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Over the last 40 years, a new paradigm has been posited where the variability observed in physiological systems is a consequence of the interactions occurring between the various components that affect the system. While quantifying the magnitude of variability can be useful, analyses that measure how the structure of the variability (dynamics) changes over time have been posited to reflect the health of the system. Many researchers interpret the results of these analyses to be indicative of the system's adaptive capacity. While there is ample indirect evidence to support this notion, a lack of direct findings has left the literature lacking a definitive foundation to move forward with this interpretation. While many physiological systems are too invasive to safely perturb, the movement-based systems are routinely perturbed in real-world environments without dire consequences. Of particular interest is the locomotor system, which is constantly challenged in real-world environments via slips and trips. Furthermore, the locomotor system can be safely and validly perturbed in the laboratory. A range of locomotor dynamics-based measures have been used to describe differences between various clinical populations, but none have been directly associated with a person's ability to remain upright when perturbed. The objectives of this study are to (1) examine the relationship between locomotor dynamics/stability to overall fall-risk prior, (2) examine how locomotor dynamics relate to the ability to recover from a trip via global stability, and (3) determine the extent to which an acute trip-training session alters locomotor dynamics and global stability. Forty healthy, older adults (75.2±4.9 yrs) were recruited by

convenience from the local community. The participants completed a variety of clinical assessments in order to determine overall fall-risk. Afterwards, they participated in three walking trials consisting of: 1) a 15-minute unperturbed walking session, 2) a 10-minute unperturbed walking session (control) or a 10-minute trip-training session (intervention), and 3) a 15-minute unperturbed walking session. Various measurements of locomotor dynamics and adaptability were calculated from full-body 3-D kinematics collected at 100Hz. Multiple regression and repeated measure analysis of variance models were calculated to determine to what extent locomotor dynamics and adaptability relate to one another and how an acute trip-training session affects their relationship. The results from our first experiment suggested that locomotor dynamics and stability during steady state do not significantly relate to overall fall-risk. However, the second experiment showed that locomotor dynamics are predictive of an individual's ability to recover from a trip. Our last experiment showed the feasibility of using an acute trip-training session to alter locomotor dynamics and stability. These data represent the first direct evidence of physiological variability being indicative of adaptive capacity in the locomotor system. Further investigation will be necessary to determine the robustness of the analyses to indicate adaptive capacity across perturbations and populations.

AN INVESTIGATION INTO THE RELATIONSHIP BETWEEN LOCOMOTOR

DYNAMICS AND ADAPTABILITY

by

Brian Lawrence Cone

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CHAPTER I

INTRODUCTION

Statement of Problem

Variability has been observed within physiological systems for over 300 years (Billman, 2011). A majority of researchers viewed this as error resulting from external and internal stressors applied to the system. However, over the last four decades, a new paradigm for studying physiological variability has emerged which suggests that the underlying structure of variability represents the system's global health (Lipsitz & Goldberger, 1992; Mackey, Glass, & others, 1977; Stergiou & Decker, 2011). Using a dynamical systems theoretical framework, it has been revealed that physiological systems are inherently complex and nonlinear in nature. A variety of mathematical analyses have been developed since then to calculate how the structure of variability (system dynamics) change throughout the lifespan or due to pathology/injury (Bravi, Longtin, & Seely, 2011).

As the literature grew, various theoretical models were introduced to summarize how aging, pathology, and injury affects a system's dynamics. After several years of research on system dynamics, the 'loss of complexity hypothesis' was introduced that suggested as adults enter older adulthood, the complexity of their dynamics decreases (Lipsitz & Goldberger, 1992). While this is a prominent trend, several observations have revealed that certain tasks and populations do not hold true to this model (Duarte &

Sternad, 2008; Newell, 1998; Vaillancourt & Newell, 2002, 2003). In the years following, the 'loss of adaptability' and 'optimal movement variability' models were developed with a bidirectional consideration, suggesting that too little or too much complexity reflects a less adaptive system (Stergiou & Decker, 2011). These new models bridged the observations supporting the 'loss of complexity hypothesis', while also explaining the increased complexity observed in certain tasks and populations. With these conceptual frameworks in mind, researchers have generally interpreted the degree of complexity within system dynamics as indicative of its adaptive capacity—a reflection of the systems global health.

