a three-dimensional (3D) motion-capture system. The external forces during both overground and treadmill walking were collected using force plates and an instrumented treadmill, respectively. The instrumented treadmill has handrails alongside it attached directly to split mounting plates. Therefore, while the subjects may hold the handrails during gait, the measured forces include only the forces applied by the feet onto the ground during stance.

The results include both raw and processed kinematic and kinetic data in different file formats: c3d and ASCII files. In addition, a metadata file is provided that contain demographic and anthropometric data and data related to each file in the dataset. All data are available at Figshare (DOI: 10.6084/m9.figshare.5722711). We foresee several applications of this public dataset, including to examine the influences of speed, age, and environment (overground vs. treadmill) on gait biomechanics, to meet educational needs, and, with the inclusion of additional participants, to use as a normative dataset.

4.2 Introduction

Gait analysis (GA) has been widely used to better understand the gait patterns of a wide range of populations. The application of this method has the ability to distinguish between normal and abnormal gaits (1), to determine the best intervention (2–4), and to detect pathologies at subclinical stages (5,6). These measures are objective and typically performed using a three-dimensional (3D) motion-capture system and force plates.

A typical clinical study commonly approaches GA by comparing a group of pathological (e.g., post-stroke) individuals with able-bodied controls. However, the control group usually consists of a small number of age-matched individuals, each walking at a comfortable speed, which is commonly faster than that of individuals in the pathological group (7). Therefore, the validity of these studies is limited by the potential bias caused by the difference in gait speeds. A possible solution to this problem is to perform walking trials at a wider range of gait speeds, from very slow to very fast, to enable comparisons that are less biased. Previous studies have reported speed dependency in kinematics and kinetics data during overground walking (8,9). However, the authors of these studies provided only the average (and standard deviation) data across participants, and no raw data were publicly available with which to validate the inferences made by the studies. In fact, recently, data sharing and increased acceptance of replication studies have been advocated to overcome the aforementioned limitations and to validate the inferences made by previous gait studies (10,11). Unfortunately, so far, only a handful of walking biomechanics datasets have been made publicly available (12–15).

Furthermore, other studies have advocated the need to share data and the importance of a normative database (16) to improve the interpretation of GA outcomes. In the early 1990s, Winter began to make gait datasets available in his book (17); however, the only data provided were those of a single healthy subject. A few other gait normative datasets are available in the literature (12,18–21), and although these datasets are valuable for a wide range of applications, their usefulness is lessened because they are usually limited to a single type of data (e.g., kinematics data), one walking surface (either overground or treadmill), and one gait speed (e.g., a self-selected speed).

To address these limitations, this study aimed to create a publicly available dataset of 3D walking kinematics and kinetics data on healthy young and older adults at a range of gait speeds in both the treadmill and overground environments.

4.3 Methods

To generate data for the dataset, we measured the kinematics and kinetics of participants walking at various speeds both overground and on a treadmill.

4.3.1 Participants

Study participants included 42 volunteers, including 24 young adults (age 27.6 ± 4.4 years, height 171.1 ± 10.5 cm, and mass 68.4 ± 12.2 kg) and 18 older adults (age 62.7 ± 8.0 years, height 161.8 ± 9.5 cm, and mass 66.9 ± 10.1 kg). All participants were free of any lower-extremity injury in the last six months before the data were collected, and all were free of any orthopedic or neurologic disease that could interfere with their gait patterns. In order to train with the equipment and design appropriate procedures, a pilot study was conducted first with five participants. The provided metadata file, WBDSinfo.xlsx, contains the demographic and anthropometric data of the participants. Prior to the collection of data, each participant read and signed a consent form that had previously been approved by the university ethics committee (CAAE: 53063315.7.0000.5594).

4.3.2 Data acquisition

Standard gait-analysis procedures were employed to collect data using a motion-capture system that had 12 cameras (Raptor-4; Motion Analysis Corporation; Santa Rosa, CA, USA), 5 force platforms (three 40 × 60-cm Optima models; AMTI, USA; two 40 × 60-cm 9281EA models; Kistler; Winterthur, Switzerland) embedded in the floor, and a dual-belt, instrumented treadmill (FIT, Bertec; USA) in a 10 × 12-m room at the Laboratory of Biomechanics and Motor Control at the Federal University of ABC, Brazil. The kinematic data were acquired at 150 Hz, and the data on ground-reaction forces were acquired at 300 Hz using a motion-capture system (Cortex 6.0; Motion Analysis; Santa Rosa, CA, USA).

4.3.3 Procedures

All gait trials were performed in barefoot conditions, and the participants wore comfortable shorts (women also wore sports bras). Each participant was asked to perform overground walking trials, first at a self-selected, comfortable speed, and then at speeds 30% faster and 30% slower than the comfortable speed. In addition, the participants walked on the treadmill at eight different controlled speeds, which are described below. Previously, a computerized random-number generator had been used to define the order of the walking trials on the treadmill. The marker-set protocol adopted for this study comprised 26 anatomical reflective markers (22), and additional markers were used on the iliac crests to enable future data users to define alternative anatomical and technical coordinate systems for the pelvis (23) (see **Table 1** in the Supplementary material). The following data-collection procedures were implemented.

1. Prior to data collection, each participant received a brief explanation of the study and signed the consent form.
2. Body height and body mass were measured.
3. Leg length was measured by assessing the distance from the anterior superior iliac spine (ASIS) to the ipsilateral medial malleolus while the participant lay in a supine position.
4. Markers were placed directly onto the skin in the pelvic and lower-extremity segments (22) (Figure 4-1).
5. A standing anatomical-calibration trial was performed with the participant standing still for 1 s with the arms crossed in front of the trunk and the feet in a standard position parallel to the X-axis of the laboratory coordinate system (LCS) (18). A template was used to ensure that the long axes of the feet were aligned with the X-axis of the LCS.
6. After the calibration trial, the medial epicondyle, medial malleolus, and second metatarsal head markers were removed from the right and left foot.
7. To determine each participant's comfortable speed, after a familiarization period, gait speed was measured during 3 walking trials along a 10-m walkway from start and end at rest, at the participant's self-selected comfortable speed. The average speed from across these trials was deemed the comfortable speed.
8. To determine the dimensionless gait speed, the Froude number, v^*, was calculated based on the participant's average self-selected comfortable speed, v, and leg length, l_0 , (24): $v^* = v/\sqrt{gl_0}$, where g is 9.81 m/s^2.
9. Participants first performed overground walking trials at their self-selected comfortable speeds, and then at speeds 30% faster and 30% slower than their comfortable speeds.
10. After this, they were asked to walk on the treadmill, and the following protocol was performed.
    a. To familiarize themselves with the treadmill speed, participants walked at their comfortable speeds for 5 min.
    b. Then, each participant walked for 90 s at each of the eight gait-speed conditions (40%, 55%, 70%, 85%, 100%, 115%, 130%, and 145% of the self-selected dimensionless speed (Froude number)) in a randomized order. At each speed, the

kinematic and kinetic data were recorded for the last 30 s of the trial. During the gait trials, the participants were asked to walk naturally and were allowed to hold the handrails of the treadmill if necessary.

11. After the treadmill task, each participant's overall perceived exertion was measured using the Borg (6–20) Perceived Exertion Scale (25).

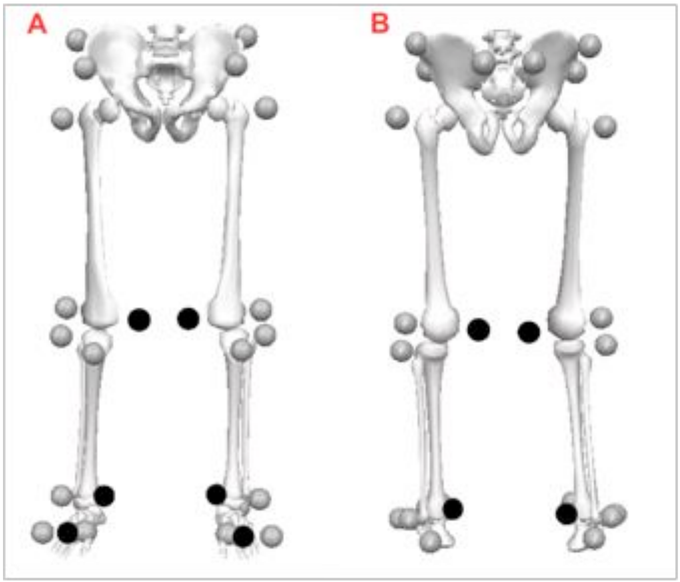

Figure 4-1. Marker-set protocol. Location of reflective markers for the pelvis segment and lower extremities during the static condition in the anterior (A) and posterior (B) views. During the walking trials, the markers shown in black were removed.

4.3.4 Data processing

The data processing was performed using Cortex software version 6.0 (Motion Analysis; Santa Rosa, CA, USA) using procedures similar to those previously reported by Fukuchi et al. (18).

Visual 3D software version 6.00.33 (C-motion Inc.; Germantown, MD, USA) was used to perform all kinematics and kinetics calculations. To enable users to process the data in the Visual 3D software, a Visual 3D pipeline file, WBDSpipelineV3D.v3s, is available at Figshare. In addition, a metadata file in .xlsx format, WBDSinfo, contains the data related to the treadmill and overground files. The analysis of the overground trials considered only those files that contained at least one full gait cycle (stance and swing phase) detected using force plates. However, further trials (i.e., incomplete gait cycles) are provided so that prospective users can decide what data to consider in their own analyses. In all, 1409 trials (right side: 657; left side: 752) contained a full gait cycle, and 1233 trials (right side: 685; left side: 548) contained only the stance phase of the gait. The public dataset consists of raw c3d files and ASCII files containing both 3D marker coordinates and external forces. In addition, time-normalized kinematic and kinetic average curves, which were considered processed data, were calculated for each participant for each walking condition tested (overground and treadmill at various gait speeds).

4.4 Results

4.4.1 Raw data

The files containing the raw data are available at Figshare (DOI: 10.6084/m9.figshare.5722711) in both c3d format and ASCII file format. The c3d files can store both the 3D coordinates of the markers (mkr) and the force signals (grf) in the same file. Separate text files were generated for the markers and force signals, as the sample frequencies of the kinematics and kinetics data differed. In addition, the data related to the static trial (the standing anatomical-calibration trial), which contain only marker trajectories, are available in both the c3d and the text formats. The metadata file, WBDSinfo.xlsx, provides a full description of these files. Furthermore, the text files also contain the time-normalized ensemble average of the kinematics and kinetics curves for each participant at each gait speed and for each environment condition (overground and treadmill). The total number of gait trials is not the same across participants because it reflects the variation in the number of valid trials per participant.

The files provided are labeled “WBDS,” which stands for Walking Biomechanics Dataset; “xx,” for the participant’s assigned number (from 01–42); and “walk,” for the walking task. After this labeling, the following specific notations are used.

- Environment: “O” for overground and “T” for treadmill.
- Trial: “yy” indicates the trial number assignment for the overground condition only.
- Speed: “01” to “08,” which corresponds to the treadmill trials at 40%, 55%, 70%, 85%, 100%, 115%, 130%, and 145% of the self-selected, dimensionless speed (Froude number); and “S”, “C,” or “F,” which correspond to the slow, comfortable, and fast speeds for the overground trials.

For example, a file named “WBDS01walkO01Smkr.txt” indicates that the file contains the marker-coordinate (mkr) data of the first participant performing the first overground trial at the slowest speed. Similarly, “WBDS01walkT01mkr.txt” indicates that the file contains the marker-coordinate (mkr) data of the first participant walking at the treadmill speed corresponding to 40% of the self-selected dimensionless speed. The c3d files contain the 3D coordinates of the 28 markers in the static trial (for example, WBDS01static1.c3d) and the coordinates of the 22 markers and the force data during the walking trials (for example, WBDS01walkT01.c3d). The force data during the walking trials were also provided as plain-text files consisting of a time column (n^{th} frame number), the forces (Fx, Fy, and Fz in Newtons), the center of pressure (COPx, COPy, and COPz in mm), and the free moment about the vertical axis (Ty in Nm). The force-data files regarding the overground condition contain 36 columns corresponding to the time column along with the data from the five force plates. In contrast, the force-data files regarding the treadmill condition contain 15 columns corresponding to the time column along with the data from the two force plates (left and right belt). An example of a MATLAB code demonstrates on how to read the data from these files and on how to conduct an exploratory data analysis.

4.4.2 Metadata

A metadata file named WBDSinfo.xlsx is available at Figshare and contains the following data in various columns (the bold word in each of the following items corresponds to the heading of a column).

1. **Subject:** the index of the subject (from 01-42).
2. **FileName:** the filename of the walking trial (WBDSxx, where xx identifies the participant), including the format extensions (*.c3d or *.txt).
3. **AgeGroup:** the “Young” or “Older” group.
4. **Age:** the participant’s age in years.
5. **Height:** the participant’s height in centimeters, measured with a calibrated stadiometer.
6. **Mass:** the participant’s body mass in kilograms, measured with a calibrated scale.
7. **Gender:** the participant’s gender (M or F).
8. **Dominance:** preferred leg for kicking a ball (R or L).
9. **LegLength:** leg length in centimeters (the average of the two legs).
10. **Static1:** whether the corresponding walking trial was assigned (Yes or No) to the Static1 file.
11. **Static2:** whether the corresponding walking trial was assigned (Yes or No) to the Static2 file. The Static2 was performed due to technical issues (e.g., markers dropping off during the session, markers needing to be repositioned, etc.).
12. **GaitSpeed:** the walking velocity at each trial (m/s).

13. **TreadHands:** whether the participant walked while hanging onto the treadmill handrails during the whole walking trial (Yes) or not at all (No).
14. **FP_RightFoot:** the force-plate number that the participant hit with the right foot.
15. **FP_LeftFoot:** the force-plate number that the participant hit with the left foot.
16. **Notes:** text strings with any notes about the treadmill or the overground trials ("--" if the trial has no notes). Ex: "FP3 signal presented offset."
17. **BorgScale:** the corresponding Borg Scale value.

In total, in both the c3d and txt formats, the WBDSinfo.xlsx file has 17 columns and 6916 rows, corresponding to the total number of trials (the rows represent the static trial (*static1), the eight trials on the treadmill (*walkT01–T08), and the overground trials at the slow (*S), comfortable (*C), and fast (*F) speeds. The processed files of kinematics (*ang.txt) and kinetic (*knt.txt) data are also included. The number of rows varies for each participant, depending on the number of overground trials.

4.4.3 Processed data

The ASCII files provide the ensemble average data for each participant throughout the full gait cycle (101 time-normalized points), which correspond to the time-normalized angles (pelvis, hip, knee, ankle, and foot), joint moments (hip, knee, and ankle), and GRF forces in the X, Y, and Z directions.

4.4.4 Data exploration

The following is a partial exploratory analysis of the data. A companion MATLAB code provides examples of how these data can be explored. The curves shown in this section represent the ensemble average across all participants at a particular gait speed. The participants in the Young group (age range: 21-37 years) walked at 8 speeds on the treadmill, whereas in the Older group (age range: 50-84 years), only 12 participants were able to walk at these 8 speeds. To clarify: this section shows only the right leg and the pelvis curves of the Young group, both when walking overground and on the treadmill. The time-series curves of the Older group are shown in the Supplementary material.

4.4.4.1 Joint kinematics

Figure 4-2 and Figure 4-3 show the joint angles of the hip, knee, and ankle joints and of the pelvis and foot segments at the sagittal, frontal, and transverse planes, respectively, during treadmill and overground walking at various speeds.

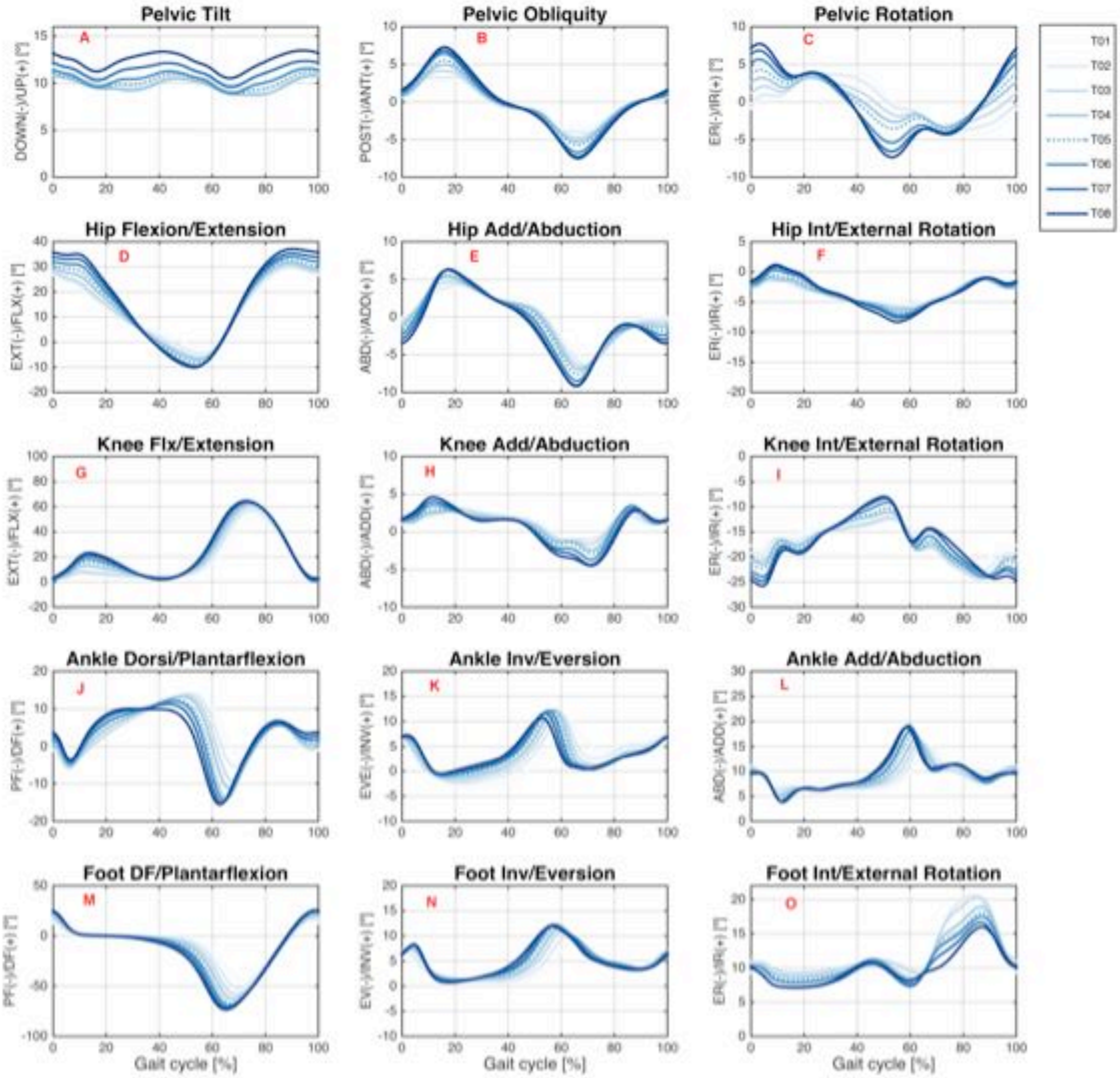

Figure 4-2. Angular kinematics during treadmill walking. Ensemble averages across Young group participants of the pelvic tilt (A), pelvic obliquity (B), pelvic rotation (C), hip flexion/extension (D), hip add/abduction (E), hip int/external rotation (F), knee flx/extension (G), knee add/abduction (H), knee int/external rotation (I), ankle dorsi/plantarflexion (J), ankle inv/eversion (K), ankle add/abduction (L), foot DF/plantarflexion (M), foot inv/eversion (N), and foot int/external rotation (O) angles during the treadmill walking condition. Each waveform represents a walking speed (light blue = T01, through dark blue = T08). The comfortable speed (T05) is represented by the dashed line.

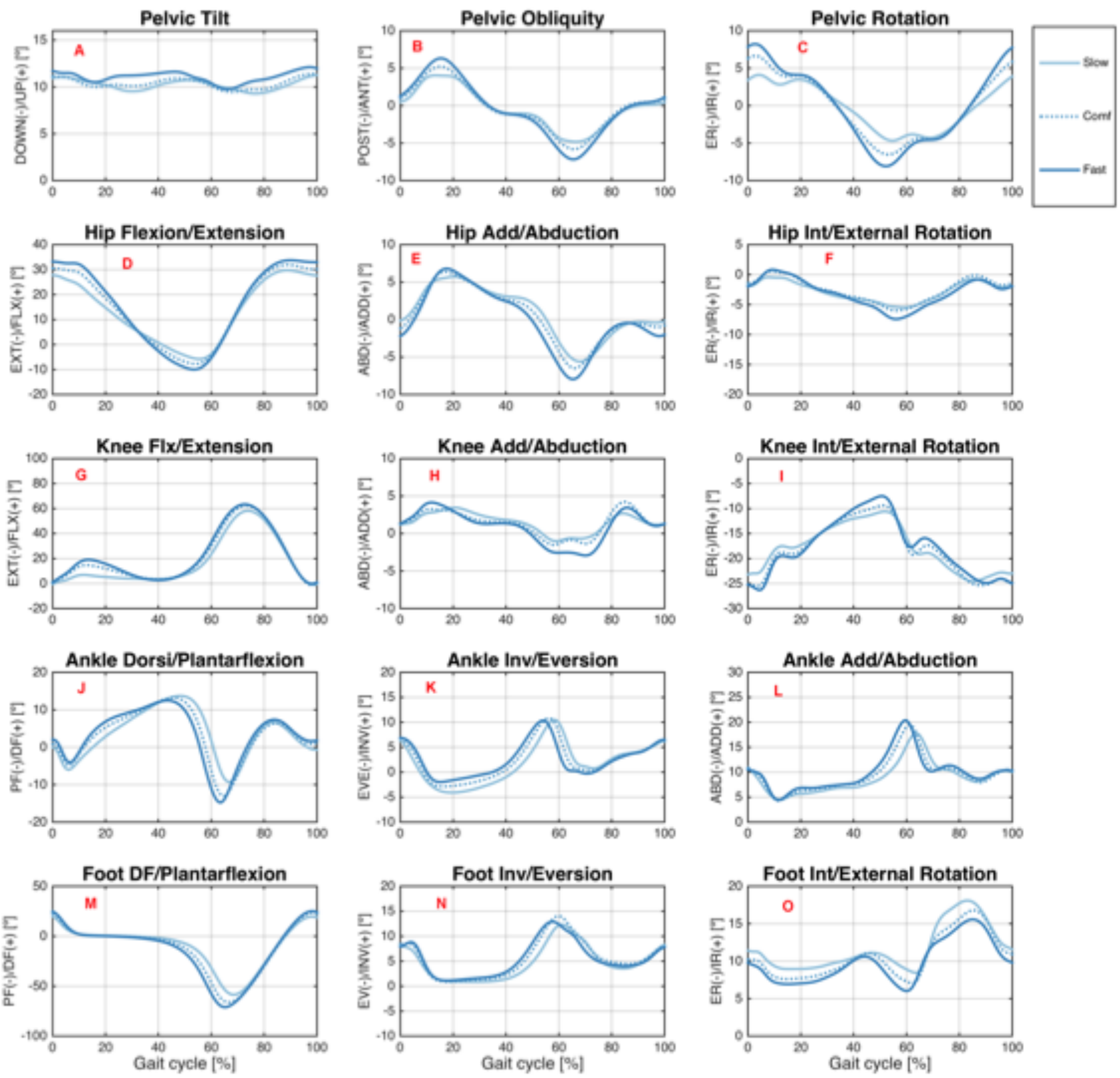

Figure 4-3. Angular kinematics during overground walking. Ensemble averages across Young group participants of the pelvic tilt (A), pelvic obliquity (B), pelvic rotation (C), hip flexion/extension (D), hip add/abduction (E), hip int/external rotation (F), knee flx/extension (G), knee add/abduction (H), knee int/external rotation (I), ankle dorsi/plantarflexion (J), ankle inv/eversion (K), ankle add/abduction (L), foot DF/plantarflexion (M), foot inv/eversion (N), and foot int/external rotation (O) angles during the treadmill walking condition. Each waveform represents a walking speed (light blue = slow, through dark blue = fast). The comfortable speed (Comf) is represented by the dashed line.

4.4.4.2 Joint kinetics

Figure 4-4 and Figure 4-5 show joint moments for the hip, knee, and ankle joints during treadmill and overground walking, respectively, at various speeds.