In order to directly study the adaptive capacity of a physiological system, an external or internal stressor must be applied to observe how the system recovers. This would require invasive testing of most physiological systems. However, movement-based systems afford the ability to perform non-invasive testing to probe adaptive capacity. Some direct evidence has been reported from the postural control system and suggests that an increase in complexity is associated with more adaptive behavior in upright stance (Cone, Goble, & Rhea, 2016; Manor et al., 2010). Due to the constraints of the postural control system, as well as the difficulty to validly perturb it, the locomotor system appears to be the ideal movement system to further observe the relationship between system dynamics and adaptability.

Locomotor dynamics have been suggested to reflect adaptive capacity in the context of global health, such as fall-risk (Hausdorff, 2007). However, there is currently a lack of direct evidence to suggest a significant association between an individual's locomotor dynamics and their ability to recover from an external stressor. Such an observation is of upmost important to demonstrate the validity of dynamical systems analyses. The locomotor system is an ideal system to test this due to the feasibility of reproducing real-world like perturbations in the laboratory. While both the dynamics and stability of the locomotor system have been suggested to be modifiable through acute interventions, no observations have been made on how they are altered from a trip-training session. Since tripping is suggested to be one of the most common causes of a fall, it is necessary to better understand how this method can enhance fall prevention programs. Finally, there is little evidence indicating how locomotor dynamics and stability are coupled. Further investigation is required to better understand how these two metrics relate in their ability to be altered.

Objectives and Hypotheses

The objectives of this study are to (1) examine the relationship between locomotor dynamics/stability to overall fall-risk prior to an acute trip-training session, (2) examine how locomotor dynamics relate to the ability to recover from a trip via global stability, and (3) determine the extent to which an acute trip-training session alters locomotor dynamics and global stability.

Hypothesis 1: There will be a significant association between locomotor dynamics/stability and overall fall-risk as calculated by a previously published method (Lajoie & Gallagher, 2004)

Hypothesis 2: Dynamical systems and stability measures of the locomotor system will significantly associate with the global stability of the locomotor system during recovery from a tripping perturbation.

Hypothesis 3: An acute trip-training session will significantly improve the dynamics and global stability of the locomotor system.

Limitations and Assumptions

1. The outcomes of this study are only be generalizable to the healthy, older adult population
2. The variety of shoes worn by the participants did not affect the measurements collected.
3. All participants' selected preferred walking speeds that are similar to when walking overground
4. The treadmill set up (belt and harness) did not alter the participants' walking or recovery patterns
5. All participants' head and eye orientation were directed forward as instructed by the lead investigator
6. All participants were not mentally prepare or otherwise constrain their body's natural response before or during perturbations
7. All perturbations were similar in magnitude and duration
8. The sampling frequency of the Qualisys Oqus system (Göthenburg, Sweden) at 100Hz was appropriate to track full-body 3-D kinematics, as well as uncover underlying dynamics and adaptability of the locomotor system.

9. A 40-marker-based 15-segment model appropriately described the body's base of support and center of mass position throughout all walking sessions.

Delimitations

1. Only healthy, older adults that are 70 years or older participated in this study.
2. All stride time, base of support, and center of mass-based events were identified automatically. False positives and negatives were either replaced, or manually removed when appropriate.

Operational Definitions

Healthy: No clinical diagnosis of any neuro-muscular-skeletal disease and no acute injury that would prevent participants from exhibiting normal movement behaviors; self-reported ability to walk for 15 consecutive minutes unaided on a treadmill at a self-selected pace.

Time Series: A consecutive series of data points collected on a measurement device.

Variability: The fluctuations observed throughout a time series that naturally occur during a physiological system's functioning

Dynamics: The various interactions that are occurring within a physiological system over multiple scales that are theorized to observe a physiological signal's structure of variability over time.

Complexity: The quality of dynamics observed through the structure of variability.

Center of mass: The mathematical representation of the mean position of all body segments.

Base of Support: The area of contact between the surfaces of the body (shoe) and the ground.

Stability: An object's ability to remain balanced when center of mass is close to a boundary of the base of support, as well as its ability to resist external forces.

Global Stability: An object's ability to maintain its center of mass within its base of support, as well as bring center of mass position back within the base of support when outside of boundaries.

Older: 70 years or older

Preferred Walking Speed: Self-selected pace on the treadmill that is described to be similar to when walking around a park.

Variables

Independent Variables

Age – Age was calculated in years from participants' birthday to the date of participation.

Sex – Sex was recorded for every participant.

Activities-Specific Balance Confidence Scale – Scores were recorded from 16 items on the questionnaire.

Simple Reaction Time – Scores were recorded by calculating the average over 30 trials.

Berg Balance Scale – Overall score was calculated from 14 balance tasks.

Strength – Three trials of hand-grip dynamometry were recorded on each hand. Higher average value will be taken as participants' overall strength.

Preferred Walking Speed – Preferred walking speed was measured before walking trials. Treadmill speed was ramped up (from .5 m/s) and down (from a higher velocity than reached in the previous trial) respectively, until each participant indicated that they reached their preferred walking speed. The average of the two trials was calculated and used as their preferred walking speed

Dependent Variables

DFA – Detrended Fluctuation Analysis alpha exponent was calculated from customized Matlab scripts as described in Chapter 3. An index of ~.5 (random) to ~1.0 (patterned) was used to describe the values observed in the study.

SE – Sample Entropy was calculated from customized Matlab scripts as described in Chapter 3. An index of 0 (patterned) to ~2 (highly random) was used to describe values observed in study.

LyE – Lyapunov Exponents was calculated from customized Matlab scripts as described in Chapter 3. Lower slope values indicated a higher amount of stability and vice versa for higher slope values.

REC, DET, ENT, MAX – Recurrence Quantification Analysis calculated a suite of metrics, including: recurrence (REC), determinism (DET), Shannon entropy (ENT), and max line length (MAX) from customized Matlab scripts as described in Chapter 3.

MOS – Was calculated via customized Matlab scripts as described in Chapter 3.

Overall Fall-Risk – Was calculated using the predictive model described in Chapter 3.

CHAPTER II

REVIEW OF THE LITERATURE

Overview

This literature review introduces the concept of variability in physiological systems and how it can be measured using a dynamical systems framework. Next, this literature review discusses the theory of dynamics-based measures as indicators of adaptability, and why the locomotor system is ideal to test this theory. Then, the review discusses the dynamical components of the locomotor system, how locomotor dynamics have been measured, and how they may be modified. Furthermore, the literature review examines how adaptability is measured and the current methods used to improve adaptability. Finally, a summary of the current gaps addressed in the dissertation is explored.

Dynamics in Physiological Systems

Dynamics refers to the change in a system over time, which can be characterized by quantifying the system's variability. The inherent variability within physiological signals has been observed for almost 300 years (Billman, 2011). Furthermore, physiological variability has been recorded through devices for 170 years. This variability was initially theorized to represent the amount of noise disrupting the system due to internal and external environmental factors (Stergiou & Decker, 2011). Thus, many scientists regarded variability as error that should be minimized. However, over time scientists focused on the mathematical underpinnings of variability began to theorize that variability might have utility in clinical diagnoses. Researchers began to observe how variability changed over time in order to detect differences between healthy and pathological behavior (Mackey et al., 1977). This was initially studied by recording cardiac and respiratory measurements of individuals with and without congestive heart failure. It was observed that the patients with congestive heart failure exhibited more periodic (i.e. less variable) behavior than healthy individuals, strengthening the hypothesis that healthy physiological function requires variable behavior (Goldberger, Findley, Blackburn, & Mandell, 1984). These initial findings led to the development of novel mathematical analyses that could be used to further investigate the utility of measuring the underlying dynamics observed in healthy and pathological variability.

Dynamical Systems Framework

The mathematical approach to observing physiological function by measuring the system's variability over time, referred to as the structure of variability, is called the dynamical systems framework. Within this framework of mathematics, physiological systems are considered to be chaotic, where the initial conditions of the system can predict its general behavior, but aperiodic fluctuations still exist in a seemingly random sequence. This behavior is observed in the noisiness of healthy physiological signals.