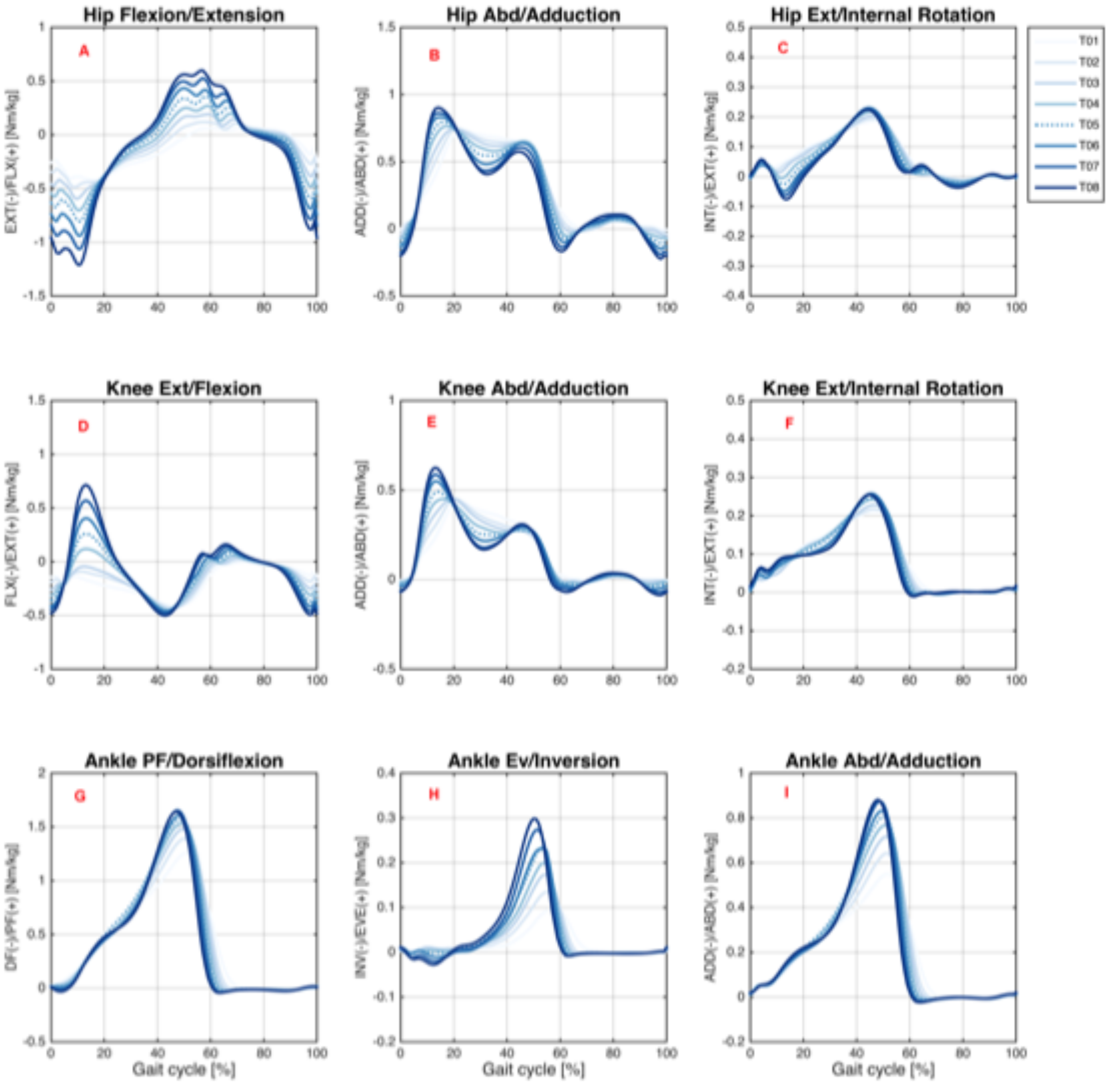

Figure 4-4. Joint moments during treadmill walking. Ensemble averages across Young group participants of the hip flexion/extension (A), hip abd/adduction (B), hip ext/internal rotation (C), knee ext/flexion (D), knee abd/adduction (E), knee ext/internal rotation (F), ankle PF/dorsiflexion (G), ankle ev/inversion (H), and ankle abd/adduction (I) joint moments during the treadmill walking condition. Each waveform represents a walking speed (light blue = T01, through dark blue = T08). The comfortable speed (T05) is represented by the dashed line.

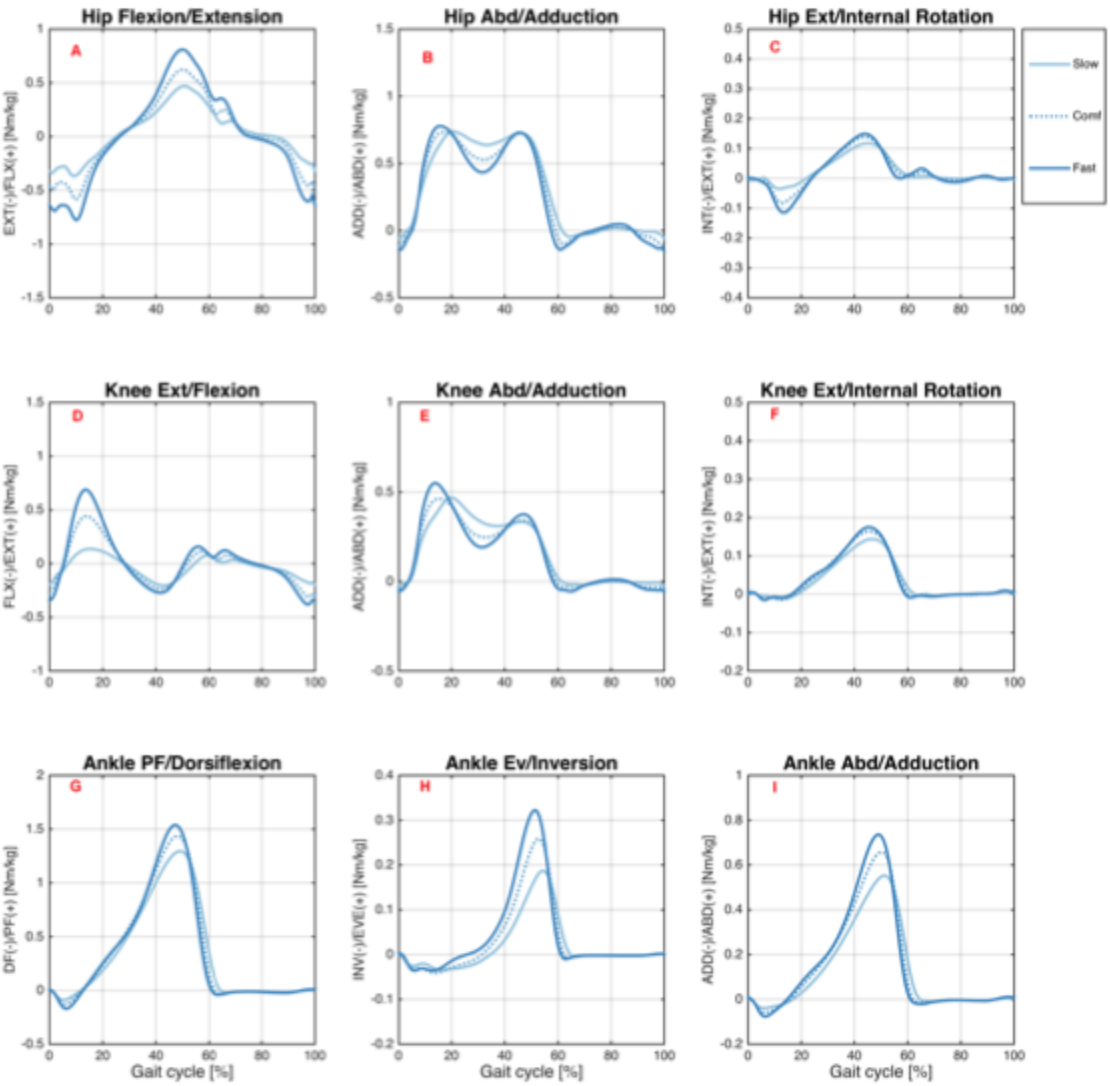

Figure 4-5. Joint moments during overground walking. Ensemble averages across Young group participants of the hip flexion/extension (A), hip abd/adduction (B), hip ext/internal rotation (C), knee ext/flexion (D), knee abd/adduction (E), knee ext/internal rotation (F), ankle PF/dorsiflexion (G), ankle ev/inversion (H), and ankle abd/adduction (I) joint moments during the treadmill walking condition. Each waveform represents a walking speed (light blue = slow, through dark blue = fast). The comfortable speed (Comf) is represented by the dashed line.

4.4.4.3 Ground reaction forces (GRF)

Figure 4-6 shows GRF data for the medial-lateral, anterior-posterior, and vertical direction during the treadmill and overground walking conditions at various speeds.

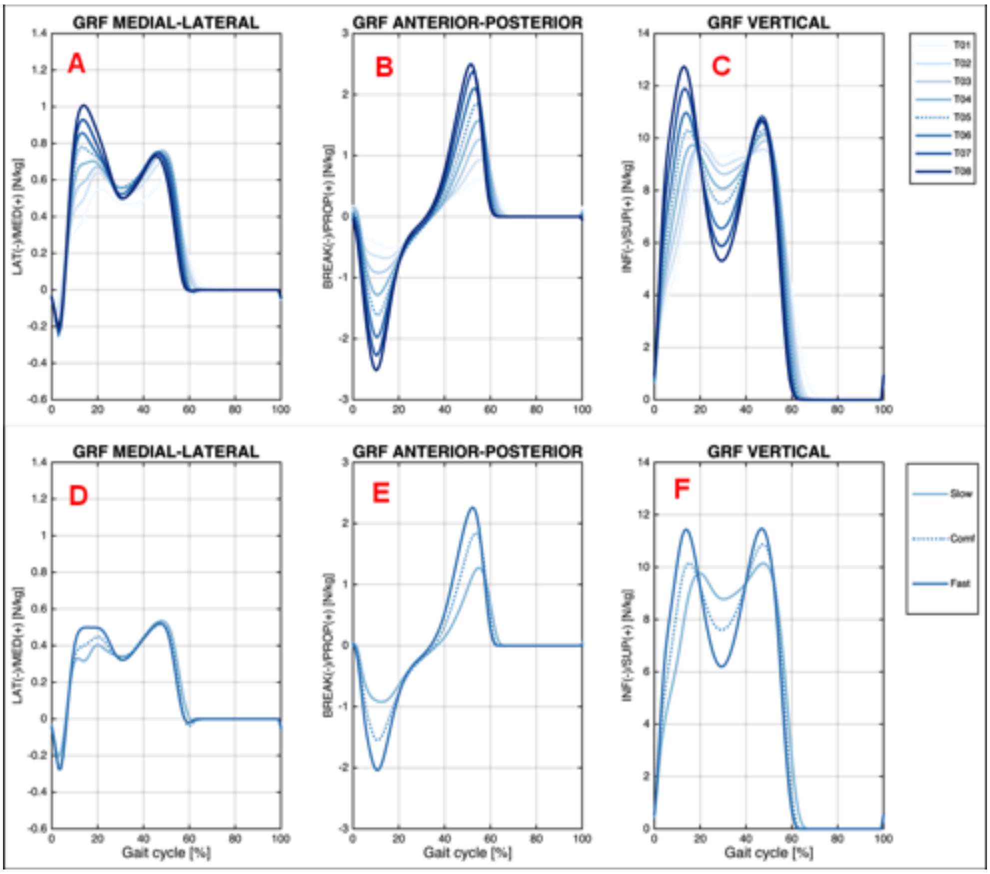

Figure 4-6. Ground reaction forces. Ensembles averages across Young group participants of the ground reaction force (GRF) on the treadmill (GRF medial-lateral (A), GRF anterior-posterior (B), and GRF vertical (C)); and overground (GRF medial-lateral (D), GRF anterior-posterior (E), and GRF vertical (F)) walking conditions. Each waveform represents a walking speed on the treadmill (light blue = T01, through dark blue = T08) and overground (light blue = Slow, through dark blue = Fast). The comfortable speed (T05 and Comf) is represented by the dashed line.

4.4.4.4 Young vs. Older group

We also present an exploratory analysis examining the kinematics patterns at the sagittal plane of the Young and Older groups at each treadmill walking speed (Figure 4-7) and overground walking speed (Figure 4-8).

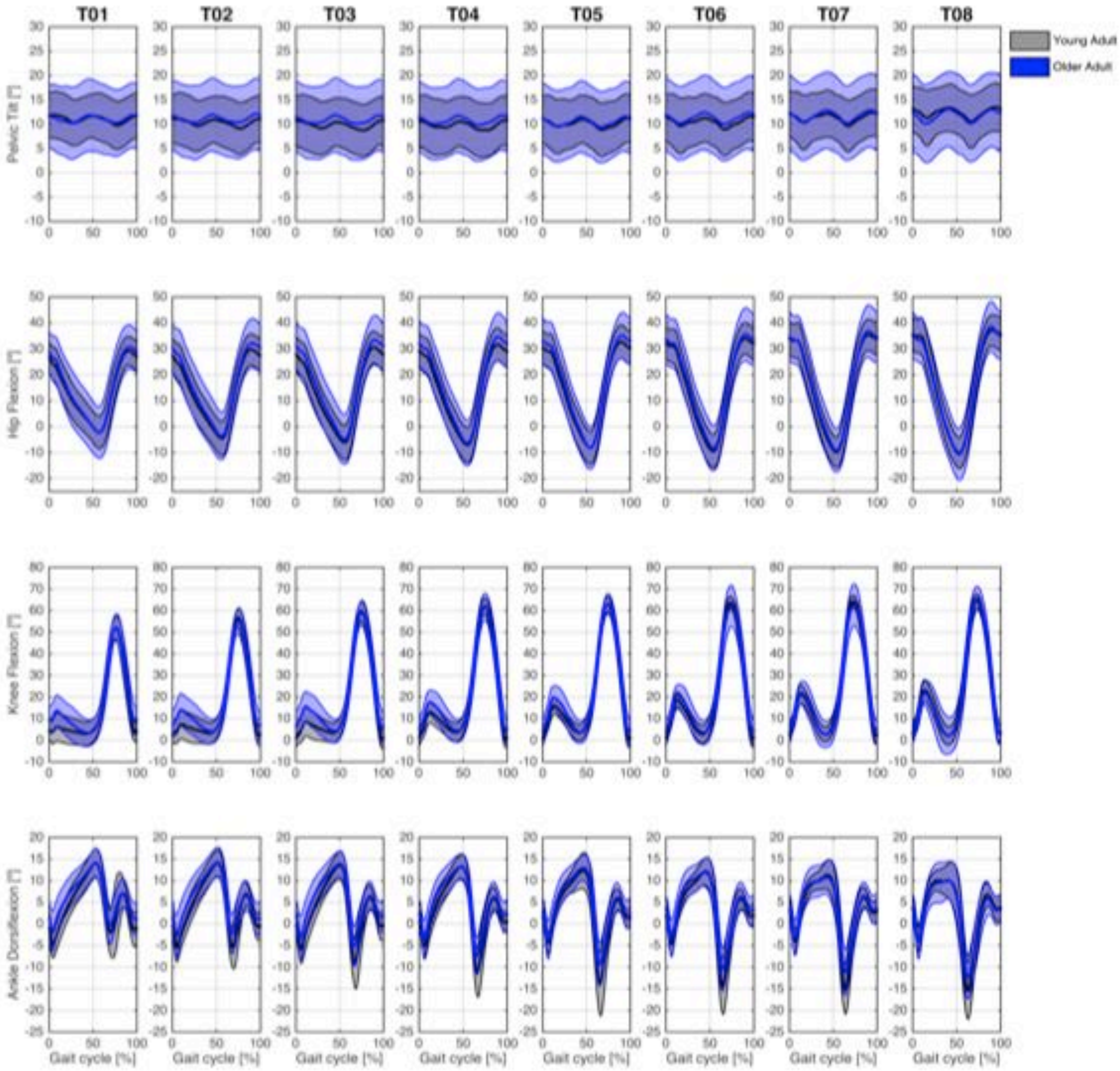

Figure 4-7. Angular kinematics during treadmill walking. Ensemble average ± 1 standard-deviation across participants of the pelvis, hip, knee, and ankle angles for the Young (grey curves) and Older (blue curves) groups at eight different gait speeds in the treadmill condition.

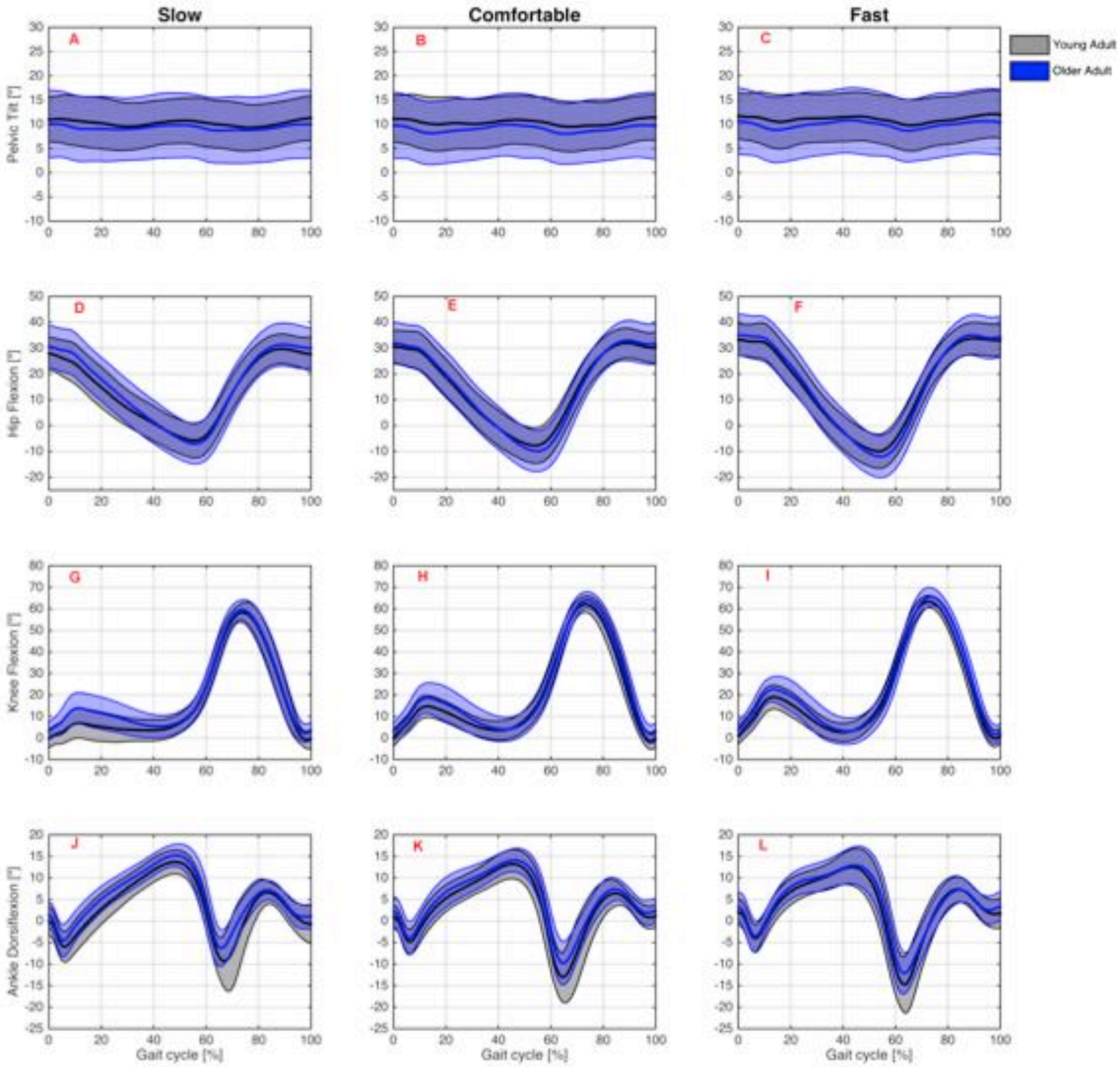

Figure 4-8. Angular kinematics during overground walking. Ensemble average ± 1 standard-deviation across participants of the pelvic tilt at the slow (A), comfortable (B), and fast (C) speeds; hip flexion at the slow (D), comfortable (E), and fast (F) speeds; knee flexion at the slow (G), comfortable (H), and fast (I) speeds; and ankle dorsiflexion at the slow (J), comfortable (K), and fast (L) speeds angles for the Young (grey curves) and Older (blue curves) groups during the overground walking condition.

4.5 Discussion

This study presents a dataset of treadmill and overground walking kinematics and kinetics in a range of gait speeds for 24 healthy young individuals and 18 healthy older individuals. The study also makes available raw data comprising marker trajectories and GRFs and processed data comprising joint angles and joint moment waveforms that characterize the gait pattern of each participant. In addition, it makes available a file with metadata containing demographic data and file-related data, among other relevant data, and general notes pertaining to the experimental conditions.

Previous walking datasets with kinematics and kinetics data have been published elsewhere (12,20). Moore et al. (12) presented the gait data of 15 healthy adults walking at 3 different speeds, and van den Bogert et al. (20) presented the gait data of 12 healthy adults walking at comfortable speeds. Although these studies presented valuable information, the data provided referred only to young adults walking only on a treadmill. To our knowledge, the present study is the first to publicly provide a unique set of data that includes both young and older individuals walking in both overground and treadmill environments at a range of gait speeds. We foresee that the present dataset will add to the knowledge provided by previous studies that have examined gait changes related to the walking environment (e.g., overground vs. treadmill) (26–28), age-related gait changes (29–31), and gait-speed changes (32–34) by enabling other groups to further address these issues in gait research, by, for example, applying various data-analysis techniques.

We see some limitations in the present dataset. First, the sample size may be insufficient for the dataset to be considered as reference data for young and older participants. However, to our knowledge, this is the largest dataset to be made publicly available that includes diverse types of biomechanics, age, walking-environment, and gait-speed data. Second, the subjects performed the overground trials in a 10-m walkway due to the dimension limitation of the laboratory. Therefore, the present results should be interpreted with cautious since the self-selected gait speeds might have been slightly underestimated, relative to longer distance trials, as demonstrated by Seethapathi and Srinivasan (35). Lastly, five participants in the Older group walked while holding the treadmill's handrails (these participants are identified in the file that contains the metadata information), and, although their biomechanical patterns do not seem to differ from those of the other participants, this fact should be considered when using the dataset.

4.6 Conclusions

The present study created a public dataset containing raw and processed kinematics and kinetics data on both overground and treadmill walking trials at a range of gait speeds in both young and older healthy adults. This dataset may be used to enhance knowledge related to the influence of age, environment, and walking speed on gait biomechanics. In addition, it may serve educational needs and, with the inclusion of additional participants, as normative gait data.

4.7 References

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4.8 Supplementary material

Table 4-1. Details of the 28 anatomical reflective markers used to determine the position and orientation of the body segments during walking trials.

#	Label	Name	Description
1	R.ASIS	Right Anterior Superior Iliac Spine	Right anterior superior iliac spine
2	L.ASIS	Left Anterior Superior Iliac Spine	Left anterior superior iliac spine
3	R.PSIS	Right Posterior Iliac Spine	Right posterior superior iliac spine
4	L.PSIS	Left Posterior Iliac Spine	Left posterior superior iliac spine
5	R.Iliac.Crest	Right Iliac Crest	Uppermost margin of the right iliac crest
6	L.Iliac.Crest	Left Iliac Crest	Uppermost margin of the left iliac crest
7	R.Heel.Bottom	Right Heel Bottom	Aspect of the Achilles tendon insertion on the right calcaneous
8	L.Heel.Bottom	Left Heel Bottom	Aspect of the Achilles tendon insertion on the left calcaneous
9	R.GTR	Right Greater Trochanter	Most lateral prominence of the right greater trochanter
10	R.Knee	Right Knee	Most lateral prominence of the right lateral femoral epicondyle
11	R.Knee.Medial	Right Knee Medial	Most medial prominence of the right lateral femoral epicondyle
12	R.HF	Right Head of Fibula	Proximal tip of the head of the right fibula
13	R.TT	Right Tibial Tuberosity	Most anterior border of the right tibial tuberosity
14	R.Ankle	Right Ankle	Lateral prominence of the right lateral malleolus

15	R.Ankle.Medial	Right Ankle Medial	Most medial prominence of the right medial malleolus
16	R.MT1	Right 1st Metatarsal	Dorsal margin of the right 1st metatarsal head
17	R.MT5	Right 5th Metatarsal	Dorsal margin of the right 5th metatarsal head
18	R.MT2	Right 2nd Metatarsal	Dorsal margin of the right 2nd metatarsal head
19	L.GTR	Left Greater Trochanter	Most lateral prominence of the left greater trochanter
20	L.Knee	Left Knee	Most lateral prominence of the left lateral femoral epicondyle
21	L.Knee.Medial	Left Knee Medial	Most medial prominence of the left lateral femoral epicondyle
22	L.HF	Left Head of Fibula	Proximal tip of the head of the left fibula
23	L.TT	Left Tibial Tuberosity	Most anterior border of the left tibial tuberosity
24	L.Ankle	Left Ankle	Lateral prominence of the left lateral malleolus
25	L.Ankle.Medial	Left Ankle Medial	Most medial prominence of the left medial malleolus
26	L.MT1	Left 1st Metatarsal	Dorsal margin of the left 1st metatarsal head
27	L.MT5	Left 5th Metatarsal	Dorsal margin of the left 5th metatarsal head
28	L.MT2	Left 2nd Metatarsal	Dorsal margin of the left 2nd metatarsal head

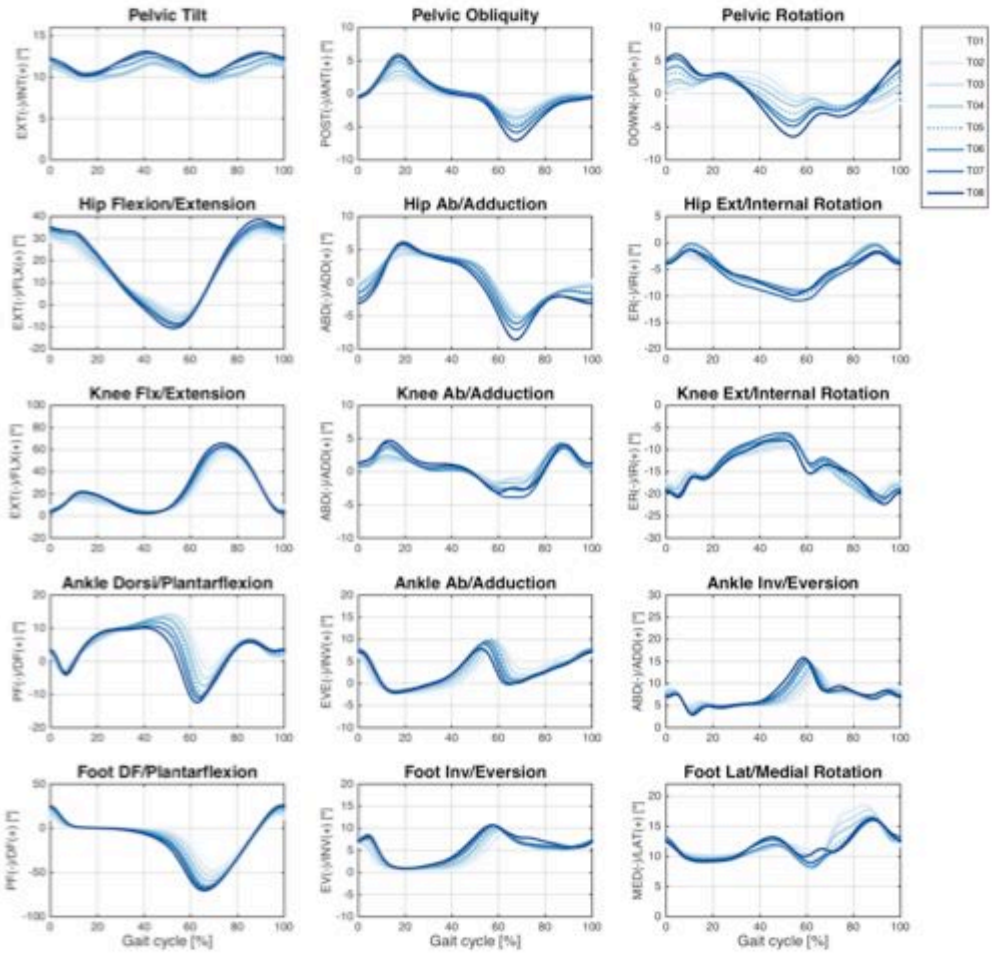

Figure 4-9. Ensemble average across Older group participants of the pelvis, hip, knee, ankle, and foot angles during the treadmill walking condition. Each waveform represents a walking speed (see legend).

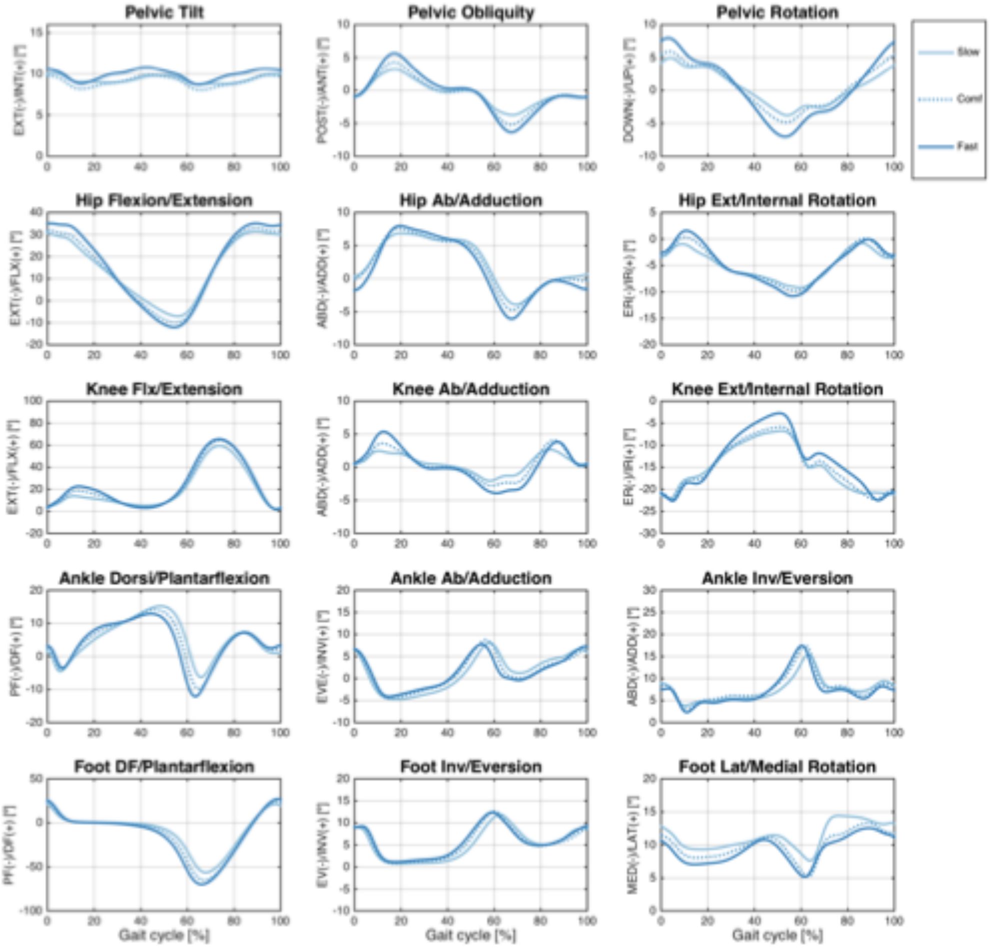

Figure 4-10. Ensemble average across Older group participants of the pelvis, hip, knee, ankle, and foot angles during the overground walking condition. Each waveform represents a walking speed (see legend).

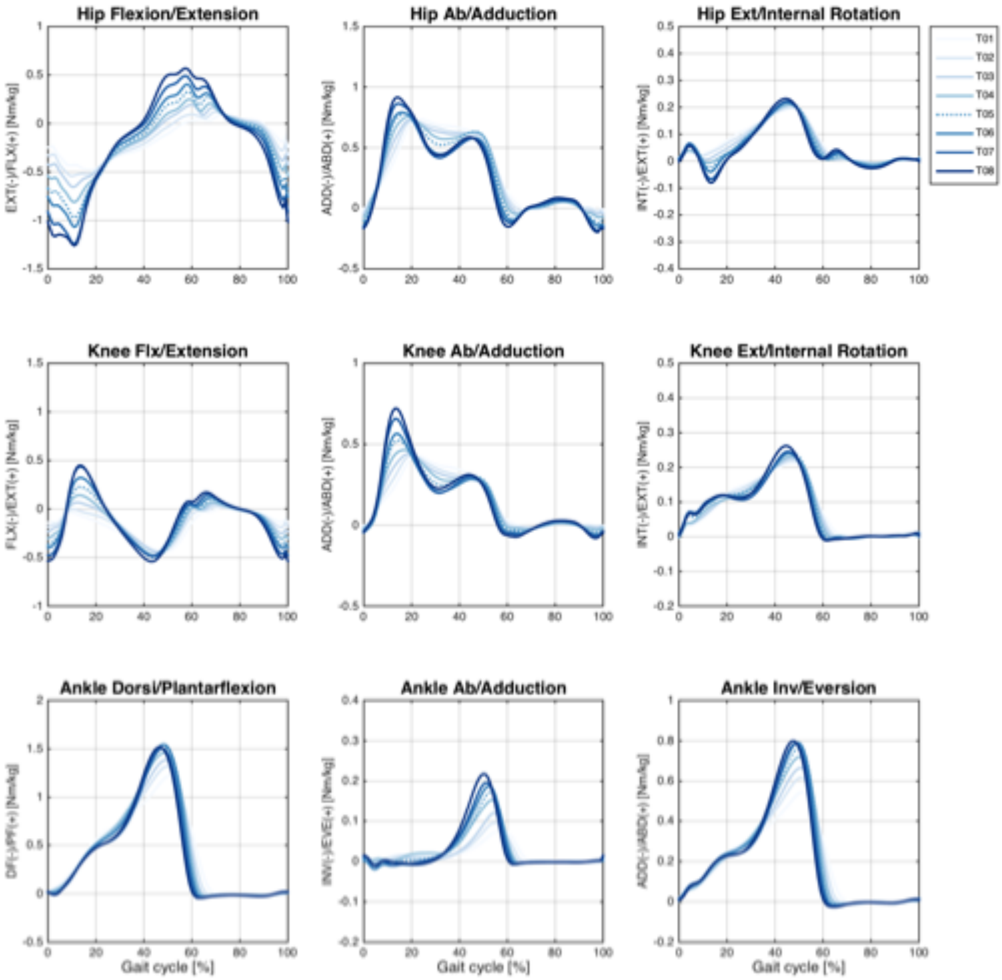

Figure 4-11. Ensemble average across Older group participants of the hip, knee, and ankle joint moments during the treadmill walking condition. Each waveform represents a walking speed (see legend).

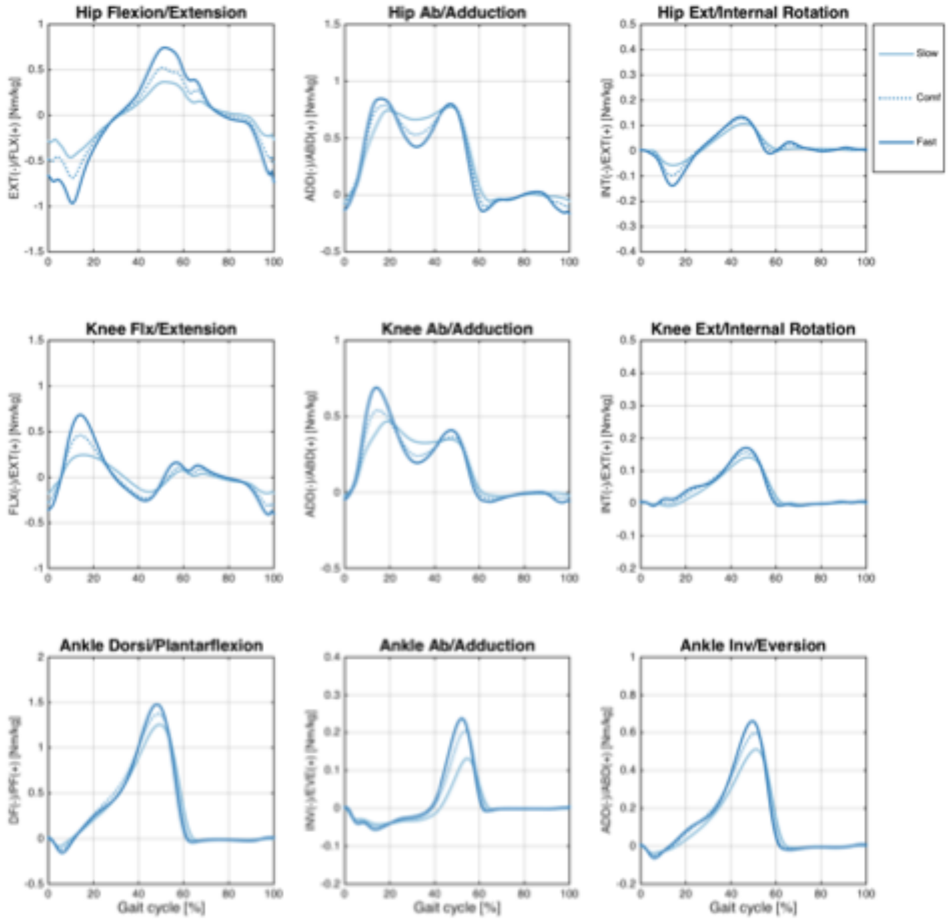

Figure 4-12. Ensemble average across Older group participants of the hip, knee, and ankle joint moments during the overground walking condition. Each waveform represents a walking speed (see legend).

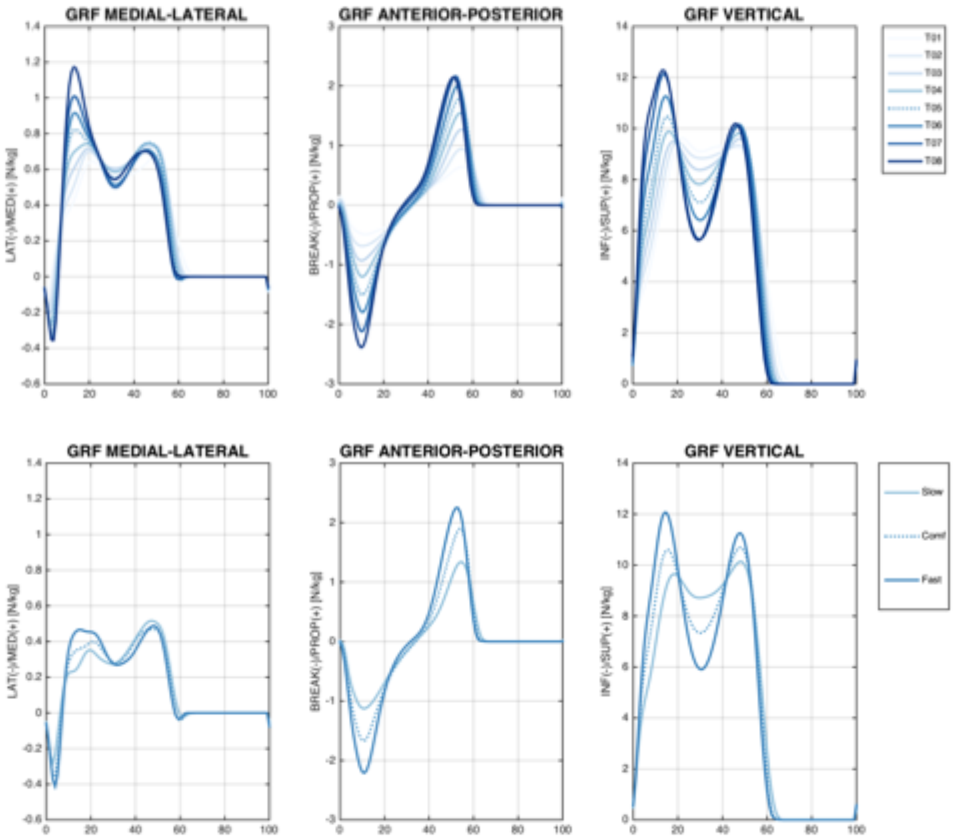

Figure 4-13. Ensemble average across Older group participants of the ground reaction force (GRF) on the treadmill (top) and overground (bottom) walking conditions. Each waveform represents a walking speed (see legend).

Chapter 5. Developing a prediction method considering the effects of walking speed

Published as:

A prediction method of speed-dependent walking patterns for healthy individuals

Claudiane Arakaki Fukuchi, Marcos Duarte

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Student contributions:

In this study, the student conceived and designed the experiments, performed the experiments, analyzed the data, prepared figures and/or tables, wrote the paper, approved the final draft.

Abbreviations:

3D: three-dimensional; SD: standard deviation; RMSE: root mean square error

5.1 Abstract

Background. Gait speed is one of the main biomechanical determinants of human movement patterns. However, in clinical gait analysis, the effect of gait speed is generally not considered, and people with disabilities are usually compared with able-bodied individuals even though disabled people tend to walk slower.

Research questions. This study proposes a simple way to predict the gait pattern of healthy individuals at a specific speed.

Methods. The method consists of creating a reference database for a range of gait speeds, and the gait-pattern prediction is implemented as follows: 1) the gait cycle is discretized from 0 to 100% for each variable, 2) a first or second-order polynomial is used to adjust the values of the reference dataset versus the corresponding gait speeds for each instant of the gait cycle to obtain the parameters of the regression, and 3) these regression parameters are then used to predict the new values of the gait pattern at any specific speed. Twenty-four healthy adults walked on the treadmill at eight different gait speeds, where the gait pattern was obtained by a 3D motion capture system and an instrumented treadmill.

Results. Overall, the predicted data presented good agreement with the experimental data for the joint angles and joint moments.

Significance. These results demonstrated that the proposed prediction method can be used to generate more unbiased reference data for clinical gait analysis and might be suitably applied to other speed-dependent human movement patterns.

Keywords: gait analysis; walking; regression analysis; kinematics; kinetics; prediction methods

5.2 Introduction

Biomechanical patterns of human motion are generally speed-dependent, that is, the amplitude of specific movement typically scales with the movement speed (e.g., walking speed is a determinant factor of the gait pattern) (1,2). In a typical gait analysis, patients perform gait trials at their comfortable speed and their gait patterns are commonly compared with a reference pattern from a normative database. While this approach may be reasonable, previous studies have reported that individuals with certain pathologies tend to walk slower than able-bodied individuals (3,4). However, the effect of gait speed is generally not accounted for when the gait pattern of pathological individuals is compared with healthy ones who do not necessarily walk at an equivalent speed.

A possible solution to this problem would be to collect several walking trials at various walking speeds to build a reference database for virtually any possible gait speed. However, the time-consuming nature of such data collection would be cost prohibitive and unviable. To overcome this challenge, researchers have proposed regression methods as a feasible alternative for predicting gait parameters based on experimental data (5–7). Those studies predicted gait patterns based only on specific events. Or, when the full gait cycle was considered, the prediction data was based solely on the normal, slow, and fast walking speeds for healthy subjects and only at each 10% interval of the gait cycle (8). However, because pathological individuals may walk slower than the typical "slow speeds" of healthy subjects, a wider range of gait speeds is likely necessary. In addition, a prediction method for the entire gait cycle at a higher temporal resolution would allow researchers and clinicians to apply standard techniques of analysis commonly employed in the field. In this context, the purpose of this study was to develop a simple way to predict the gait pattern of able-bodied individuals at a given speed, considering a broad range of speeds and the entire gait cycle.

5.3 Materials and Methods

To nullify the possible effect of speed when comparing a patient's gait with a normative database, we proposed to predict the gait patterns of the reference dataset at the speed of the investigated patient by creating a reference dataset with walking data at different speeds. Then, we determined regression models for the gait patterns with speed as the predictor variable. This prediction method can be implemented with the following procedure:

1. Build a reference dataset of the gait pattern acquired at different speeds, ranging from very slow to very fast, and perform the standard signal processing of these data (e.g., see graph A on Figure 5-1);
2. For each instant of the gait cycle (e.g., 101 instants) of a given kinematic or kinetic variable of each participant, plot the average value across trials (the dependent variable or response) versus the corresponding dimensionless gait speeds (the independent variable or predictor) (e.g., see graph B on Figure 5-1);
3. To these data, at each instant for all subjects of the reference dataset, adjust a second-order polynomial using a least-squares method:

$$y(i) = av^2 + bv + c$$

where *y(i)* represents each kinematic/kinetic variable at instant i, *v* is the dimensionless walking-speed, and *a, b,* and *c* are the coefficients of the regression curve.

4. These adjusted curves (e.g., 101 parabolas for the entire gait cycle of each kinematic and kinetic variable) can now be used to predict the new gait cycle value for a given dimensionless speed.

A one-standard-deviation interval (±1 SD) for the prediction data at each instant (e.g., see graph C on Figure 5-1) can be estimated by calculating the 68% prediction interval for the polynomial regression using the equation (9):

$$PI(i) = t_{68}\, s_{err} \sqrt{1 + \frac{1}{N} + \frac{(y_i - \bar{y})^2}{\sum_i (y_i - \bar{y})^2}}$$

where t_{68} represents the 68th percentile of the Student's t-distribution with *N-3* degrees of freedom. *N* is the number of observations, s_{err} is the standard deviation of the error, and $\bar{y}$ is the mean of *y*.

The second-order polynomial may in fact not be the best model to fit the data, and a first-order polynomial might be sufficient (however, this was seldom true for the present data). The selection of the order of the polynomial was based on the statistical significance of the coefficient *a* of the second-order polynomial regression. If this coefficient was not significant (not statistically different from zero), then a first-order polynomial was employed.

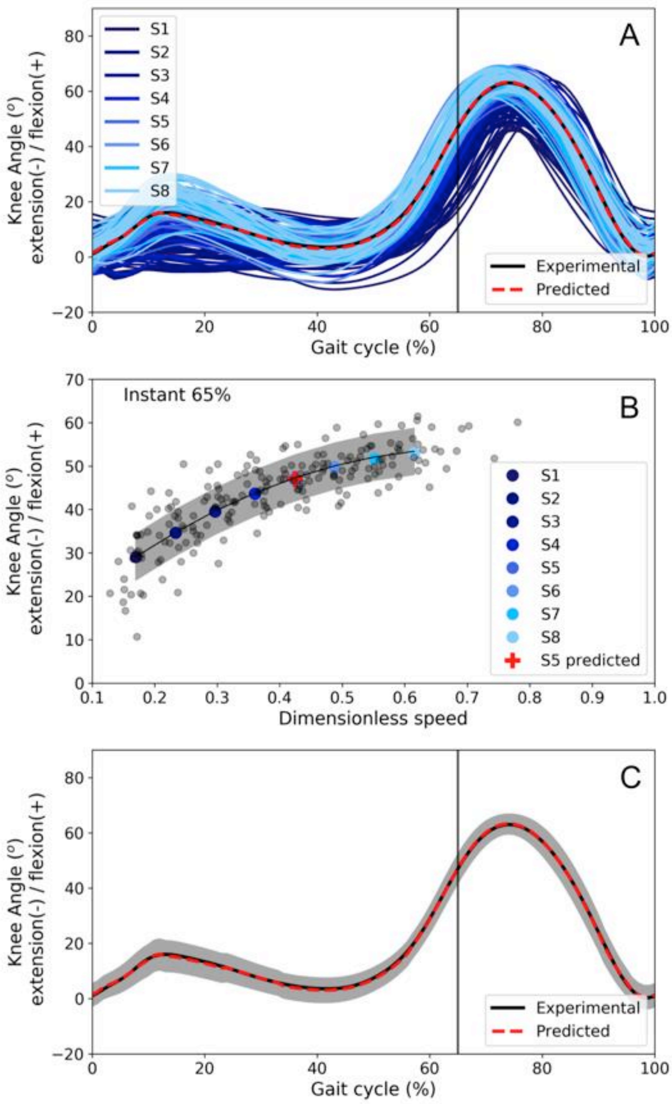

Figure 5-1. A. Example of knee angle at the sagittal plane versus the gait cycle of all participants over the range of gait speeds (thin curves). The average pattern of the experimental data across all participants at the self-selected comfortable speed (S5) is displayed by the thick curve and the respective predicted data by the dashed thick curve. The vertical line marks the instant 65% of the gait cycle. B. Knee angle versus the dimensionless gait speed at instant 65% of the gait cycle to illustrate the prediction method. The adjusted curve also shows the predicted values for the eight speeds (filled circles) and the ±1 SD interval. The experimental values (dots) and the predicted value for the comfortable speed (S5) (plus symbol) are also drawn. C. Average pattern of the experimental data across all participants at the self-selected comfortable speed (S5) (continuous curve) and its respective predicted data (dashed line) with the 68% (±1SD) prediction interval (shaded curve).

5.3.1 Participants

Twenty-four able-bodied adults (14 males and 10 females; age: 27.6±4.4 years; height: 171.1±10.5 cm; mass: 68.4±12.2 kg) were recruited for this study. All participants were free of any lower extremity injury and presented no history of any orthopedic or neurologic disease.

5.3.2 Procedures

Each participant performed walking trials in a barefoot condition at different speeds, ranging from very slow to very fast based on their self-selected comfortable speed. Because leg length can affect the walking speed (10), the gait speed was previously adjusted based on the dimensionless speed (the square root of the Froude number). The comfortable speed was obtained based on the average of three overground walking trials at their self-selected comfortable speed along a 10-m walkway. After, each participant walked on a treadmill at his or her self-selected comfortable speed for 5 minutes. Following this, they walked at each of the eight controlled speeds in a randomized order: 40%, 55%, 70%, 85%, 100%, 115%, 130%, and 145% of their self-selected comfortable speed. For each walking trial, at each speed, the data were recorded in the last 30 seconds of the trial. More details about the data collection and procedures are reported by Fukuchi et al. (11).

The biomechanical model of the lower limbs and pelvis adopted was based on a previous protocol proposed for gait analysis (12). Kinematic data were acquired using a motion capture system with 12 cameras (Raptor-4, Motion Analysis Corporation, Santa Rosa, CA, USA) at 150 Hz, and kinetic data were collected via an instrumented dual-belt treadmill (FIT, Bertec, Columbus, OH, USA) at 300 Hz.

5.3.3 Data analysis

Marker trajectories and force data were filtered using a fourth-order low-pass Butterworth filter with cut-off frequency of 10 Hz. The kinematic and kinetic curves were time-normalized with 101 points evenly distributed over the gait cycle. The data processing and calculations were performed in Visual3D software (C-motion Inc., Germantown, MD, USA).

5.3.4 Statistical analysis

A linear or second-order polynomial for the fitting gait variable versus gait speed was adjusted by the least-squares method and a 68% prediction interval (±1 standard-deviation interval) for the adjusted function was also determined. The validation of the prediction method was done by using the root mean square error (RMSE) as a metric for the accuracy of the prediction comparing the comfortable data with the experimental gait pattern (RMSE c-e), and the experimental data with the predicted gait pattern (RMSE e-p) of the reference dataset. Differences between the two metrics were compared performing Students *t-test* or Mann-Whitney *U* tests (α = 0.05). Additionally, 10-fold stratified cross-validation was applied to evaluate the performance of the prediction method and to evaluate its generalizability (13). For this, the dataset was divided into ten equal random subsets with nine subsets used to fit the data and the remaining subset was used to test the method.