Using dynamical systems analyses, researchers have observed that the signal outputs of physiological systems are both nonlinear and complex. Having a nonlinear output simply means that the behavior that has been observed in the system is not numerically proportional to its inputs, and a complex system is one that meets the following criteria: 1) its behavior is not governed by a central controller, but instead relies upon the interactions occurring within its components, 2) these interactions create a global behavior naturally without the need of external forces, and 3) there is functional redundancy between the system's components. These analyses are theorized to detect the amount of underlying dynamics within the system, which indicates the health of the components and/or their ability to communicate with the other functional components of the dynamical system. From this framework, a variety of constructs and corresponding analyses have been further developed and/or created to answer clinical and research questions regarding the health of a physiological system, including fractals, entropy, local stability, and recurrence (Bravi et al., 2011). Hence, the measurements stemming from nonlinear dynamics have been utilized more and more frequently in health research over the past three decades (Manor & Lipsitz, 2013; van Emmerik & van Wegen, 2002). An overview of each analysis is provided below, with an in-depth description of each analysis provided later in this literature review.

Fractals

Some of the original nonlinear methodologies used to measure physiological function were based on the mathematics of fractals (Goldberger et al., 1984; Mandelbrot & Pignoni, 1983). The concept of fractals stems from geometry, where a figure or shape has similar patterns recurring at progressively smaller scales. Preliminary studies on the fractal nature of physiological function determined that the fractal-like structures (spatial self-similarity) of the cardiopulmonary system led to the production of fractal-like signals (temporal self-similarity in heart rate) over time (Goldberger, Bhargava, West, &

Mandell, 1985; Hooge & Tacano, 1993; Kobayashi & Musha, 1982; Lipsitz, 2004). These fractal-like signals are theoretically indicative of the complex interactions occurring across multiple scales of time and space (Goldberger et al., 2002; Lipsitz & Goldberger, 1992). While the initial experiments were conducted on pathologies detected within the cardiopulmonary system, a variety of physiological signals (e.g. electroencephalogram, computerized posturography, gait analysis, etc.) have since been observed to produce fractal-like behavior, also known as 1/f or pink noise (Duarte & Sternad, 2008; Hausdorff et al., 1995; Lee, Kim, Kim, Park, & Kim, 2004).

Entropy

Over the past 25 years, entropy measures have been utilized to measure the systematic behavior occurring at both single and multiple time scales (Costa, Peng, & Goldberger, 2008; Duarte & Sternad, 2008; Lake, Richman, Griffin, & Moorman, 2002; S. Pincus, 1995; Richman & Moorman, 2000; Yang et al., 2013). Stemming from Shannon's Information Theory, entropy metrics calculate the probability of new information (novel pattern) generation using a physiological signal's time-series (Bravi et al., 2011; S. Pincus, 1995; Richman & Moorman, 2000; Shannon, 2001). The literature on entropy measures is growing at a rapid rate, with novel variations constantly being developed to address specific conceptual concerns of clinical interpretation (Bravi et al., 2011).

Local Stability

Stability is defined as the ability of an object to resist change. Unlike global stability that is considered the body's overall ability to resist change, local stability measures use the dynamical systems framework to determine the stability of a "local" component of the system (e.g. joint) by determining how irritable the system is to the inherent variability being produced in a state of behavior during a specific task (van Emmerik, Ducharme, Amado, & Hamill, 2016). These are measured by calculating the direction or the rate of convergence/divergence of a physiological signal. Such analyses are among the first to have shown the ability to predict specific pathological behavior via fall-risk in the older adult population (Granata & Lockhart, 2008; Lockhart & Liu, 2008).

Recurrence

The idea to use recurrence to measure the behavior of dynamical systems stems from concepts developed by Henri Poincaré (Marwan, Carmen Romano, Thiel, & Kurths, 2007). He observed that system behavior will most likely recur within its intended state, unless an "exceptional trajectory" occurs. In a physiological system, an "exceptional trajectory" would be the outcome from internal or external stresses pushing the intended state of behavior past the critical point and creating a new state of behavior (Glass & Mackey, 1979, 1988; Poincaré, 1890). In 1987, Eckmanm et al. developed recurrence plots as a means to visualize the behavior of dynamical systems (Eckmann, Kamphorst, & Ruelle, 1987).