5.4 Results

Participants' average walking speeds ranged from 0.13 to 0.78 dimensionless speed (from 0.39 m/s to 2.20 m/s). Figure 5-2 shows average patterns of experimental and predicted joint angles and moments across subjects at all eight speeds. Individual curves of the experimental and predicted joint angles and joint moments are plotted in the Supplemental material.

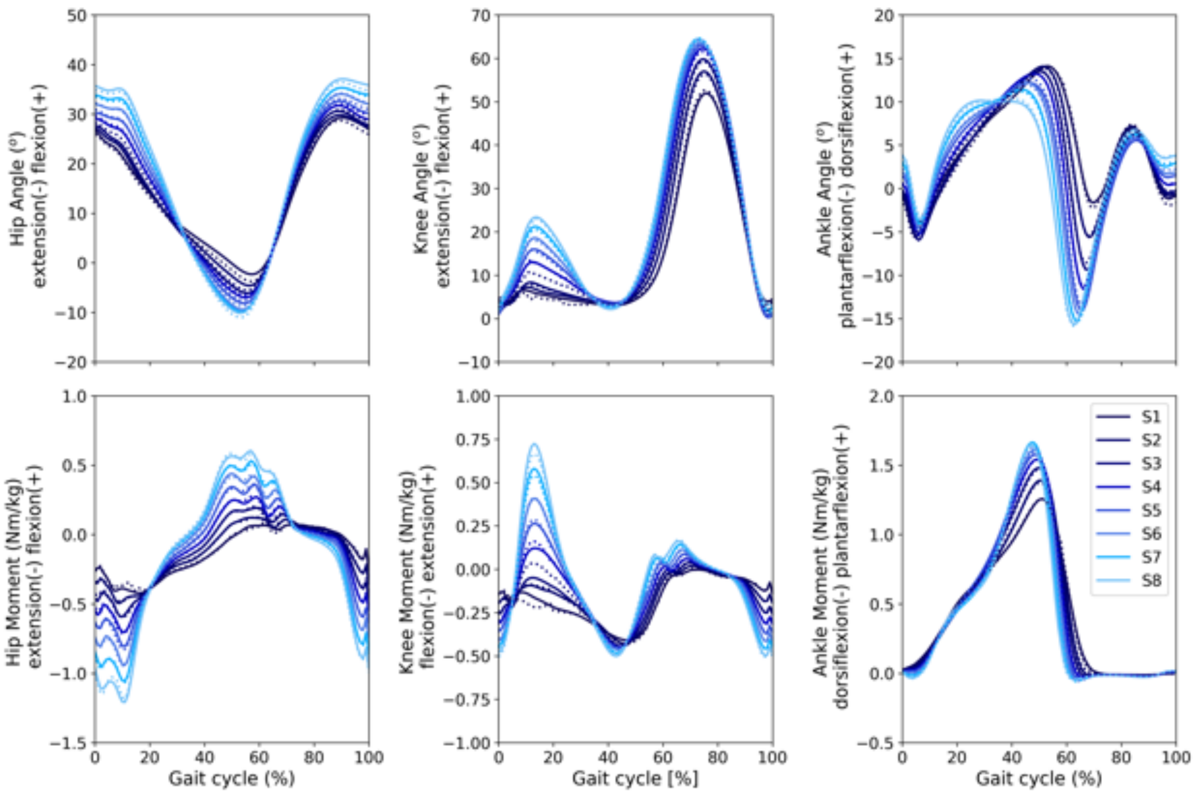

Figure 5-2. Average patterns for the joint angles (top) and joint moments (bottom) of the experimental data across all subjects (solid lines) and predicted data (dashed lines) based on the dataset at the different gait speeds.

Overall, the predicted data corresponded well to the experimental data for the dataset; the RMSE between the experimental and the predicted data (RMSE e-p) across all speeds, variables, and subjects was 0.48±0.22° for the joint angles and 0.02±0.01 Nm for the joint moments. In contrast, the RMSE between the comfortable and experimental (RMSE c-e) was 2.79±2.05° for the joint angles and 0.10±0.07 Nm for the joint moments. The 10-fold stratified cross-validation presented an accuracy of 96.9% for the joint angles, and 98.6% for the joint moments. The prediction for the gait data of each subject at different speeds was performed based on the average of the entire experimental data (the dataset). We found that the RMSE values were lower for the comparison "experimental data versus predicted data" (RMSE e-p) than for the comparison "comfortable speed versus experimental data" (RMSE c-e) for all the slower walking speeds as well as for walking speeds that were faster than the comfortable speed for the majority of joint angles and joint moments ($p<0.05$) (Figure 5-3 and Table 5-1 of the Supplementary material). Individual RMSE values for each joint angle and joint moment graphs are also plotted in the Supplemental material.

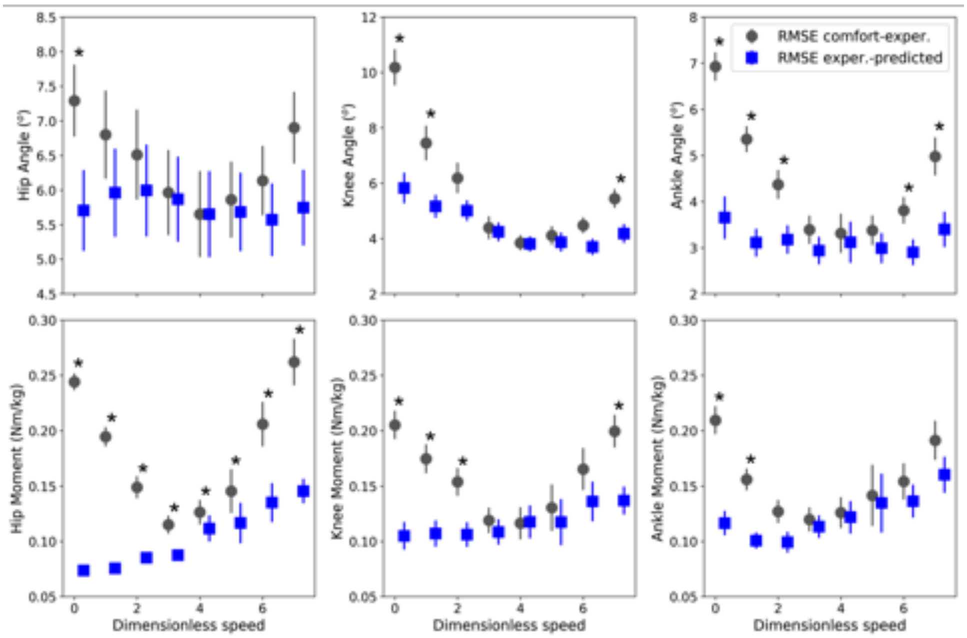

Figure 5-3. RMSE values (mean ±1 standard error of the mean) across subjects of the joint angles and moments at the sagittal plane for the comparisons "comfortable speed versus experimental data" at different speeds (comfort-exper., circles) and "experimental versus predicted data" (exper.-predicted, squares).

5.5 Discussion

We proposed a simple technique to predict the gait pattern of able-bodied individuals at a specific speed. This prediction method was validated in two ways. First, we compared the patterns acquired experimentally at different speeds with the predicted pattern for that speed based solely on the data of the same subject (RMSE e-p) (we performed this comparison for 24 subjects). Second, we created a reference dataset with the gait patterns of those 24 subjects and compared with the average of the dataset (acting as a reference dataset) (RMSE c-e). This second comparison mimics a real scenario where a reference gait dataset is available, and one wants to compare these data with the experimental data of a patient likely evaluated at a different gait speed (in the present case, each subject of the dataset acted as an experimental subject versus the control given by the entire dataset).

The method we proposed to predict the gait pattern at a given speed presented good agreement with the experimental data of each subject for the joint angles and joint moments in a range of speeds from 0.39 m/s to 2.20 m/s. The greater the difference in gait speed between the reference dataset and the experimental data, the greater the difference between the predicted data and the reference dataset without the prediction. The prediction method proposed, seems to mitigate the effects of the gait speed especially at lower speeds in some subjects, but did not totally nullify them. Thus, future study with a larger sample is needed to improve this method.

Compared with the present study, previous prediction methods were based on specific gait events (e.g., peaks) (5–7) or on walking data acquired either at the comfortable speed (7) or only at comfortable, slow, and fast speeds (6–8). One study employed a prediction method based on the entire curve at each 10% interval of the gait cycle by applying a linear regression method (8). However, only a linear regression prediction method was implemented, which was different from the quadratic regression used in the present study.

Given the characteristics of the prediction method proposed, the range of speeds used to build the dataset must include the speed at which one wishes to predict; the proposed method can only perform interpolation, not extrapolation, to predict the pattern. To parameterize the relation between the amplitude of motion and gait speed, a linear or a second-order polynomial function was chosen. Overall, the relationship between the kinematic and kinetic variables and speed were typically non-linear. The parabola is a convenient mathematical function able to capture the observed nonlinearities, and it has only three parameters for adjustment. Nevertheless, another function for adjustment could be used as long as this function can capture the behavior of the data.

To make the prediction method more accessible, we prepared two Excel spreadsheets as supplementary material. The Adults.xlsx spreadsheet contains the equations derived from the present data to predict the gait patterns at any gait speed (reliable for a range of 0.13 to 0.78 dimensionless speed). The Children.xlsx spreadsheet contains the prediction equations derived from data in the Schwartz and collaborators (1) study of children with an average age of 10.5 years walking at five different speeds. Since previous studies stated that walking speed and not age is the main determinant of the gait pattern in this population (1,2), this range of speed would be necessary to understand this condition better. Contrary to this, as age has been reported to influence the gait pattern in children with an average age of 3.6 years (14), the gait pattern in younger children that is not maturated yet seems to be more affected at a greater extent by age than speed. Nevertheless, future study should further explore the relative contribution of age on the gait pattern.

In summary, the proposed technique successfully predicted speed-specific joint angles and joint moments patterns in able-bodied individuals for any gait speed. This prediction reduces the difference compared with the reference dataset since it compares the experimental gait pattern with the predicted one at the same gait speed. This method may be adapted to generate a more unbiased reference normative data to be used to evaluate the gait pattern of pathological individuals, or it may even be suitable for application to other speed-dependent human movement patterns.

5.6 References

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5.7 Supplementary material

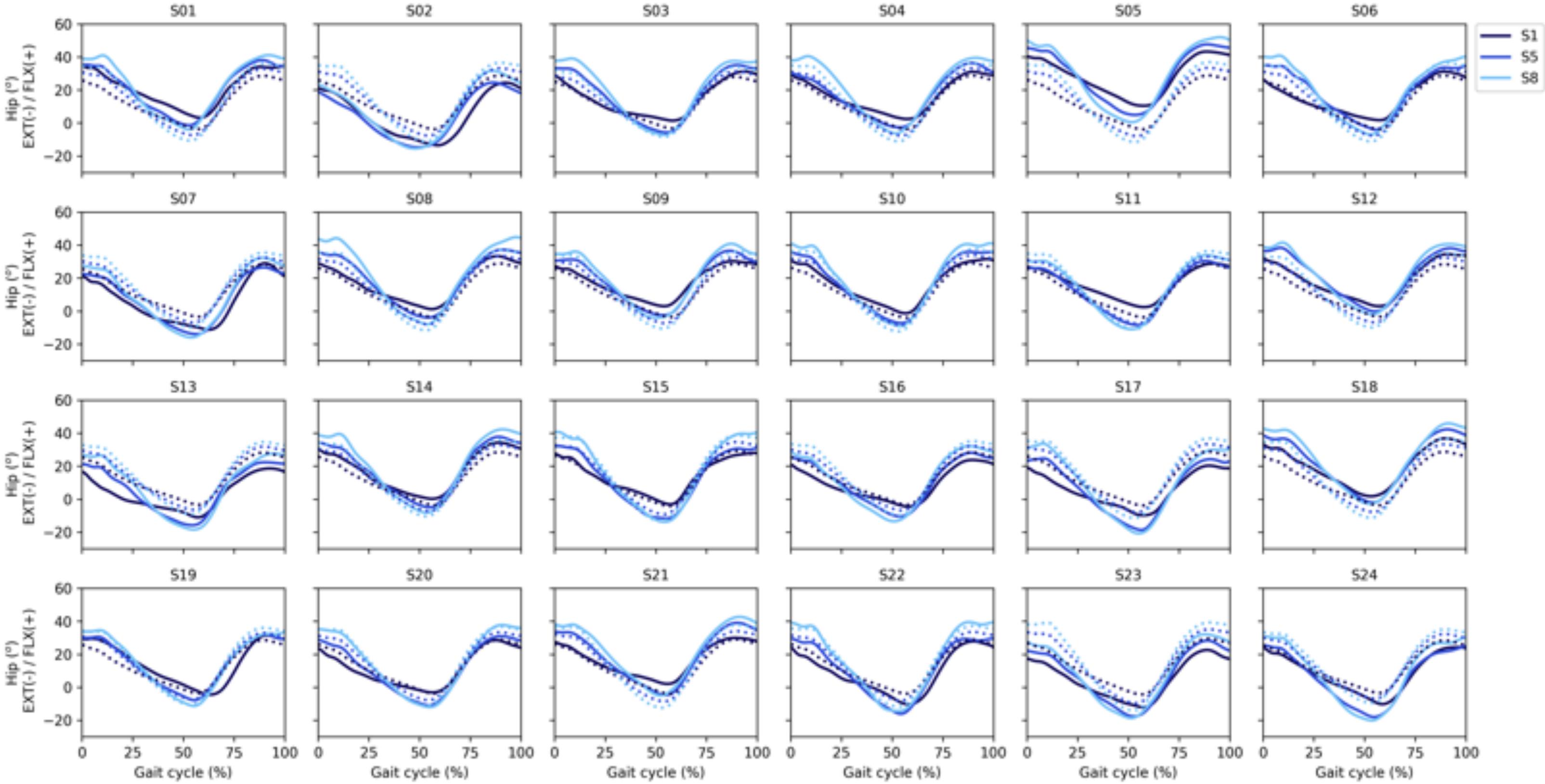

Figure 5-4 Individual curves of the hip joint angles of the experimental data (solid lines) and predicted data (dashed lines) based on the dataset at the slowest (S1), comfortable (S5), and fastest (S8) gait speeds.

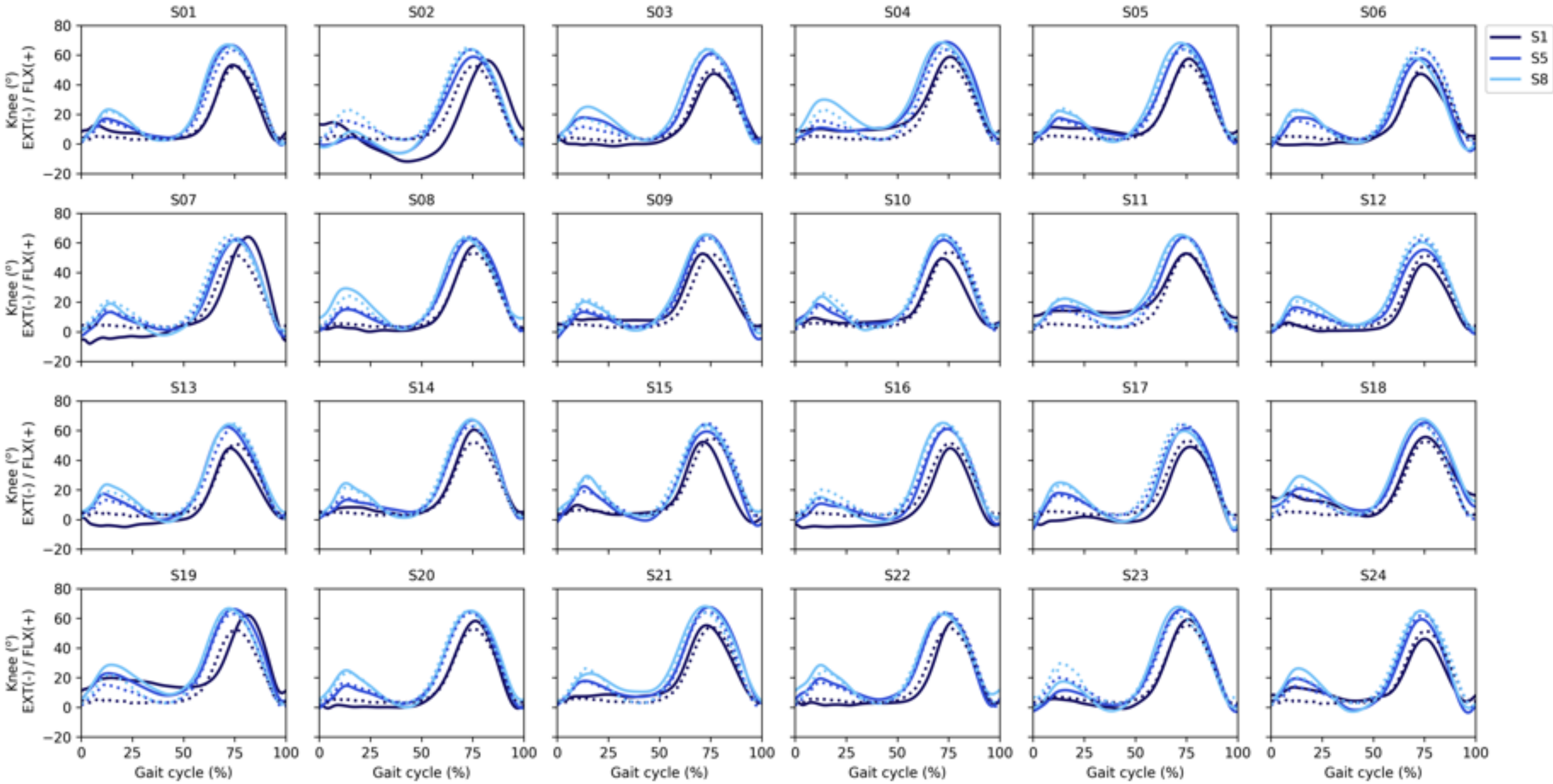

Figure 5-5 Individual curves of the knee joint angles of the experimental data (solid lines) and predicted data (dashed lines) based on the dataset at the slowest (S1), comfortable (S5), and fastest (S8) gait speeds.

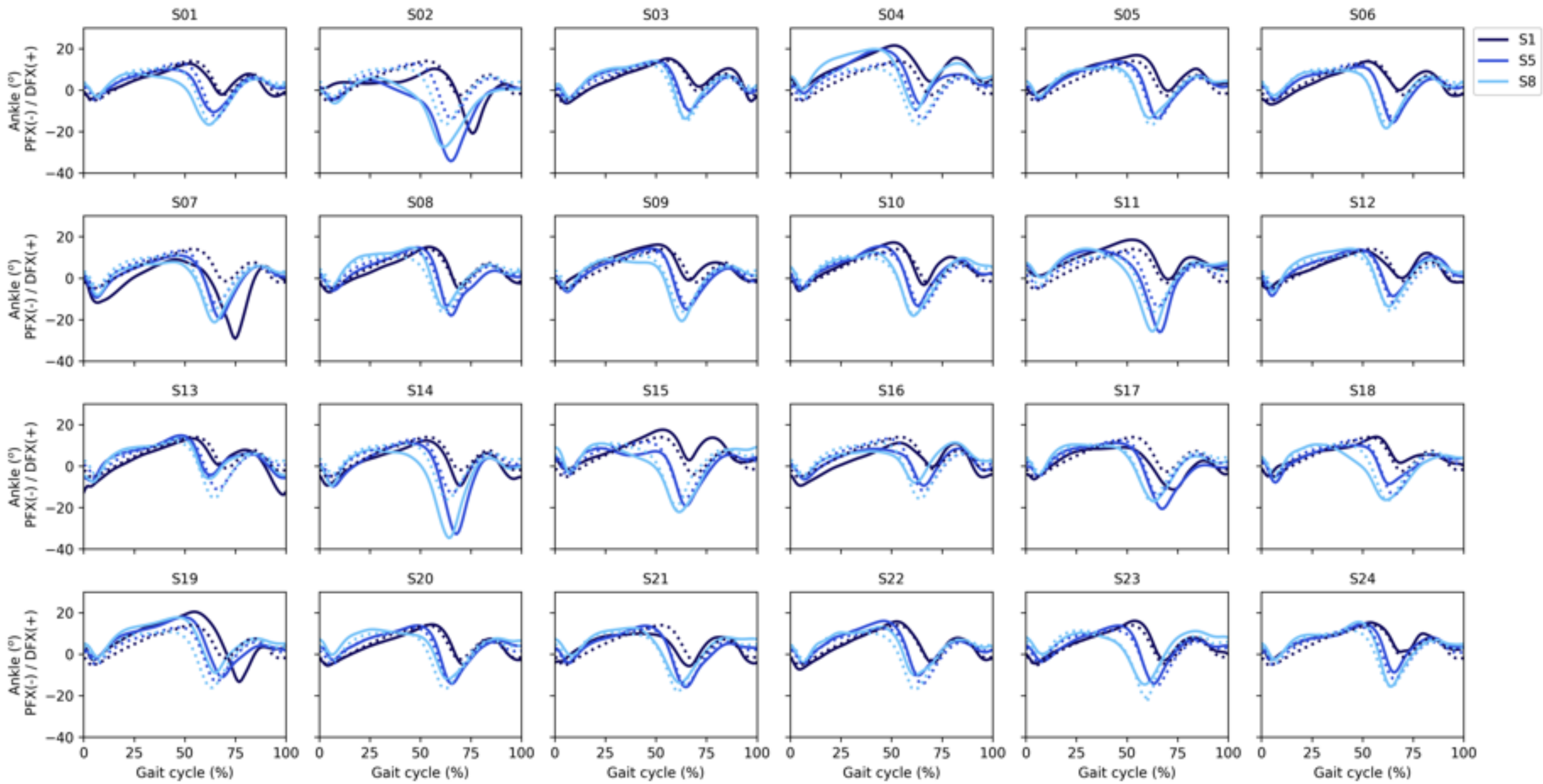

Figure 5-6 Individual curves of the ankle joint angles of the experimental data (solid lines) and predicted data (dashed lines) based on the dataset at the slowest (S1), comfortable (S5), and fastest (S8) gait speeds.

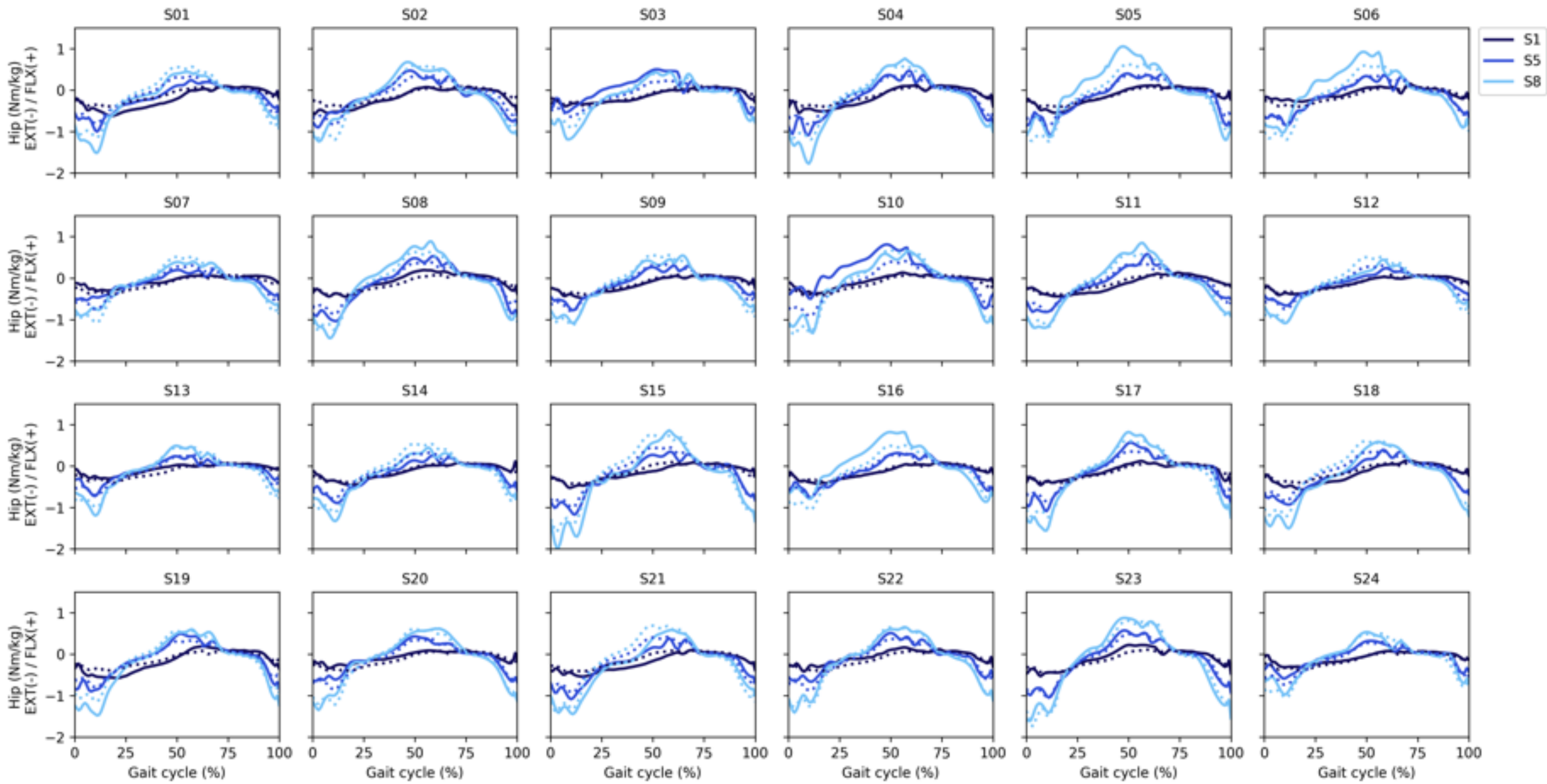

Figure 5-7 Individual curves of the hip joint moments of the experimental data (solid lines) and predicted data (dashed lines) based on the dataset at the slowest (S1), comfortable (S5), and fastest (S8) gait speeds.

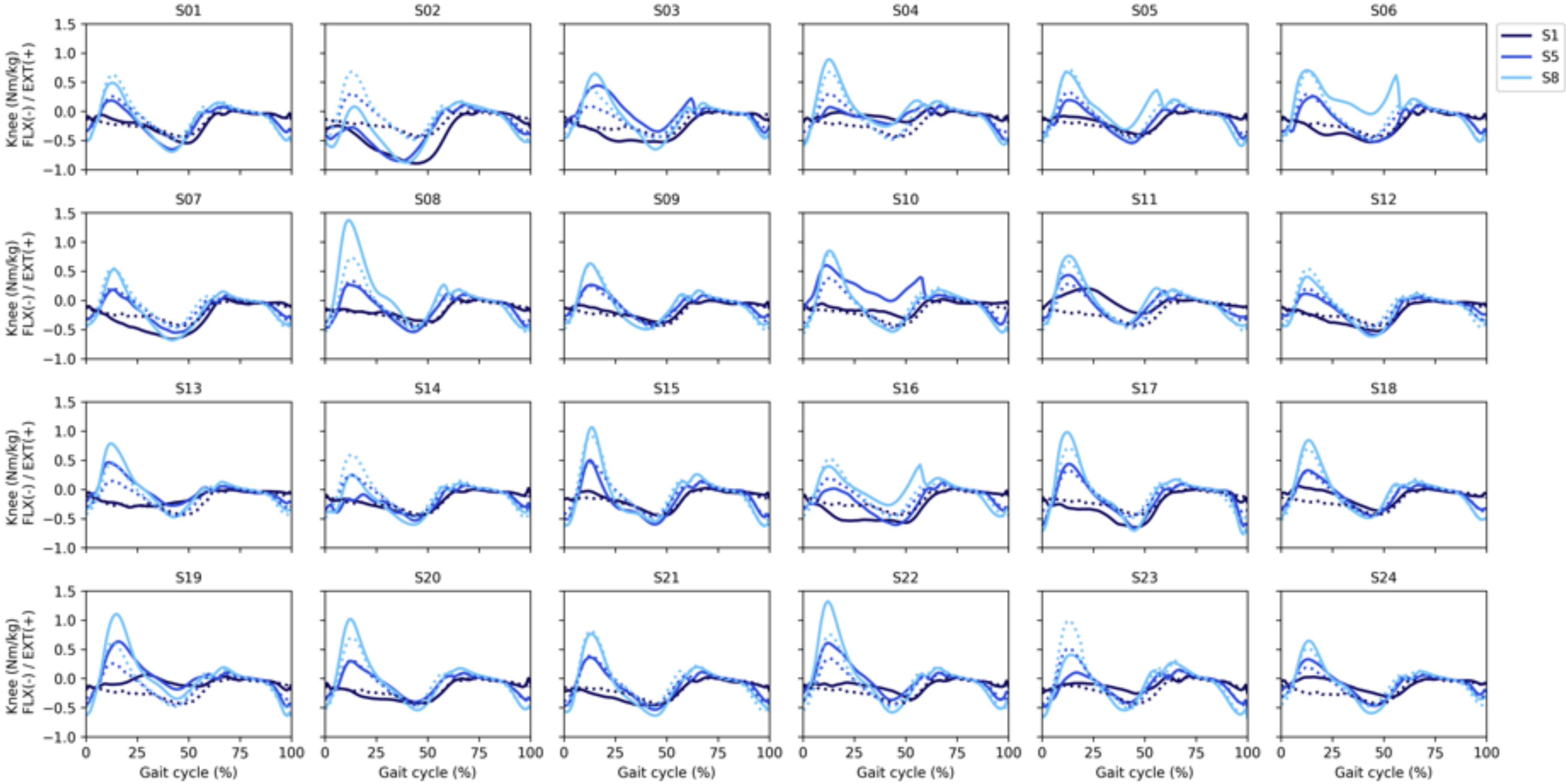

Figure 5-8 Individual curves of the knee joint moments of the experimental data (solid lines) and predicted data (dashed lines) based on the dataset at the slowest (S1), comfortable (S5), and fastest (S8) gait speeds.

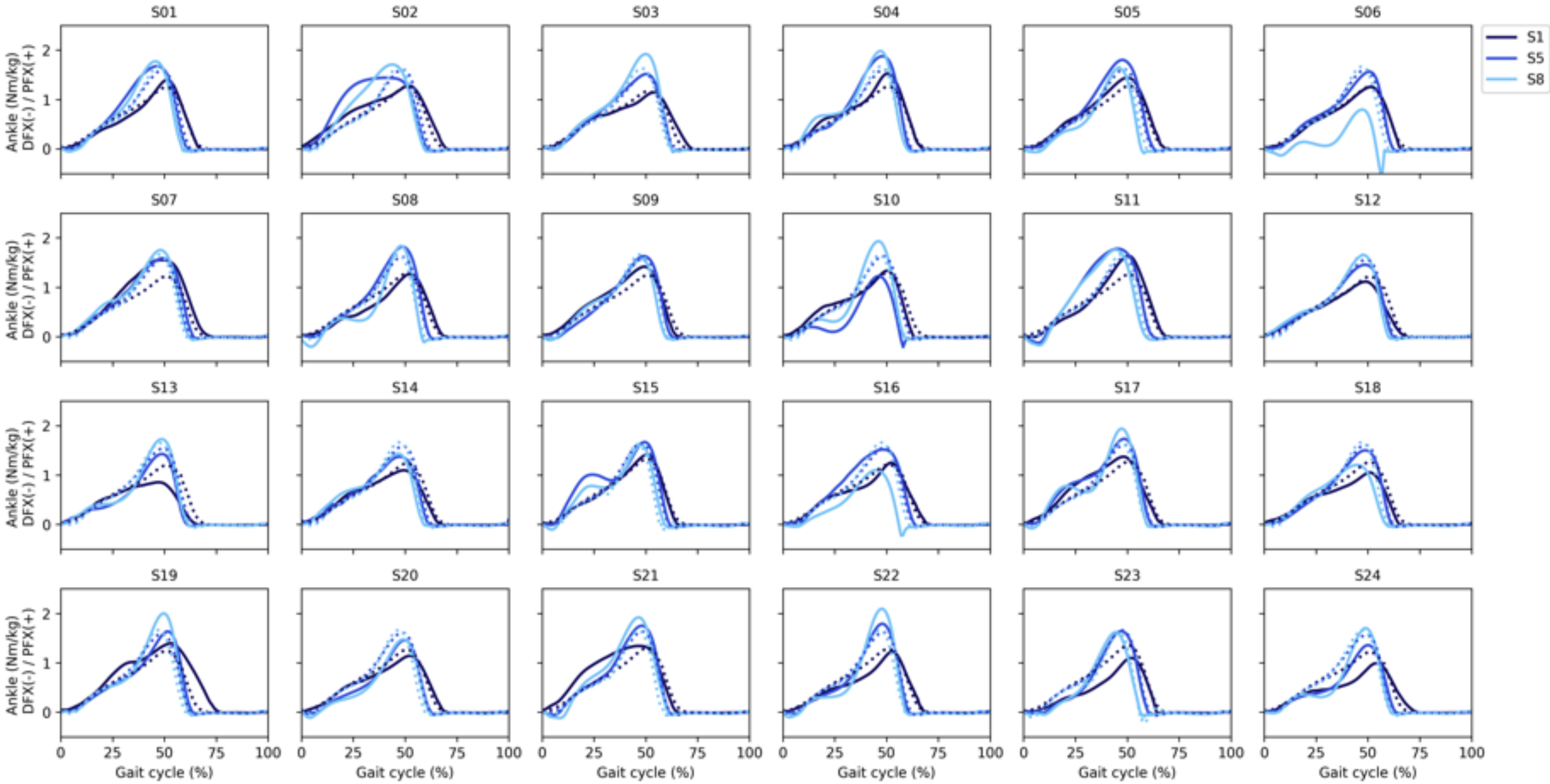

Figure 5-9 Individual curves of the ankle joint moments of the experimental data (solid lines) and predicted data (dashed lines) based on the dataset at the slowest (S1), comfortable (S5), and fastest (S8) gait speeds.

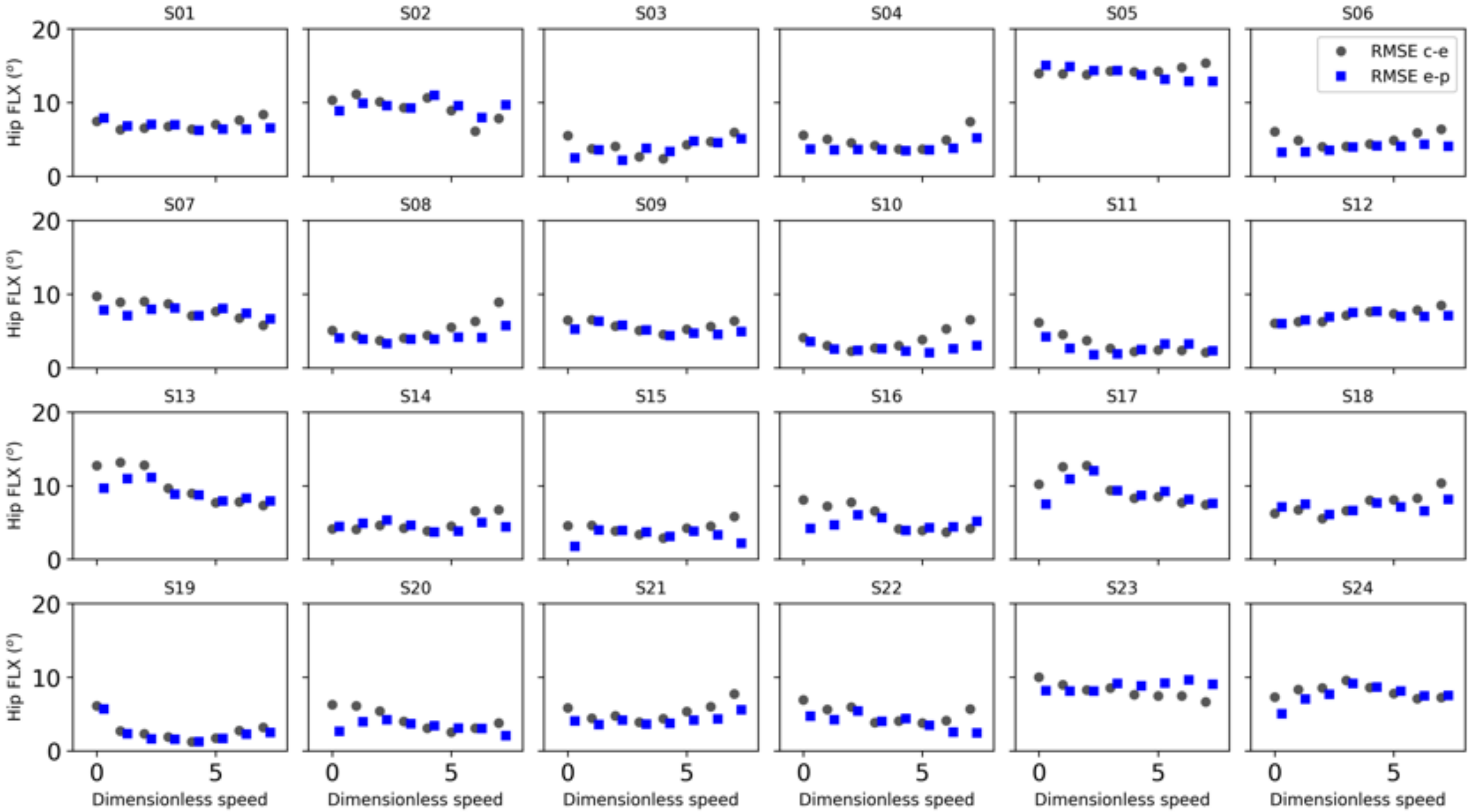

Figure 5-10 Individual RMSE values of the hip joint angles at the sagittal plane for the comparisons "comfortable speed versus experimental data" at different speeds (comfort-exper., circles) and "experimental versus predicted data" (exper.-predicted, squares).

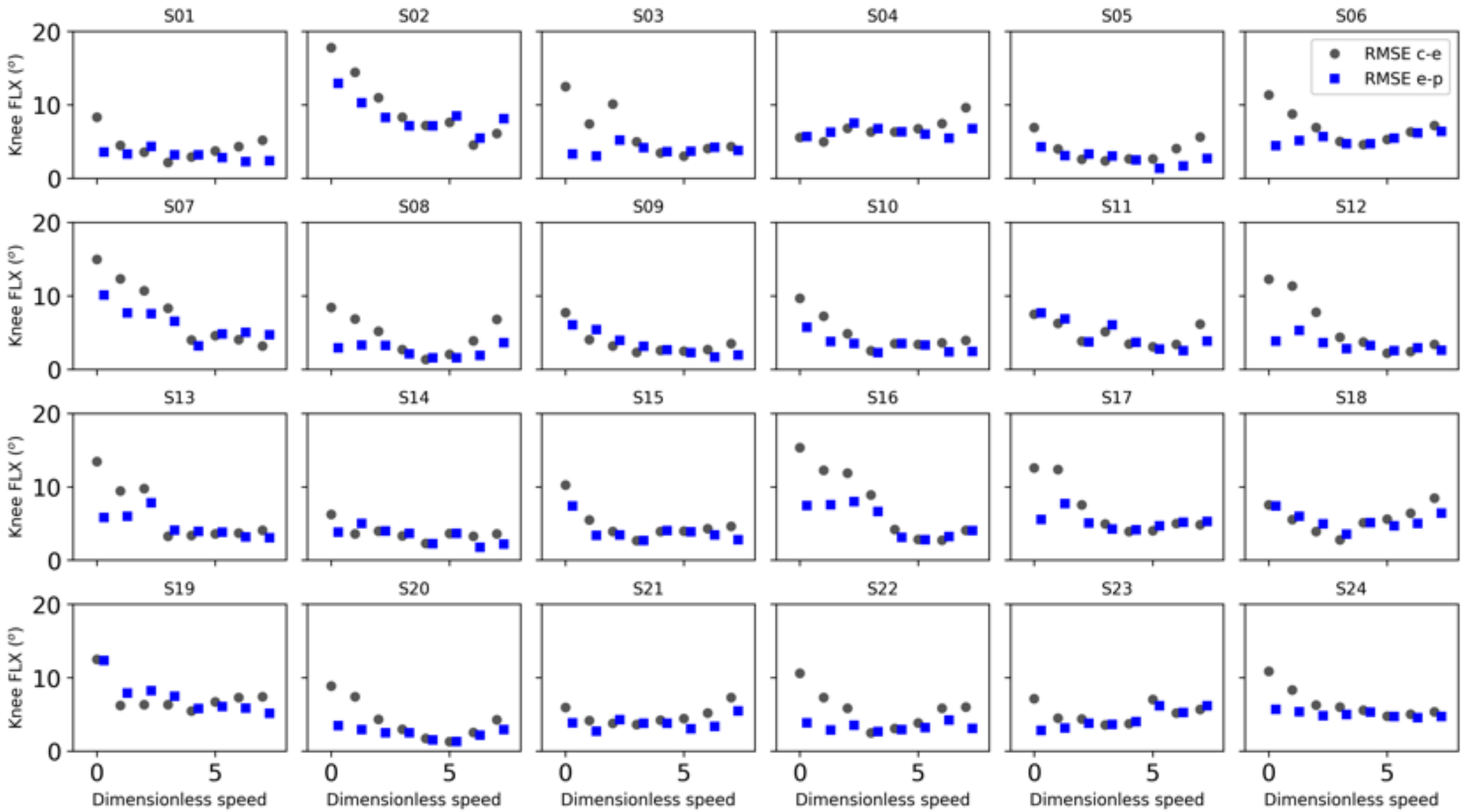

Figure 5-11 Individual RMSE values of the knee joint angles at the sagittal plane for the comparisons "comfortable speed versus experimental data" at different speeds (comfort-exper., circles) and "experimental versus predicted data" (exper.-predicted, squares).

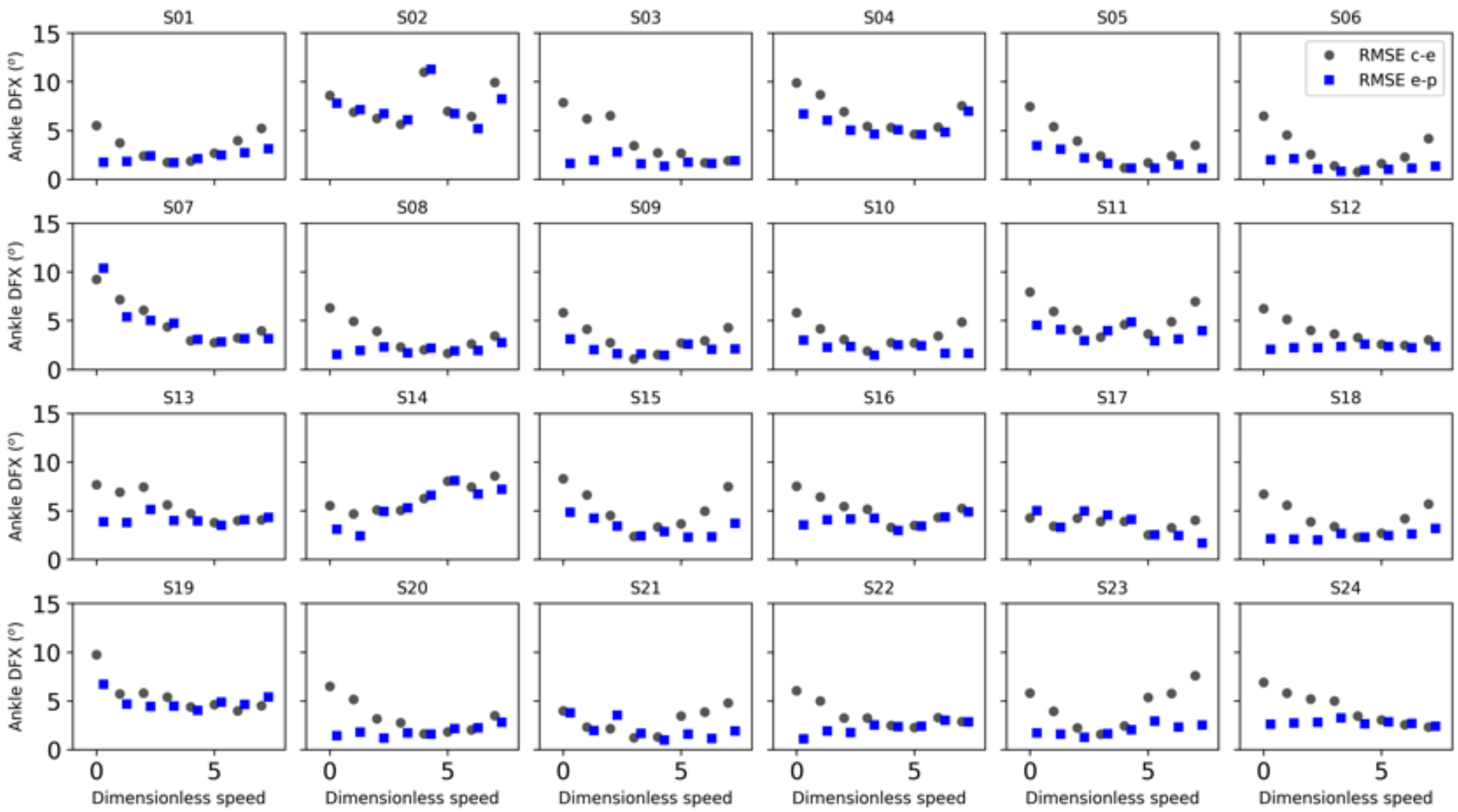

Figure 5-12 Individual RMSE values of the ankle joint angles at the sagittal plane for the comparisons "comfortable speed versus experimental data" at different speeds (comfort-exper., circles) and "experimental versus predicted data" (exper.-predicted, squares).

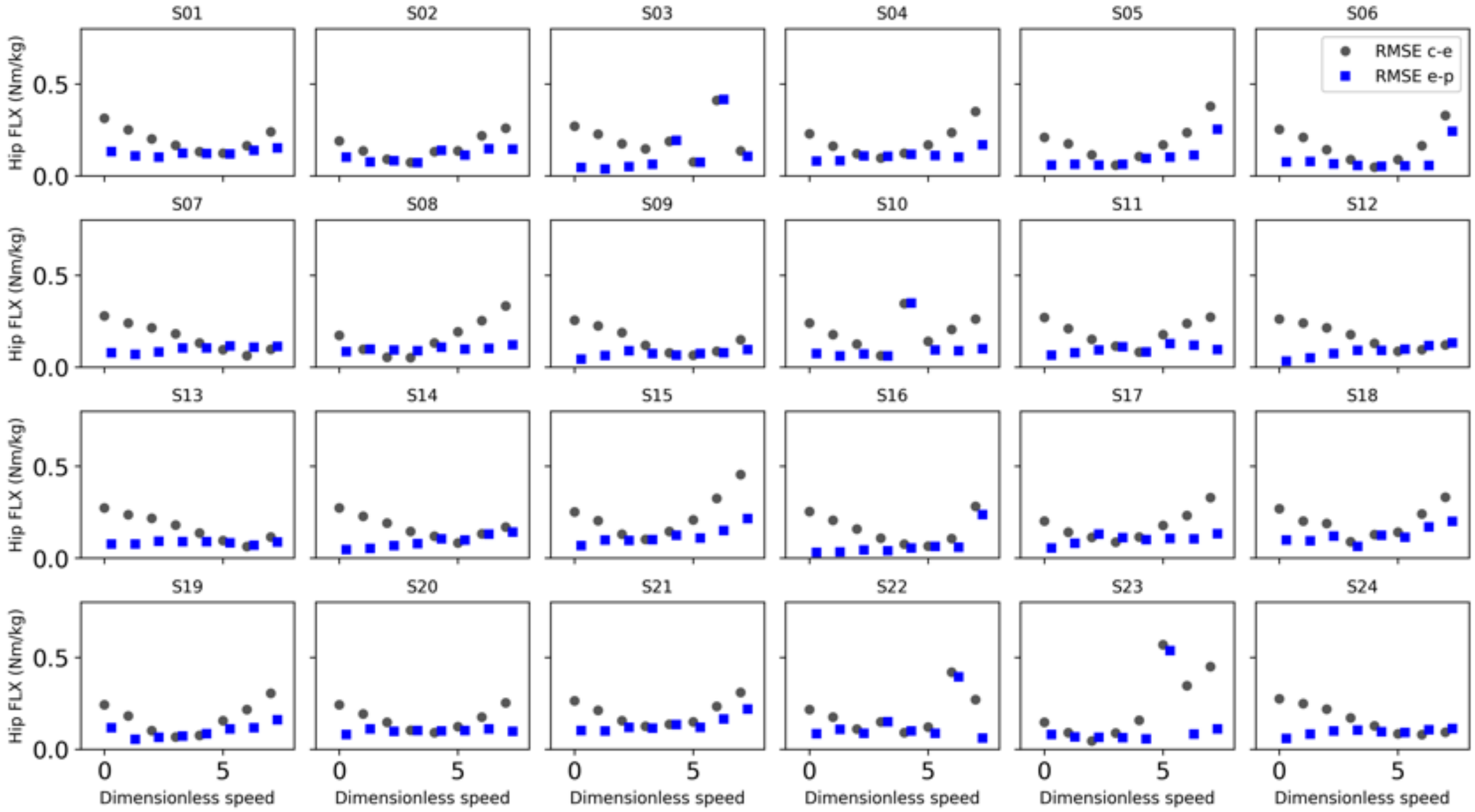

Figure 5-13 Individual RMSE values of the hip joint moments at the sagittal plane for the comparisons “comfortable speed versus experimental data” at different speeds (comfort-exper., circles) and “experimental versus predicted data” (exper.-predicted, squares).

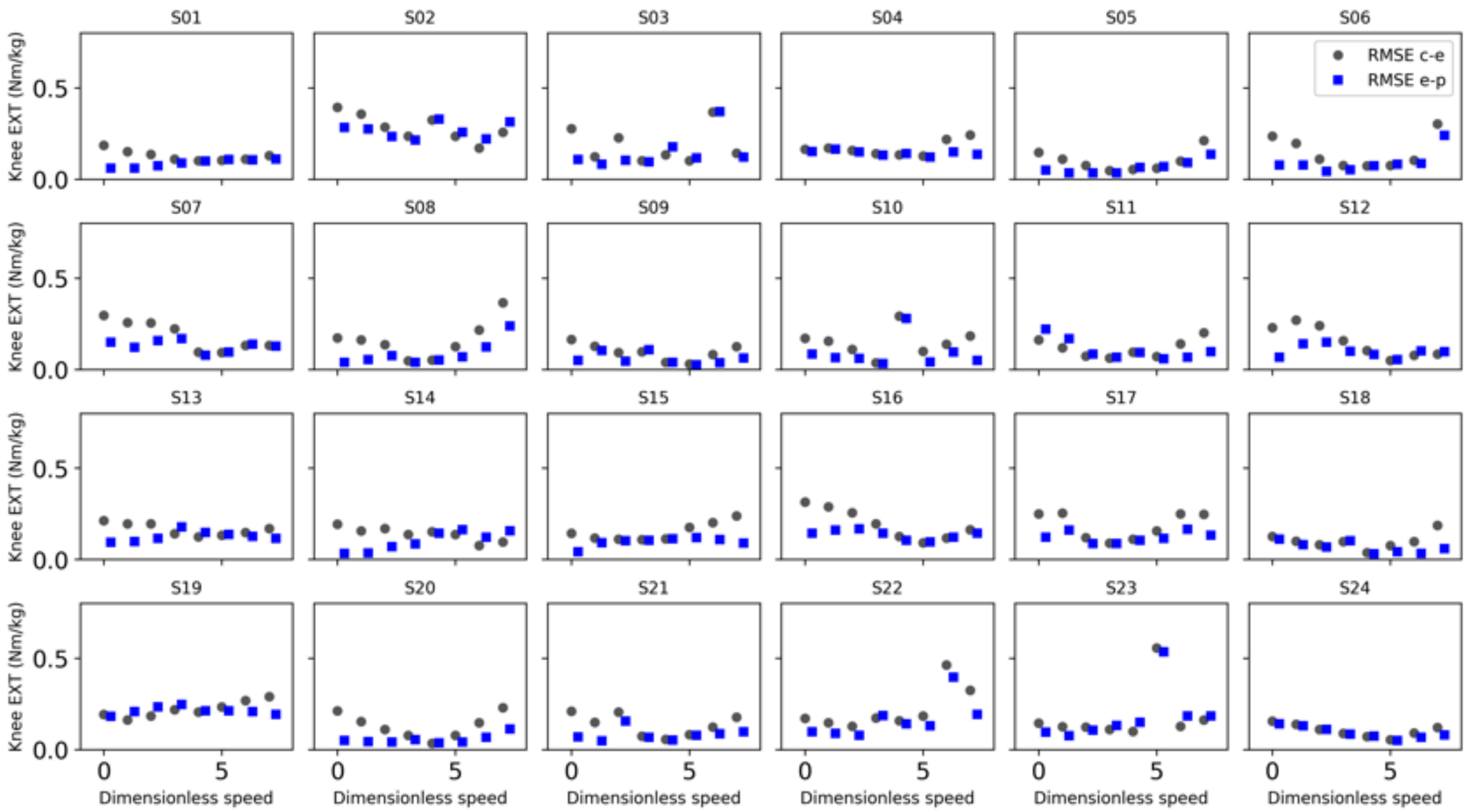

Figure 5-14 Individual RMSE values of the knee joint moments at the sagittal plane for the comparisons “comfortable speed versus experimental data” at different speeds (comfort-exper., circles) and “experimental versus predicted data” (exper.-predicted, squares).

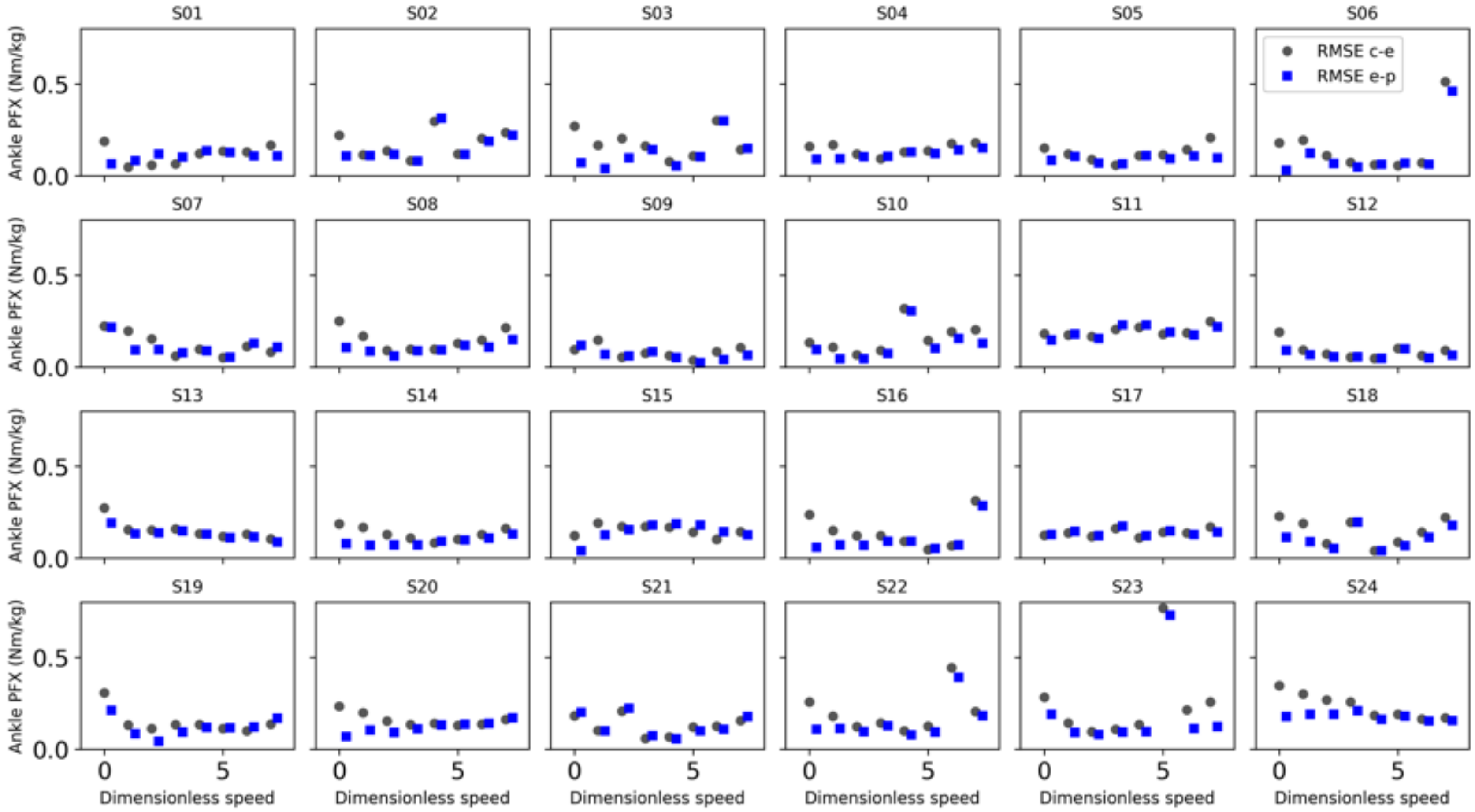

Figure 5-15 Individual RMSE values of the ankle joint moments at the sagittal plane for the comparisons “comfortable speed versus experimental data” at different speeds (comfort-exper., circles) and “experimental versus predicted data” (exper.-predicted, squares).

Table 5-1. Gait dimensionless speed, RMSE c-e (Comfortable - Experimental), and RMSE e-p (Experimental – Predicted) mean values across individuals for the joint angles and joint moments at each gait speed (S1 – S8). *Statistical significance difference (p<0.05) between RMSE c-e and RMSE e-p.

	S1		**S2**		**S3**		**S4**	
Gait speed [dimensionless speed]	0.17		0.23		0.30		0.36	
Joint Angles [°]	**RMSE c-e**	**RMSE e-p**	**RMSE c-e**	**RMSE e-p**	**RMSE c-e**	**RMSE e-p**	**RMSE c-e**	**RMSE e-p**
Hip Flexion	7.29	5.70*	6.80	5.96	6.51	5.99	5.96	5.87
Knee Flexion	10.18	5.82*	7.45	5.16*	6.19	5.01	4.39	4.24
Ankle Dorsiflexion	6.93	3.65*	5.35	3.11*	4.37	3.18*	3.39	2.94
Joint Moments [Nm/kg]	**RMSE c-e**	**RMSE e-p**	**RMSE c-e**	**RMSE e-p**	**RMSE c-e**	**RMSE e-p**	**RMSE c-e**	**RMSE e-p**
Hip Flexion	0.24	0.08*	0.19	0.08*	0.15	0.09*	0.11	0.09*
Knee Extension	0.21	0.11*	0.17	0.11*	0.15	0.11*	0.12	0.11
Ankle Plantarflexion	0.21	0.13*	0.16	0.10*	0.13	0.10	0.12	0.12

	S5		**S6**		**S7**		**S8**	
Gait speed [dimensionless speed]	0.43		0.49		0.55		0.62	
Joint Angles [°]	**RMSE c-e**	**RMSE e-p**	**RMSE c-e**	**RMSE e-p**	**RMSE c-e**	**RMSE e-p**	**RMSE c-e**	**RMSE e-p**
Hip Flexion	5.78	5.65	5.97	5.69	6.17	5.57	6.90	5.75
Knee Flexion	3.89	3.80	3.99	3.87	4.26	3.70	5.09	4.18*
Ankle Dorsiflexion	3.48	3.12	3.60	2.99	4.11	2.90*	5.03	3.40*
Joint Moments [Nm/kg]	**RMSE c-e**	**RMSE e-p**	**RMSE c-e**	**RMSE e-p**	**RMSE c-e**	**RMSE e-p**	**RMSE c-e**	**RMSE e-p**
Hip Flexion	0.13	0.11*	0.15	0.12*	0.21	0.14*	0.26	0.15*
Knee Extension	0.12	0.12	0.13	0.12	0.17	0.14	0.20	0.14*
Ankle Plantarflexion	0.13	0.13	0.14	0.14	0.15	0.13	0.19	0.16

Chapter 6. Applying the prediction method in pathologic individuals

Published as:

Gait Profile Score in able-bodied and post-stroke individuals adjusted for the effect of gait speed

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Gait Profile Score in post-stroke subjects accounting for the effect of gait speed

Claudiane Fukuchi, Richard Baker, Marcos Duarte

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Student contributions:

In this study, the student conceived and designed the experiments, performed the experiments, analyzed the data, prepared figures and/or tables, wrote the paper, approved the final draft.

Abbreviations:

GPS: Gait Profile Score; GVS: Gait Variable Score; MAP: Movement Analysis Profile; ASIS: anterior superior iliac spine; RMS: root-mean-square; MCID: minimal clinically important difference

6.1 Abstract

Background. The Gait Profile Score (GPS) measures the quality of an individual's walking by calculating the difference between the kinematic pattern and the average walking pattern of healthy individuals.

Research questions. The purposes of this study were to quantify the effect of speed on the GPS and to determine whether the prediction of gait patterns at a specific speed would make the GPS outcome insensitive to gait speed in the evaluation of post-stroke individuals.

Methods. The GPS was calculated for able-bodied individuals walking at different speeds and for the comparison of post-stroke individuals with able-bodied individuals using the original experimental data (standard GPS) and the predicted gait patterns at a given speed (GPS velocity, GPS^v). We employed standard gait analysis for data collection of the subjects. Sixteen participants with a stroke history were recruited for the post-stroke group, and 15 age-matched, able-bodied participants formed the control group.

Results. Gait speed significantly affects the GPS and the method to predict the gait patterns at any speed is able to mitigate the effects of gait speed on the GPS. Overall, the gap between the GPS and GPS^v values across the post-stroke individuals was small (0.5° on average, range from 0.0° to 1.4°) and not statistically significant. However, there was a significant negative linear relationship in the absolute difference between the GPS and GPS^v values for the participants of the post-stroke group with gait speed, indicating that a larger difference between the speeds of the post-stroke participant and the reference dataset resulted in a larger difference between the GPS and GPS^v.

Significance. The modified version of the GPS, the GPS^v, is effective in reducing the impact of gait speed on GPS; however, the observed difference between the two methods is only around 1° for the slowest individuals in comparison to the reference dataset.

Keywords: gait, Gait Profile Score; walking speed; post-stroke; regression analysis

6.2 Introduction

The Gait Profile Score (GPS) measures the quality of an individual's walking by calculating the difference between the kinematic pattern (angles for the pelvic tilt, obliquity, and rotation; and for both sides of the body, hip flexion, abduction and rotation, knee flexion, ankle dorsiflexion, and foot progression) and the average walking pattern of healthy individuals (1). Compared with other gait indices, such as Gait Deviation Index (2), Gait Deviation Index Kinetic (3), and Gillette Gait Index (4), GPS has the advantage of also revealing the separate contribution of each kinematic variable (angles for the pelvic tilt, obliquity, and rotation; and for both sides of the body, hip flexion, abduction and rotation, knee flexion, ankle dorsiflexion, and foot progression) by first calculating the Gait Variable Score (GVS), thereby creating the Movement Analysis Profile (MAP). The GPS has been used to evaluate gait abnormalities in different populations (5–7). In such evaluations, comparisons are made between one or more patients and a dataset of healthy individuals walking at their comfortable pace at speeds typically higher than the patients. A likely problem with this approach is that it is known that walking speed affects gait patterns of healthy individuals (8,9) and for instance, people with a stroke history (10–13) or with Parkinson's disease (14) tend to walk slower than healthy controls. In fact, gait speed, not age, has been suggested to be the primary determinant of kinematic and kinetic alterations in children (15). Therefore, the GPS would be influenced by either the physical condition (the pathology per se) or the walking speed, or both, potentially hampering the ability of the GPS to quantify the exact effect of a disorder on the gait pattern. When the GPS was correlated with walking speed, only a small correlation (ρ=-0.28) was found (1). However, since these data were predominantly from individuals with different disabilities or at distinct stages of impairment, these factors alone may have confounded the effect of speed on the gait patterns. I.e., ideally, a study where the same subjects walk at several different speeds would be more appropriate to capture the effect of speed on the gait patterns.

Previous studies have proposed methods to lessen the effect of walking speed on gait (15–19). For instance, Schreiber et al (20) proposed a method where a correction for the effect of speed is introduced directly on the computation of the gait indices rather than on the gait patterns and they demonstrated the validity of the method on a healthy population. Another method proposed elsewhere (15,17–19) is to estimate the patterns at a given speed using regression methods to predict the new data based on a dataset of experimental data and then using the estimated patterns in the calculation of the gait indices. A regression method for gait-pattern prediction at a specific speed recently proposed has the advantage of being able to predict the entire pattern for the gait cycle successfully (19). While this method has been tested on a broad range of gait speeds for healthy individuals, it hasn't yet been applied to a clinical context; neither has it been used to make the GPS outcome insensitive to gait speed. In this context, we designed a study where we applied the GPS to evaluate the gait of able-bodied individuals walking at different speeds, and individuals with stroke histories walking at their comfortable speed. The GPS was calculated for the comparison of post-stroke individuals with able-bodied individuals using the original experimental data (standard GPS) and for the comparison with the predicted gait patterns at the speed of the post-stroke individuals (referred to here as Gait Profile Score velocity, GPS^v). Since the GPS^v compares the individual's gait pattern with speed-adjusted gait pattern, rather than with an average control group gait pattern as employed in the standard GPS, we hypothesize that the proposed GPS^v will lessen the effect of gait speed compared to the standard GPS.

6.3 Materials and Methods

6.3.1 Participants

Sixteen participants who had stroke histories (8 males, age: 66.9±7.0 years, height: 168.6±7.2 cm, mass: 65.5±7.5 kg; and 8 females, age: 60.1±11.4 years, height: 155.4±5.7 cm, mass: 67.0±12.3 kg) were recruited for the post-stroke group. There were six individuals with left hemisphere stroke (right paretic) and ten with right hemisphere stroke (left paretic), of which, 12 ischemic and 4 hemorrhagic and with a mean time after stroke of 76.8 months. Inclusion criteria were that they: 1) had experienced a single stroke episode at six months or more prior to the data collection, 2) could walk at least 10 m without any type of assistance, 3) had no history of any musculoskeletal disorders that could substantially impact the gait pattern, and 4) were able to understand experimental tasks. A control group was formed with 15 age-matched, able-bodied participants (6 males, age: 59.7±6.1 years, height: 168.7±3.9 cm, mass: 74.9±8.2 kg; and 9 females, age: 58.9±5.8 years, height: 159.6±11.4 cm, mass: 63.9 ±14.6 kg). These participants were free of any orthopaedic or musculoskeletal injury in the six months before the data collection and had no history of neurologic disease. All participants read and signed a consent form approved by the local University.

6.3.2 Construction of the reference data

To predict the kinematic patterns of the reference dataset at a certain speed, data collection of able-bodied subjects walking at a range of gait speeds was required to later interpolate the gait patterns at any desired speed within this range based on the method previously proposed (19). For such, we had to employ a treadmill to specify and control these different speeds because subjects could not reproduce overground walking trials at so many varied speeds. However, most of the older adults we evaluated who had stroke histories were unable to walk independently on a treadmill. Given that and to avoid a direct overground-treadmill gait comparison between different populations, which would introduce another confounding factor into our group comparison, we adopted a hybrid procedure to create the reference dataset with a range of gait speeds. We collected data for able-bodied subjects walking on the treadmill at different speeds as well as overground at their comfortable speed. Then, for each kinematic variable (*X*) of an able-bodied subject walking at each speed on the treadmill (*vi*) ($X_{\mathrm{Vi@treadmill}}$), we subtracted its mean value at the comfortable speed on the treadmill ($\bar{X}_{\mathrm{Vcomf@treadmill}}$) and added its mean value at the comfortable speed on overground ($\bar{X}_{\mathrm{Vcomf@overground}}$). That is, we simply shifted the values on the treadmill by a constant value based on a possible variation between the two environments at the comfortable speed, mathematically:

$$X_{\mathrm{Vi@treadmill-overground}} = X_{\mathrm{Vi@treadmill}} - \bar{X}_{\mathrm{Vcomf@treadmill}} + \bar{X}_{\mathrm{Vcomf@overground}}$$

This reference data is designated as a treadmill-overground dataset (see Figure 6-5 in the Supplementary material for an example of data before and after this procedure).

6.3.3 Data acquisition

We employed standard gait analysis procedures for data collection using a motion capture system with 1) 12 cameras (Raptor-4, Motion Analysis Corporation, Santa Rosa, CA, USA); 2) five force platforms (three 40×60 cm model Optima, AMTI, Watertown, MA, USA; two 40×60 cm model 9281EA, Kistler, Switzerland) embedded on the floor; and 3) a dual-belt instrumented treadmill (FIT, Bertec, Columbus, OH, USA) in a 10×12 m room at the Laboratory of Biomechanics and Motor Control, Federal University of ABC, Brazil. Kinematic data were acquired at 150 Hz, and the ground reaction force data were acquired at 300 Hz by the motion capture system (Cortex 6.0, Motion Analysis Corporation, Santa Rosa, CA, USA). For this study, ground reaction forces data were used for gait event detection purposes. Before the data collection, leg length (defined as the distance from the anterior superior iliac spine [ASIS] to the ipsilateral medial malleolus), mass, and stature of each participant were measured. Twenty-six retro-reflective markers were attached to the pelvis and lower limbs according to a biomechanical model previously described (19,21).

For the control group, to define the comfortable speed, each participant performed three walking trials barefoot at their comfortable speed along a 10-m flat walkway. The mean gait speed was calculated and then normalized based on the participant's leg length (22). Following this, each participant performed at least five walking trials at their comfortable speed, and these data were used in further analysis. For a more reliable gait evaluation at different speeds, we also asked each participant in the control group to walk on an instrumented treadmill. First, they walked for 5 min at their previously defined and self-selected comfortable speed. Next, they walked at each of the eight different controlled speeds (40%, 55%, 70%, 85%, 100%, 115%, 130%, and 145% of their self-selected speed) in a randomized order for 90 s where the data were recorded in the last 60 s of the trial. For the post-stroke group, each participant walked barefoot only at their comfortable speed on a 10-m walkway.

6.3.4 Data analysis

Kinematic and kinetic data were filtered with a fourth-order low-pass Butterworth filter and a cut-off frequency of 10 Hz. The definition of the segment anatomical reference frames was performed according to Leardini et al. (21). The 15 kinematic variables proposed on the GPS (1) were calculated: angles for the pelvic tilt, obliquity, and rotation; and for both sides of the body, hip flexion, abduction and rotation, knee flexion, ankle dorsiflexion, and foot progression. Kinematic time-series curves were time-normalized with 51 points over the gait cycle, and the data were processed in Visual3D software (C-motion Inc., Germantown, MD, USA). We calculated the time-normalized ensemble average across participants at their comfortable speed to serve as the reference dataset. The GVS was computed as the root-mean-square (RMS) difference between the participant's speed and the average from the reference dataset for each of the kinematic variables. Then, the GPS was computed as the RMS average of all the GVS values (1).

We predicted the kinematic patterns of the reference dataset for the participant's speed based on a regression method previously described (19) using the following steps. First, we adjusted a first or a second-order polynomial (based on the goodness of fit) to the values of the reference dataset versus the corresponding gait speeds for each instant of the gait cycle to obtain the parameters of the regression. Second, we employed these regression parameters to predict the new values of the gait pattern at any specific speed. The GVS and GPS values were then calculated on these speed-adjusted data and are referred to as GVS^{v} and GPS^{v}, respectively.

6.3.5 Statistical analysis

Descriptive statistics of the dependent variables are presented as a mean and standard deviation. Shapiro-Wilk's tests were applied to examine the normal distribution for both GVS/GVS^v and GPS/GPS^v methods. To determine the difference between groups, either Student's *t*-test or the non-parametric Mann-Whitney test was applied when the normality assumption was not found. Additionally, we calculated the absolute difference between GPS and GPS^v methods and then, we verify the relationship of it with the dimensionless speed. For that, the Pearson correlation coefficient and linear regression by least squares were calculated. The adjusted correlation coefficient and the 68% prediction interval were also calculated for the fits. A statistically significant difference was considered for a *p*-value <0.05.

6.4 Results

Gait speed at the comfortable condition for each subject in the control and post-stroke group is described in Table 6-1. For the control-group subjects, the GPS index presents a non-linear relation with gait speed ($r=0.45$, $p<0.001$; see Figure 6-1). However, there is a significant variation between subjects for the GPS vs. speed. Once part of this between-subject variability is removed by computing only the change of GPS for each subject at different speeds in relation to the GPS at the comfortable speed (ΔGPS), the non-linear relationship between speed and GPS is more pronounced ($r=0.79$, $p<0.001$). When we employ the prediction method to adjust the reference data for the difference in speed, the effect of speed is mitigated for both the GPS^v and ΔGPS^v (see Figure 6-1).

Table 6-1. Comfortable speed (m/s) of each subject in the Control and Post-stroke groups.

# subject	Control	Post-stroke
1	1.01	1.02
2	1.20	1.27
3	1.33	0.39
4	1.45	0.70
5	1.44	0.55
6	1.10	0.65
7	1.10	1.19
8	1.30	0.51
9	0.98	0.65
10	1.28	0.68
11	1.41	1.11
12	1.33	0.62
13	1.19	0.58
14	0.91	0.98
15	1.27	1.03
16	-	0.71

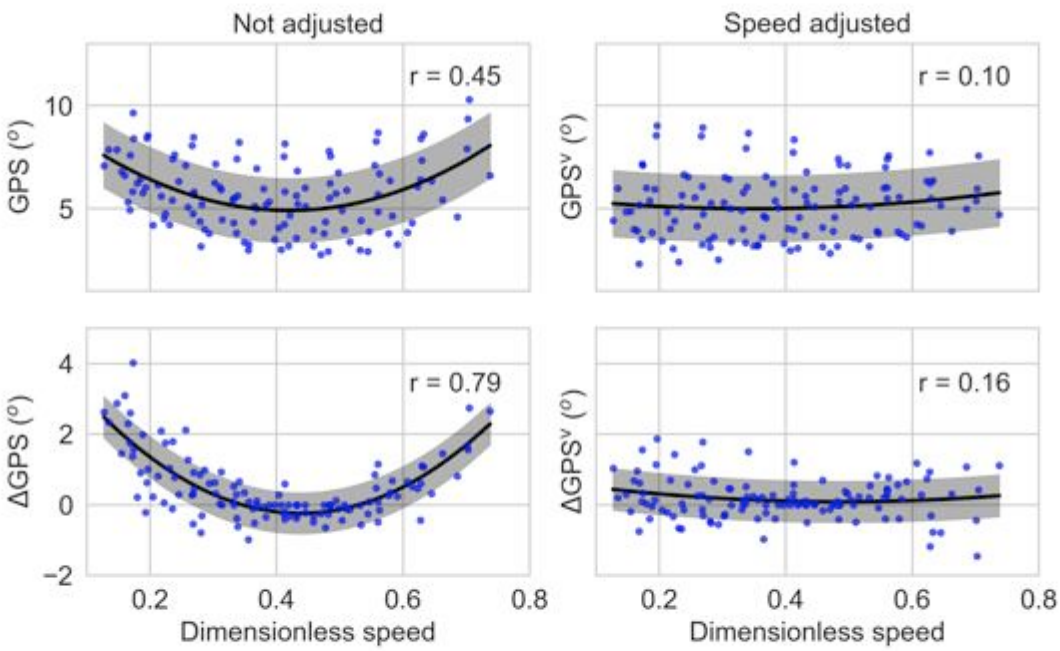

Figure 6-1 GPS (top graphs) and the change in the GPS in relation to its value at the comfortable speed (ΔGPS, bottom graphs) for the not adjusted (GPS, left graphs) and speed adjusted (GPS^v, right graphs) versus dimensionless speed for all participants and gait speeds in the control group. Also shown are 1) the least-square fit by a parabola (tick line), 2) the 68% prediction interval (shaded area), and 3) the adjusted coefficient of correlation for the fit (r).

On average, the post-stroke group walked at a comfortable gait dimensionless speed slower than the control group (stroke: 0.28±0.09, control: 0.42±0.06; d=1.86, p<0.001). For example, Figure 6-2 shows plots of the knee flexion angle for the gait cycle of a post-stroke participant compared with the same variable from the experimental reference data at the comfortable speed and the predicted speed-dependence variable for this post-stroke participant. Table 6-2 shows the average gait variable score (GVS and GVS^v) across subjects of each group (plots with the individual values per subject can be found in the supplementary material to this article). When comparing the post-stroke with the control subjects as a whole, none of the differences between the GVS and GVS^v values were statistically significant, nor were the overall differences between the GPS and GPS^v values (GPS: 8.0±3.1°, GPS^v: 7.7±3.2°; d=0.10, p=0.774). However, a negative correlation between the absolute difference in the GPS and GPS^v values for the participants of the post-stroke group and the gait speed was observed (ρ=−0.63, p=0.009, see Figure 6-3).

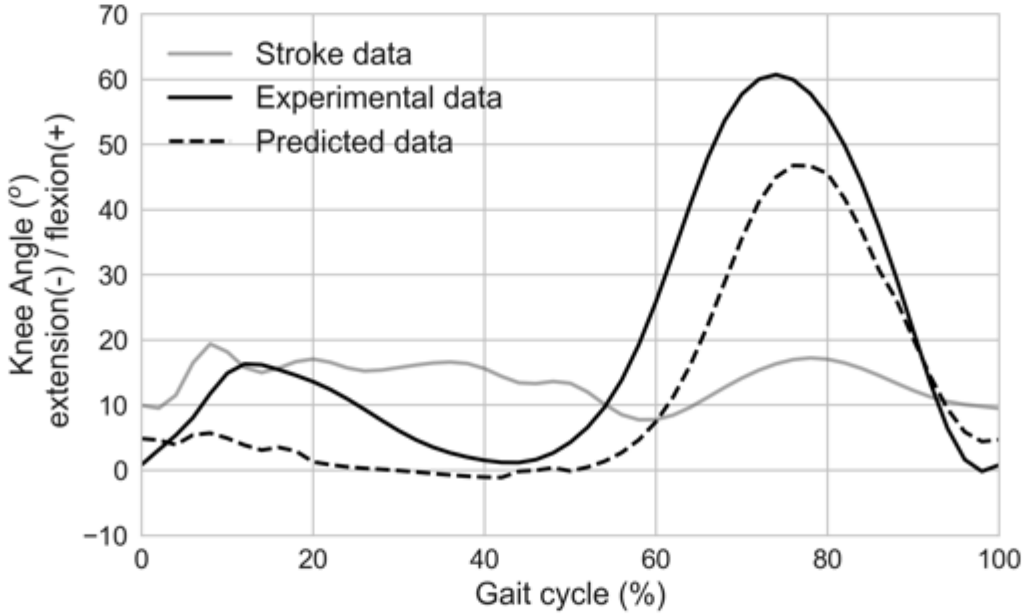

Figure 6-2 Example of the variable knee flexion angle for the post-stroke participant with the slowest gait speed (Stroke data: v= 0.13, grey line) compared with the data from the database at the comfortable speed (Experimental data: v = 0.42, solid line) and the data after the speed-dependent prediction (Predicted data: v = 0.13, dashed line). The GVS and GVS^{v} for this variable are then calculated based on the RMS difference between the two corresponding curves.

Table 6-2. Mean (±1 SD) across subjects of the GVS and GVS^v values for the right and left sides and the corresponding effect size (*d*) and *p*-value for the statistical test.

Variable [°]	**Right side**			**Left side**		
	GVS	**GVS^v**	***d, p***	**GVS**	**GVS^v**	***d, p***
Pelvic tilt	-	-	-	5.2±3.4	5.1±3.2	0.04, 0.910
Pelvic obliquity	-	-	-	3.2±1.4	2.8±1.4	0.30, 0.133
Pelvic rotation	-	-	-	5.4±5.0	5.6±4.8	-0.03, 0.346
Hip flexion	10.1±5.6	9.0±5.3	0.20, 0.255	8.0±3.8	7.6±3.9	0.10, 0.771
Hip adduction	6.4±2.7	4.9±2.5	0.56, 0.127	3.8±1.6	3.7±1.7	0.02, 0.492
Hip rotation	8.4±7.8	8.6±8.1	-0.02, 0.462	8.3±4.1	8.0±4.6	0.07, 0.855
Knee flexion	7.6±3.4	7.3±3.6	0.08, 0.827	10.2±5.0	9.6±4.3	0.12, 0.731
Ankle dorsiflexion	5.3±3.5	5.1±3.4	0.05, 0.433	5.6±2.2	4.8±2.7	0.30, 0.068
Foot progression	7.3±7.1	7.5±7.0	-0.02, 0.418	9.6±6.8	9.6±6.9	0.01, 0.492

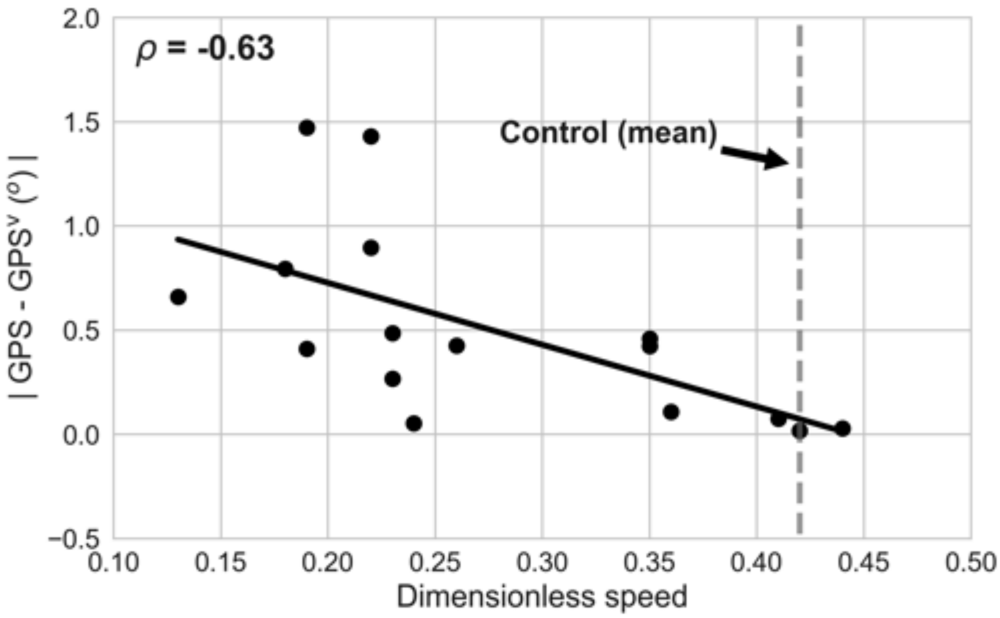

Figure 6-3 Absolute difference between the GPS and GPS^v values versus the dimensionless speed for all participants in the post-stroke group. The vertical dashed line represents the mean gait speed of the control group.

Figure 6-4 shows the Movement Analysis Profile for the post-stroke participant with the largest absolute difference between the two techniques (v=0.19 dimensionless gait speed). The greatest difference for this participant between the GVS and GVS^v values was for the left knee angle (5.1°), and on average across all variables, the absolute difference between the GPS and GPS^v values was 1.5°.

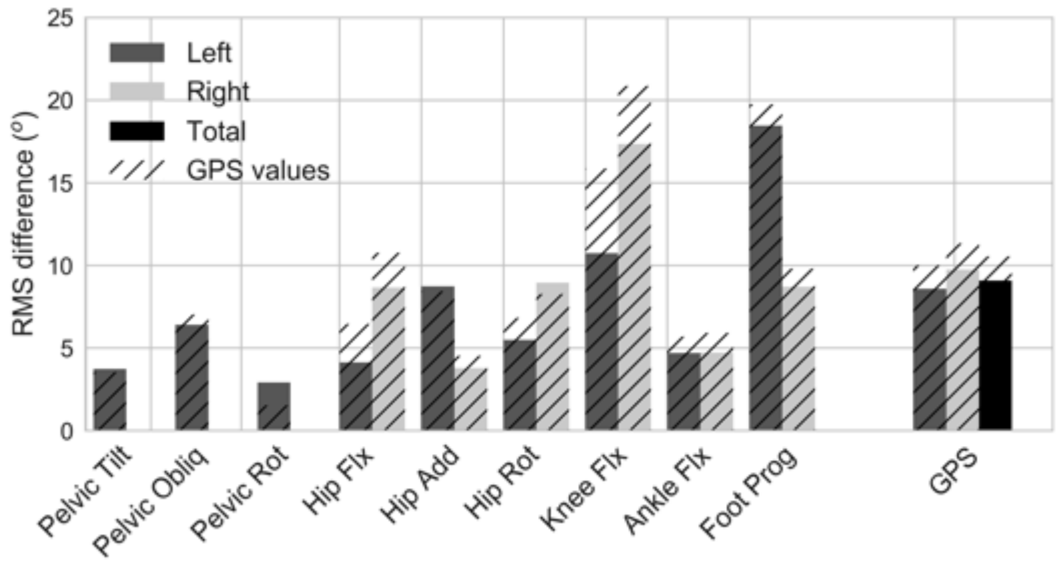

Figure 6-4 The Movement Analysis Profile for the post-stroke participant with the greatest absolute difference between GPS and GPS^v values (0.19 dimensionless speed). GPS^v values for the left, right, and total scores are shown as dark grey bars, light grey bars, and black bars, respectively, and GPS values are presented as dashed bars.

6.5 Discussion

The purpose of this study was to investigate the effect of gait speed on the GPS of post-stroke individuals who tend to walk slower than typical able-bodied subjects, employing a technique for predicting the gait patterns of the able-bodied subjects at the similar speeds of the post-stroke individuals for the comparison. The method for the prediction of gait patterns at a specific speed was successfully tested in controlled conditions with able-bodied subjects walking at different speeds (19).

The relationship between gait speed and the GPS index for the control-group subjects, where each one walked at different speeds ranging from very slow to very fast, is nonlinear, and a concave-upward parabola with a minimal GPS value captured it at the subject's comfortable speed. Such nonlinear dependence hasn't been described before and serves as an awareness for the application of linear methods to investigate the relationship between gait speed and biomechanical variables.

The GPS index has been widely used as a measure of the overall gait pattern. It has been applied to different clinical conditions (1,5,6,23–26) including post-stroke individuals (27). However, they were either studies comparing the walking pattern of pathological individuals with healthy controls walking at their self-selected comfortable speed (1,5,6,23,24) or assessing the reliability of GPS (27). Given that pathological individuals tend to walk slower than healthy people, the results of these studies may be biased since it is not possible to determine whether the differences were due to gait impairment or only because of gait speed differences. In the present study, individuals in the post-stroke group walked slower than healthy controls. Previous studies have reported a slower gait speed in post-stroke individuals compared with healthy ones, but the comfortable walking speed of the post-stroke individuals in the present study was 0.80 m/s (range: 0.39 – 1.27 m/s), which was more extensive than reported in other studies for individuals with a similar clinical condition: on average, 0.44 m/s and 0.56 m/s (12,13). The larger comfortable speed of the post-stroke individuals investigated here is likely because individuals in the present study had their stroke episodes a longer time ago (on average 76.8 months) than the individuals of those studies (median of 31 days (12) and mean of 36.4 months (13)).

We hypothesized that the proposed GPS^v would be less affected by the difference in gait speeds between groups than the standard GPS. Overall, the difference between the GPS and GPS^v across the post-stroke individuals was small (0.50° on average, range from 0.02° to 1.43°) and not statistically significant, contrary to our hypothesis. However, a subject-by-subject analysis revealed that the participants of the post-stroke group were very heterogeneous regarding their comfortable speed; some of them even presented similar speeds to the control group.

There was also a significant negative linear relationship between the absolute difference of the GPS and GPS^v values for the participants of the post-stroke group with gait speed (Figure 6-3, ρ=−0.63, p=0.009). A similar relationship was observed for the individuals in the control group at both ranges of slower and faster speeds than the comfortable speed (Figure 6-8, Supplemental material). This indicated that a greater difference between the speeds and the normative database resulted in a greater difference between the GPS and GPS^v values, which is in agreement with our hypothesis. For instance, the differences between GPS and GPS^v for the individuals in the post-stroke group with the slowest speeds ranged between 0.4° and 1.47° (see the Movement Analysis Profile in Figure 6-4 for the post-stroke individual with one of the slowest gait speeds, v=0.19 dimensionless speed or 0.55 m/s, with a difference of about 1.4°). If we consider that a previous study reported a minimal clinically important difference (MCID) for the GPS of 1.6° (1), a variance between GPS and GPS^v around 1° could be enough to alter the interpretation of an individual's gait pattern based solely on the GPS result. However, bear in mind that for such individuals walking so slowly, their GPS would already be very high (the slowest post-stroke individuals in our study presented a GPS around 10º; see the supplemental material), and a difference around 1° would likely have a non-significant impact on the interpretation of the gait evaluation. The computation of both GPS and GPS^v might also be useful to understand how the gait patterns of individuals with gait abnormality might be differently affected by speed. In Figure 6-3, the plot of the absolute difference between GPS and GPS^v versus gait speed, the two subjects at speed ~ 0.2 presented the largest deviations from the regression line and their distinct GPS and GPS^v values are shown in Figure 6-7 of the supplementary material (third and fifth subjects at that plot). Note that for those two subjects, the alterations in their gait patterns were more affected by speed than for the other individuals because when the correction for speed was introduced, their GPS^v dropped relatively more than for the other individuals. So, looking at both GPS and GPS^v values, one can infer which individuals have their gait patterns more affected by speed; this information might be useful in the rehabilitation process.

There were limitations in this study that need to be acknowledged. Despite the advantages of the GPS compared with other gait indices, the application of other methods such as GDI and GGI were not considered in the present study. Additionally, as only older adults were analyzed, the results of the present study are applicable particularly to this age group. Moreover, due to the higher variability of the walking speed among our participants, it seems thus necessary to consider a larger sample size to conclusively demonstrate the usefulness of such method in the clinical context.

In conclusion, a modified version of the GPS, the Gait Profile Score velocity (GPS^V), is effective in reducing the impact of gait speed on GPS; however, the observed difference between the two methods is only around 1° for the slowest individuals in comparison to the reference dataset. As the MCID for the GPS is 1.6 °, a difference of 1° might be enough to alter the understanding of the gait pattern. Therefore, the influence of gait speed should also be accounted for prior to interpretation of the GPS result.

6.6 References

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6.7 Supplementary material

Figure 6-5 shows plots of the gait variables employed to compute GPS averaged across subjects of the control group at the comfortable speed walking overground, on the treadmill, and of the resultant data after the hybrid procedure to adjust the data as described in the Methods. Overall, the difference between the overground with treadmill-overground data (RMSE = 1.5±0.7°) was smaller than the difference between the overground and treadmill data (RMSE = 2.3±0.8°), d = 0.54, p = 0.034.

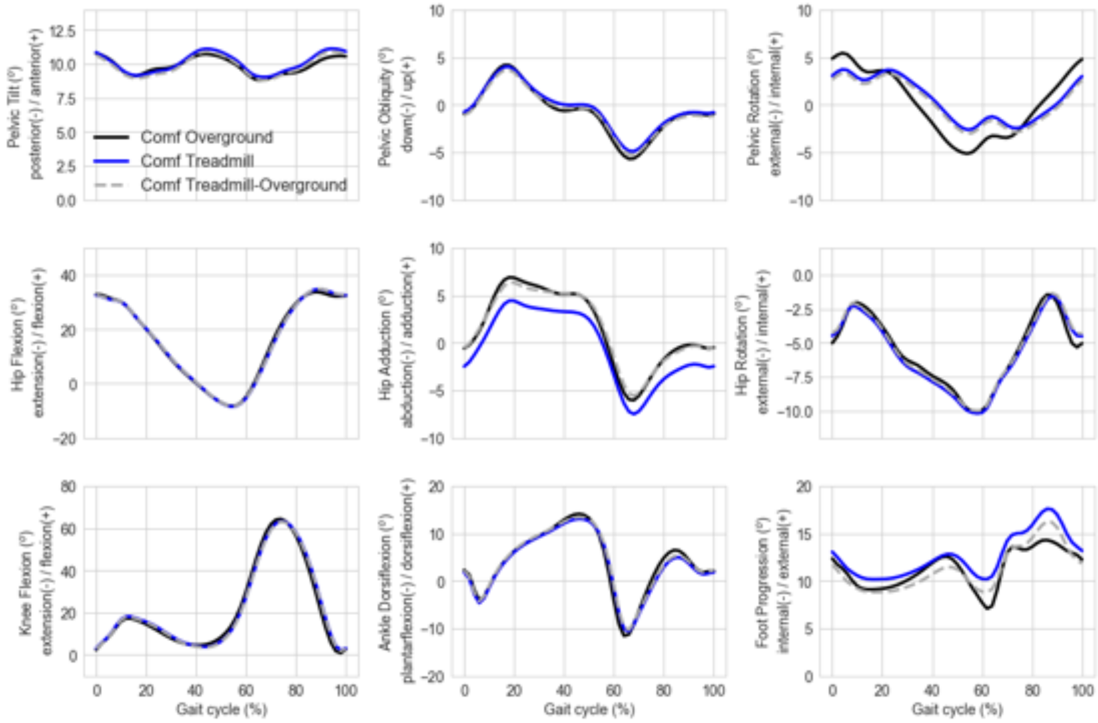

Figure 6-5 Average patterns across all participants of the control group for each of the gait variables at the comfortable speed of the overground data, treadmill data, and treadmill-overground data.

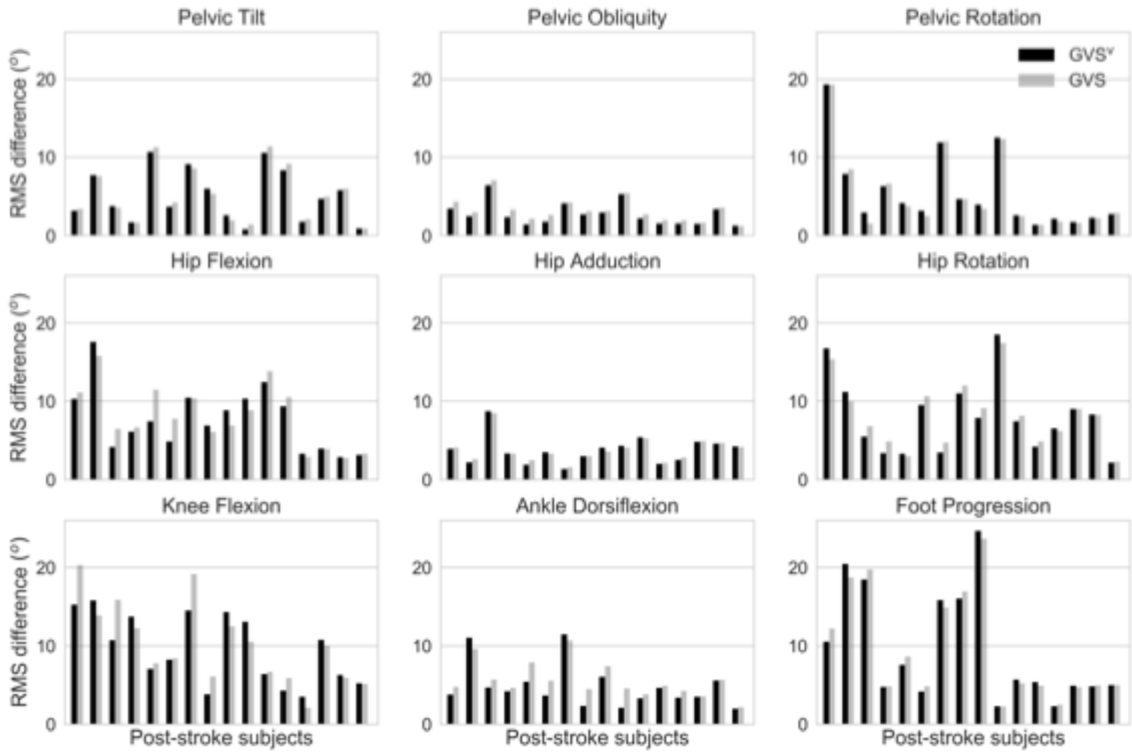

Figure 6-6 GVS^v and GVS values for each gait variable corresponding to each post-stroke subject from the slowest to the fastest gait speed.

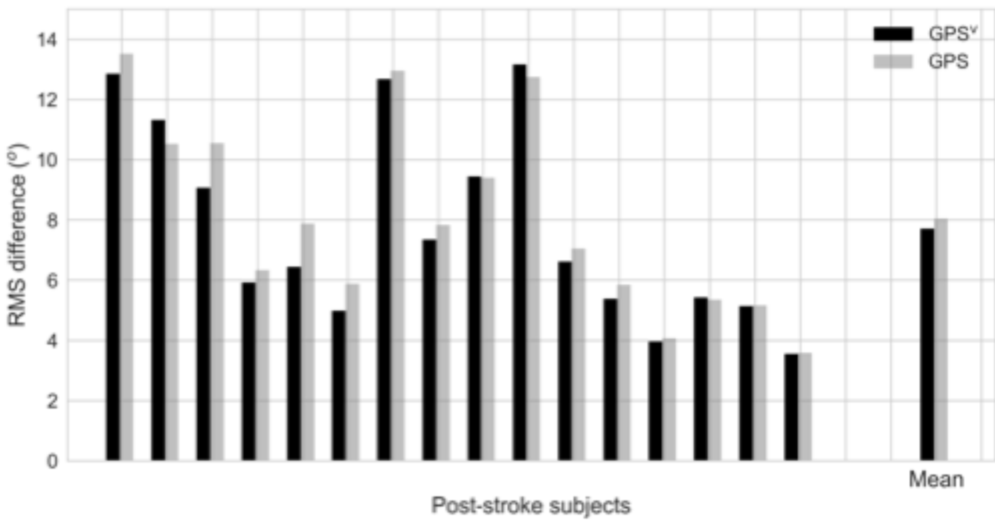

Figure 6-7 GPS^v and GPS values corresponding to each post-stroke subject from the slowest to the fastest gait speed and the mean value across all subjects.

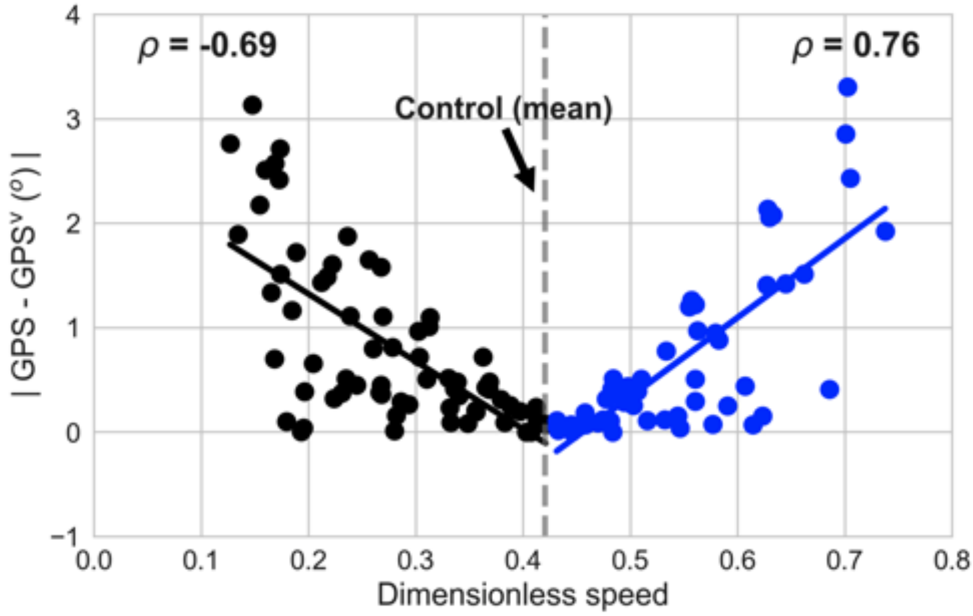

Figure 6-8 Absolute difference between the GPS and GPS^v values versus the dimensionless speed for all participants and gait speeds in the control group. The vertical dashed line represents the mean gait speed.

Chapter 7. Applying the prediction method to calculate the minimum and maximum values

Submitted as:

Test of two prediction methods for minimum and maximum values of gait kinematics and kinetics data over a range of speeds

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Gait & Posture (Short Communication)

Student contributions:

In this study, the student conceived and designed the experiments, analyzed the data, prepared figures and/or tables, wrote the paper, reviewed drafts of the paper, approved the final draft.

Abbreviations:

R^2: coefficient of determination; RMSE: root mean square error; $X^2_{red:}$ reduced chi-squared

7.1 Abstract

Background. Minimum and maximum values of gait kinematics and kinetics data are commonly used to quantitatively describe a walking pattern.

Research question. The purposes of this study were to determine the effect of speed on the minimum and maximum values of gait kinematics and kinetics variables and to test two prediction methods for the estimation of these minimum and maximum values at different gait speeds.

Methods. An open dataset with the data of 24 healthy adults (age: 27.6±4.4 years, height: 171.1±10.5 cm, body mass: 68.4±12.2 kg) walking on a treadmill at eight gait speeds was employed in this study. The minimum and maximum angles and moments of the hip, knee, and ankle joints were extracted from speed-dependent prediction curves solely for the minimum and maximum values (PEAK method) and from speed-dependent prediction curves for the entire gait cycle (CYCLE method). The overall error, computed as the root-mean-square error (RMSE), for the minimum and maximum values predicted by these two methods were compared with the experimental true values.

Results. The RMSEs for the joint angles were PEAK: 0.31±0.23°, CYCLE: 0.46±0.28 and for the joint moments were PEAK: 0.008±0.005 Nm/kg, CYCLE: 0.013±0.008 Nm/kg. There were no statistically significant differences between these values and the experimental true values.

Significance. The two prediction methods tested can be used to estimate the minimum and maximum values of biomechanical gait variables at a certain speed.

Keywords: walking speed, prediction methods, peak value, kinematics, kinetics

7.2 Introduction

In gait analysis, it is common to compare individuals walking at different speeds, e.g., (1-2). Since speed itself affects biomechanical gait variables (3-5), isolating the effect of pathology or aging from the gait speed when comparing the gait patterns between different populations is problematic. A solution is to employ prediction methods for estimating joint kinematics and kinetics variables (6-9) or gait indices (10) of normative gait data at any given speed. The general approach of these methods is to acquire experimental data at different gait speeds and then adjust regression models to the gait data versus speed to determine prediction equations with speed as the predictor variable.

Minimum and maximum values of gait variables are commonly used to quantify them, and there are at least two methods to predict these values at a given speed. In one method (7-8), hereafter referred to as the PEAK method, regression equations are adjusted directly to only the experimental minimum and maximum values of the gait data versus speed. However, these equations are only suitable for predicting the minimum and maximum values of a single desired speed. In a second method (9), hereafter referred to as the CYCLE method, regression equations are adjusted to the entire gait cycle versus speed (e.g., an equation at every 1% of the cycle for a given gait variable), and then the minimum and maximum values of this predicted gait cycle can be found. Although the CYCLE method might be more advantageous because it can predict data for the entire gait cycle, it might be less accurate than the PEAK method if one is only interested in the minimum and maximum values. Therefore, the goals of this study were to investigate the effect of gait speed on biomechanical variables and to test two prediction methods for the minimum and maximum values of gait patterns at different speeds.

7.3 Methods

The rationale is to use the normative reference data of healthy subjects with actual experimental data acquired at different gait speeds to test the prediction equations against these true values. For such, we used an open dataset (11) with the gait data of 24 healthy adults walking at different speeds (age: 27.6±4.4 years, height: 171.1±10.5 cm, body mass: 68.4±12.2 kg). These data were collected performing a standard three-dimensional gait analysis, where the subjects walked barefoot on a treadmill at eight different gait speeds as a percentage of her/his comfortable speed: 40%, 55%, 70%, 85%, 100%, 115%, 130%, and 145% (V1–V8), with gait speeds adjusted based on the dimensionless speed (the square root of the Froude number).

The joint angles and joint moments data at the sagittal plane of the hip, knee, and ankle joints of each gait cycle (from one right heel strike to the subsequent) were normalized to 0–100% with a step of 1%. At each gait speed, an average across the gait cycle trials was calculated for each subject and each biomechanical variable, and then the mean pattern across subjects and a 95% confidence interval (95% CI) for the mean were calculated. For each variable, the minimum and maximum values were detected at the same specific phases of the gait cycle utilized by LELAS and collaborators (7). These values will be considered as the true experimental minimum and maximum values of the dataset (see Figure 7.1), for which we will derive prediction equations based on the two methods, PEAK and CYCLE.

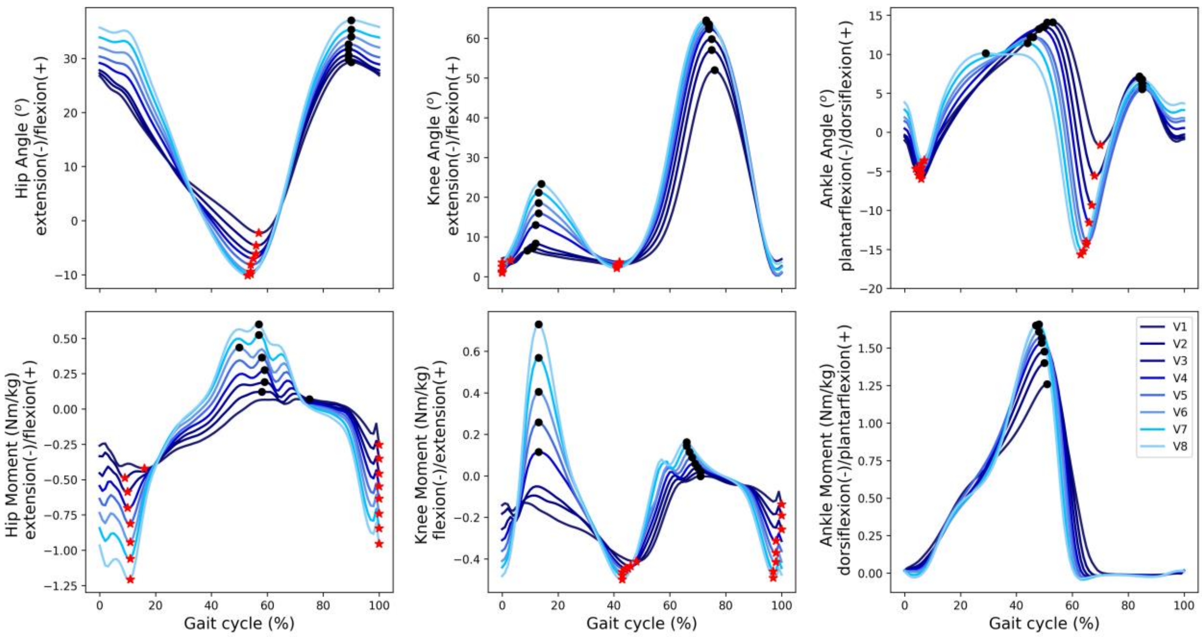

Figure 7-1Average patterns across subjects for the joint angles (top) and joint moments (bottom) of the experimental data and the minimum (*) and maximum (•) values at the eight gait speeds (V1–V8).

For the PEAK method, second-order polynomials were adjusted to the minimum and maximum experimental true values versus speed to directly obtain regression equations for the minimum and maximum values. For the CYCLE method, second-order polynomials were adjusted to every 1% of the experimental gait cycle data versus speed to obtain prediction curves for the entire gait cycle (for more details, see (9)), and minimum and maximum values at a desired speed were found for these predicted data. The second-order polynomial was adjusted by least squares, and its goodness of fit was verified with the adjusted coefficient of determination (R^2_{adj}), the reduced chi-squared (χ^2_{red}), and by examining the distribution of the residuals for the PEAK method.

For comparison with the literature, the minimum and maximum values will also be predicted with the equations presented in (7), hereafter referred to as LELAS equations.

The overall error of the predictions for the minimum and maximum values using the PEAK and CYCLE methods and LELAS equations across all gait speeds was computed as the RMSE between the experimental true values and the corresponding predicted values. A statistical difference ($p<0.05$) between the values using the PEAK and CYCLE methods and LELAS equations at each gait speed (V1–V8) was ascertained when these predicted values were outside the 95% CI for the mean of the corresponding experimental true values.

7.4 Results

The data for the experimental true minimum and maximum values of the joint angles and moments versus gait speed and the regressions to these data are plotted in Figure 2, and the corresponding statistics are shown in Table 7.1.

With the exception of the ankle dorsiflexion swing and plantarflexion loading response angles, all regressions for the PEAK and CYCLE methods resulted in high values for the R^2_{adj} and low values of $\square^2_{red}$. The mean-across-variables RMSE for the joint angles were PEAK: 0.31±0.23°, CYCLE: 0.46±0.28, LELAS: 2.95±1.84°, and for the joint moments were PEAK: 0.008±0.005 Nm/kg, CYCLE: 0.013±0.008 Nm/kg, LELAS: 0.148±0.146 Nm/kg. There were no statistically significant differences between the experimental true values and the predicted values using the PEAK and CYCLE methods, but for most variables, the experimental true values were significantly different from the values predicted with the LELAS equations (see Figure 7.2).

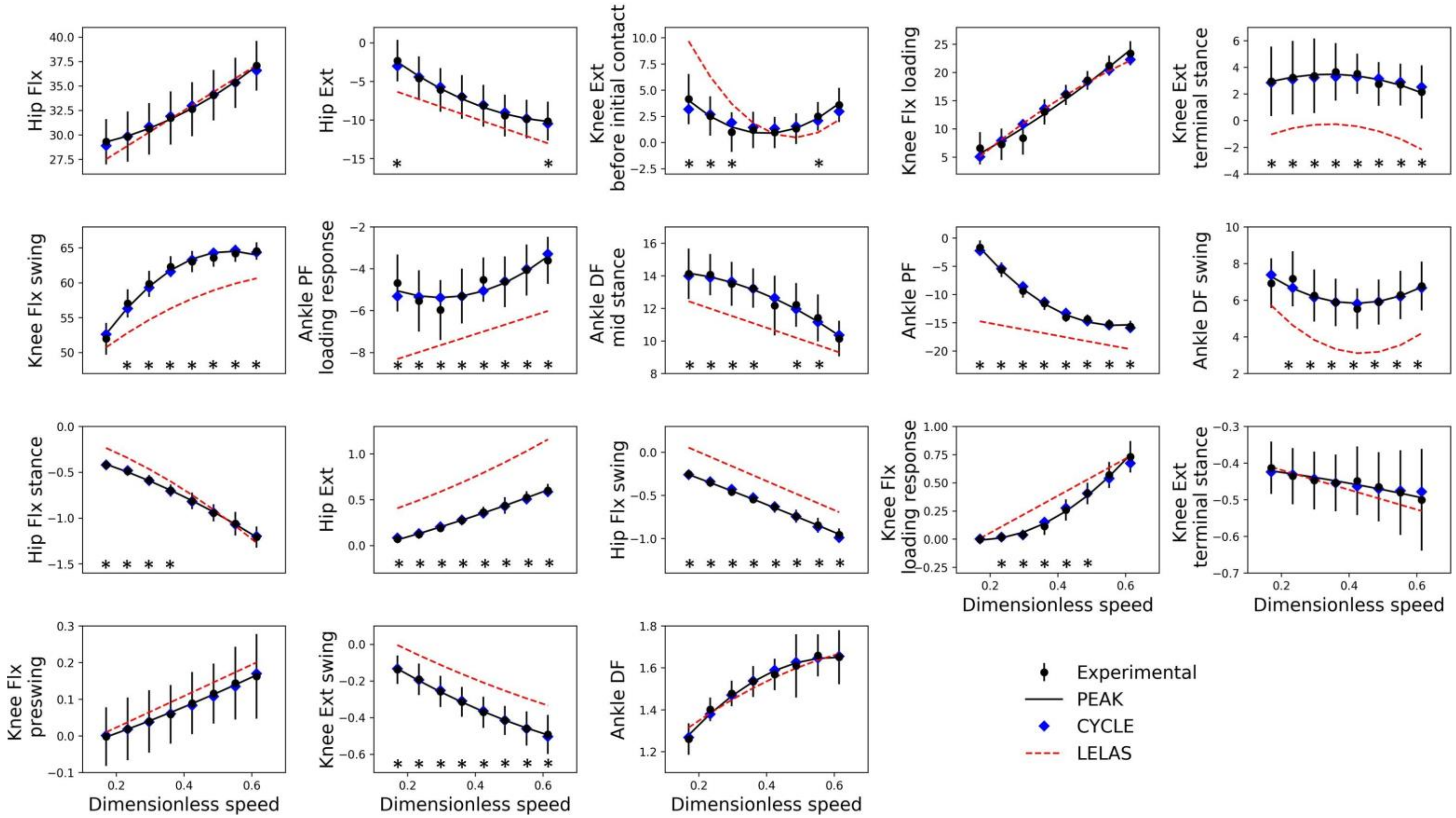

Figure 7-2 Minimum and maximum values averaged across subjects of the experimental (□) hip, knee, and ankle joint angles (in o, first two rows) and joint moments (in Nm/kg, third and fourth rows) versus the dimensionless gait speed. The vertical bars indicate the 95% CI for each of these values. For each variable, the curves represent the quadratic regression to these values using the PEAK method (solid line) and the LELAS equations (dashed line). The corresponding values predicted by the CYCLE method are also shown (◆). Statistically significant differences between experimental true values and the values predicted with LELAS equations are marked with an asterisk.

Table 7-1. Coefficients [β_0, β_1, β_2] for the quadratic regressions ($y=\beta_0 v^2+\beta_1 v+\beta_2$) to the experimental minimum and maximum values of the hip, knee, and ankle joint angles and moments as function of gait speed (in the dimensionless unit) using the PEAK prediction method (see Figure 7.2). Also shown, the χ^2_{red} and R^2_{adj} goodness-of-fit metrics and the RMSE between the experimental values and the predicted values using the PEAK and CYCLE methods and LELAS equations.

Variable	PEAK coefficients [β_0, β_1, β_2]	χ^2_{red}	R^2_{adj}	PEAK RMSE	CYCLE RMSE	LELAS RMSE
Joint angles (°)						
Hip Flexion	[20.581, 1.290, 28.448]	0.010	0.999	0.078	0.279	0.769
Hip Extension	[30.497, -41.238, 3.620]	0.058	0.992	0.191	0.344	2.583
Knee Extension before initial contact	[61.001, -48.500, 10,491]	0.076	0.950	0.217	0.571	2.688
Knee Flexion loading response	[17.934, 27.325, 0.421]	1.180	0.972	0.859	1.168	1.249
Knee Extension terminal stance	[-18.598, 12.698, 1.310]	0.037	0.853	0.151	0.265	3.914
Knee Flexion swing	[-88.269, 94.703, 39.104]	0.472	0.975	0.543	0.564	4.550
Ankle Plantarflexion loading response	[19.603, -11,685, -3.640]	0.178	0.708	0.334	0.385	2.436
Ankle Dorsiflexion mid stance	[-13.150, 1.695, 14.246]	0.076	0.961	0.218	0.243	1.792
Ankle Plantarflexion	[84.504, -96.985, 12.309]	0.141	0.995	0.296	0.475	7.094
Ankle Dorsiflexion swing	[23.294, -19.571, 9.934]	0.102	0.688	0.252	0.265	2.443
Joint moments (Nm/kg)						
Hip Flexion stance	[-1.176, -0.865, -0.233]	0.000	0.999	0.007	0.006	0.106
Hip Extension	[0.381, 0.927, -0.108]	0.000	0.997	0.008	0.012	0.440
Hip Flexion swing	[-0.207, -1.394, -0.016]	0.000	0.999	0.005	0.019	0.278
Knee Flexion loading response	[3.661, -1.166, 0.083]	0.000	0.994	0.017	0.027	0.126
Knee Extension terminal stance	[-0.087, -0.097, -0.403]	0.000	0.894	0.007	0.011	0.023
Knee Flexion preswing	[0.114, 0.291, -0.056]	0.000	0.996	0.003	0.006	0.028
Knee Extension swing	[0.563, -1,255, 0.063]	0.000	0.999	0.004	0.006	0.152
Ankle Dorsiflexion	[-1.981, 2.388, 0.930]	0.000	0.981	0.015	0.014	0.028

7.5 Discussion

We observed that speed affected the minimum and maximum values of the joint angles and moments, and this effect was nonlinear at the range of speeds investigated. Previous studies (6, 7, 12) have also reported such an effect of speed, but, qualitatively, those reports described a more linear relationship between gait speed and biomechanical variables during gait than observed here.

The values predicted by the PEAK and CYCLE methods agreed with the experimental true values for all the biomechanical variables, but overall, the error of the PEAK method in predicting the true values was lower than that of the CYCLE method. The fundamental difference between these two methods is that the PEAK method is based on always fitting the experimental true minimum and maximum values of the data. In contrast, because the CYCLE method is based on fitting data at certain percentages of the experimental data, likely the minimum and maximum values at different speeds will not coincide at the same percentage of the gait cycle.

The regression equations presented here can be readily used by anyone interested in predicting the minimum and maximum values of the joint angles and moments for reference data of healthy adults walking at any desired speed from 0.39 to 2.20 m/s; bear in mind that the independent variable for these equations, gait speed, should be specified as dimensionless speed (Froude number). Given the smaller errors in the prediction, if one is only interested in the minimum and maximum values, the regression equations based on the PEAK method is indicated.

The observed minimum and maximum values for most of the biomechanical variables investigated in this study are significantly different from the values predicted by LELAS equations (7). Possible factors that might explain such a discrepancy are different surface conditions (treadmill *vs.* overground) and different data collection protocols between laboratories. This question deserves to be investigated in more detail because it may hamper the use of prediction equations for comparison to the gait data of a subject evaluated in a different laboratory.

7.6 References

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Chapter 8. General discussion and overall conclusion

8.1 Summary and future directions

The overarching goal of this thesis was to investigate the effects of speed on the gait patterns of young and older healthy individuals. Three independent studies were conducted to address research questions related to the main goal. As follows, I present the objective of each study as well as a summary of their findings.

8.1.1 To examine the available evidence regarding the effects of walking speed on gait biomechanics variables of young and older adults;

A systematic review and meta-analysis were conducted to understand the effects of gait speed on biomechanical variables. In total, 19 articles that addressed the inclusion criteria were considered in the review. We found that gait speed affects spatiotemporal parameters, joint kinematics, joint kinetics, and ground reaction forces. In general, faster gait speed increased the values of these biomechanical variables whereas the opposite effects were observed at slower speeds. These results thus indicate that gait speed should be considered, as a covariate, when comparing the gait analysis of pathological individuals with normal or control ones.

8.1.2 To create a public dataset of walking biomechanics of young and older adults in different gait speeds;

A public dataset of kinematics, kinetics and ground reaction forces data of 42 healthy individuals (young and older adults) walking at eight different gait speeds on both treadmill and overground surfaces was created. This dataset is available in a public repository along with exemplary scripts and biomechanical model templates. We thus anticipate several applications of this dataset such as to examine the influences of speed, age, and environment (overground vs. treadmill) on gait biomechanics, to meet educational needs, and, with the inclusion of additional participants, to use as a reference dataset.

8.1.3 To investigate the influence of gait speed on Gait Profile Score and on the joint kinematic and kinetic peak values;

Since the outcomes of the systematic review and the public dataset studies indicated that speed affects gait biomechanical variables, its influence should thus be accounted when comparing walking patterns across different populations (e.g. young vs. older individuals). Hence, to address this issue, a prediction method was developed to offer a speed-adjusted gait pattern of healthy individuals. This prediction method was then validated and showed good agreement for joint angles and moments. After the validation in able-bodied subjects, this prediction method was then applied to compare speed effects on gait patterns of healthy and post-stroke individuals using a composite score, the Gait Profile Score. We could conclude from the results of this study that the modified version of the GPS, the GPS^{v} that considered the speed-effects, was effective in reducing the impact of gait speed. Following this study, the same prediction method was then employed to predict the peak and valley values of gait kinematics and kinetics. The prediction method named CYCLE (considered the gait cycle) was then compared with the prediction method previously reported in the literature, PEAK, that was based solely on the peak values. With the exception of the ankle dorsiflexion swing and plantarflexion loading response angles, all regressions for the PEAK and CYCLE methods resulted in high values for the R^2_{adj} and low values of χ^2_{red}.

8.2 Future directions

The outcomes of the present thesis contributed to enhance the understanding about the effect of gait speed on walking biomechanical patterns. This knowledge was applied to improve and further test a gait composite score (Gait Profile Score) widely used in the literature. While the present results helped to advance knowledge in the field, there are issues that remain poorly understood and need to be addressed in future studies.

For example, the muscle contributions to accelerate the body during gait and thus, change gait speed and how the muscle coordination to perform gait is affected by pathologies remain poorly understood. The forward dynamics approach may help to enhance the knowledge about muscle function during gait since it is convenient because once you have established the model considering the subject-specific state and parameters data as well as experimental gait data, one is able to perform computer simulation of the movement and it is even possible to predict the gait pattern by changing some parameters in the model. The dataset of participants in this study may be used for this purpose because it comprises of gait biomechanics data of a variety of walking speeds.

The complexity, high-dimensionality, redundancy nature of gait analysis data has motivated the use of novel data analysis methods to address the nature of these data. GPS was developed to quantify the gait pattern in a single score based solely on kinematics variables. However, currently 3D gait analysis typically considers other sources of data such as kinetics, EMG, pressure distribution let alone the data that can be derived from these sources (i.e., the outcomes from forward or inverse dynamics approaches). Therefore, composite scores such as GPS may be considered too simple to tackle the complex nature of gait biomechanics data. Therefore, there might be a need for more robust data analysis approaches such as advanced multivariate analysis and machine learning techniques.

Chapter 9. References

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Chapter 10. Appendices

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PARECER CONSUBSTANCIADO DO CEP

DADOS DO PROJETO DE PESQUISA

Título da Pesquisa: Avaliação da postura e do movimento humano no laboratório de biomecânica.
Pesquisador: Reginaldo Kisho Fukuchi
Área Temática:
Versão: 1
CAAE: 53063315.7.0000.5594
Instituição Proponente: FUNDACAO UNIVERSIDADE FEDERAL DO ABC - UFABC
Patrocinador Principal: MINISTERIO DA CIENCIA, TECNOLOGIA E INOVACAO

DADOS DO PARECER

Número do Parecer: 1.417.054

Apresentação do Projeto:
Neste projeto, os pesquisadores apresentam um estudo que tem como objetivo caracterizar as características biomecânicas ao desempenhar algumas atividades motoras comuns: andar/correr, manter postura ereta, pular e agachar. As atividades seriam realizadas por um número bastante grande (500) de voluntários de diferentes grupos: jovens e idosos saudáveis, além de jovens e idosos com lesão musculo-esquelético. Durante estas atividades, serão registrados parâmetros de força, o padrão de movimento como registrado através de um sistema de captação por câmera, e com eletrodos de eletromiografia telemétrica. O objetivo dos pesquisadores é compor um banco de dados com a tipificação biomecânica destas atividades para acesso futuro.

Objetivo da Pesquisa:
O projeto tem como objetivo fornecer uma base de dados com parâmetros caracterizando o movimento durante o exercício de atividades motoras comuns, para servir como banco de consulta e referência para pesquisadores em momento futuro.

Avaliação dos Riscos e Benefícios:
O risco, no protocolo submetido ao Plataforma Brasil, está sucintemente descrito como 'mínimo', sendo não são invasivos. Os riscos são gerenciados através da avaliação clínica por uma fisioterapeuta. As condições físicas dos voluntários que terão correr como atividade, serão

atestadas com um exame ergométrico prévio.

Comentários e Considerações sobre a Pesquisa:
A pesquisa é altamente relevante e, de ponto de vista ética, sem problemas significativos.

Considerações sobre os Termos de apresentação obrigatória:
O TCLE é redigido de forma adequada, com uma autorização separada e específica para a inclusão dos dados dos voluntários em um banco.

Recomendações:
Espera-se, em uma folha de rosto, que todos os campos relevantes sejam preenchidos. Falta o número de telefone do responsável pela instituição.

Sugere-se a substituição do termo 'tratamento na instituição' por 'atendimento na instituição', já que não se trate de um estudo clínico propriamente dito, e a instituição, neste caso, é a UFABC e não um hospital.

É sugerido que no TCLE o trecho:

"Os procedimentos experimentais não serão invasivos e não envolverão nenhum risco à saúde física e/ou mental."

seja substituído por:

"Os procedimentos experimentais não serão invasivos e os riscos envolvidos são mínimos."

Conclusões ou Pendências e Lista de Inadequações:
Não há deficiências no projeto ou na documentação que requerem uma ressubmissão.

O pesquisador se compromete a entregar relatórios de pesquisa semestrais para o acompanhamento do projeto. O primeiro relatório deverá ser entregue até o dia 01/09/2016.

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Os modelos e a forma de entrega do relatório serão disponibilizados no site cep.ufabc.edu.br

Considerações Finais a critério do CEP:

Este parecer foi elaborado baseado nos documentos abaixo relacionados:

Tipo Documento	Arquivo	Postagem	Autor	Situação
Informações Básicas do Projeto	PB_INFORMAÇÕES_BÁSICAS_DO_PROJETO_626536.pdf	08/12/2015 11:38:30		Aceito
Projeto Detalhado / Brochura Investigador	ProjetoPesquisa_v3.docx	08/12/2015 11:37:38	Reginaldo Kisho Fukuchi	Aceito
TCLE / Termos de Assentimento / Justificativa de Ausência	BMC_TCLE_v3.doc	08/12/2015 11:37:20	Reginaldo Kisho Fukuchi	Aceito
Folha de Rosto	FolhaDeRostoAssinada.pdf	08/12/2015 11:36:56	Reginaldo Kisho Fukuchi	Aceito

Situação do Parecer:
Aprovado

Necessita Apreciação da CONEP:
Não

SANTO ANDRE, 21 de Fevereiro de 2016

Assinado por:
Andre Mascioli Cravo
(Coordenador)

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