Through the quantitative analysis of recurrence plots, a variety of measures have been developed to quantify the probability of recurring or novel behavior to describe certain dynamical properties of the system (Webber & Zbilut, 1994; Zbilut & Webber, 1992).

Theoretical Models in Physiological-Based Nonlinear Dynamics

As the literature using nonlinear dynamics to determine physiological function grew, a general trend was observed that showed as individuals age, their systems' dynamical properties diminish. This led a group of researchers to propose the "loss of complexity" hypothesis (Goldberger, 1996; Lipsitz & Goldberger, 1992). Analyses across a spectrum of physiological systems, including: neural, skeletal, cardiac, endocrine, and auditory observations indicated a general deterioration of structural and temporal dynamics due to natural aging in late adulthood (Deboer, Karemaker, & Strackee, 1984; Greenspan, Klibanski, Rowe, & Elahi, 1991; Kaplan et al., 1991; Lipsitz, Mietus, Moody, & Goldberger, 1990; Mandell & Schlesinger, 1990; Mosekilde, 1988). It was proposed that this loss of 'complexity' is due to a decrement in a system's components functionality and/or their ability to interact with other components, hindering an individual's ability to adapt (Lipsitz & Goldberger, 1992). However, subsequent studies observed certain motor tasks and endocrine functions have an increased complexity in older adults. These observations conflict with the original "loss of complexity" hypothesis and led to the development of the "loss of adaptability" hypothesis and subsequently the optimal movement variability theory (Duarte & Sternad, 2008; Harbourne & Stergiou, 2009; Hartman et al., 1994; Hausdorff, Mitchell, et al., 1997; Newell, 1998; Pincus et al., 1996; Stergiou & Decker, 2011; Stergiou, Harbourne, &

Cavanaugh, 2006; Vaillancourt & Newell, 2002, 2003). The loss of adaptability and optimal movement variability theoretical models allow for a bidirectional explanation of complexity, with a moderate level of complexity reflecting healthy, adaptive behavior in the middle of a continuum and a shift toward lower or higher complexity representing less adaptive behavior (Goldberger et al., 2002; Hausdorff, Mitchell, et al., 1997; Keil, Elbert, Rockstroh, & Ray, 1998; Lipsitz & Goldberger, 1992; Newell, 1998; Pincus et al., 1996; Vaillancourt & Newell, 2002, 2003). According to these conceptual models, the structure of the variability within the system is indicative of its ability to complete tasks (i.e. maintain regulatory breathing and heart rate, remain upright in a variety of environments, etc.). Researchers have theorized through this framework that dynamical systems analyses reflect a system's adaptability, which is thought to be optimized when displaying a moderate amount of complexity within the behavior (Cignetti, Schena, & Rouard, 2009; Goldberger et al., 2002; Stergiou & Decker, 2011). This adaptability is observed in chaotic-like behavior where the system remains within a general state of behavior, yet continuously fluctuates. Theoretically, each fluctuation represents a possible strategy that the system can utilize to appropriately respond to internal and environmental stresses, while retaining its global behavior. Thus, the dynamics observed from such analyses are oftentimes interpreted or inferred to as a system's adaptive capacity.

Empirical Evidence of Dynamics Measuring Adaptability

The connection between physiological dynamics and function is largely supported by indirect evidence. The majority of this evidence in the literature has focused on the comparison of complexity and/or stability between groups, with older adults and those with pathology or injury typically displaying diminished dynamics. Such results have been observed in the cardiovascular, respiratory, central nervous, and neuromuscular systems (Cavanaugh et al., 2005, 2006; Costa et al., 2007; Costa et al., 2008; Dingwell, Cusumano, Sternad, & Cavanagh, 2000; Iyengar, Peng, Morin, Goldberger, & Lipsitz, 1996; Kaplan et al., 1991; Lockhart & Liu, 2008; Manor et al., 2010; Moraiti, Stergiou, Ristanis, & Georgoulis, 2007; Peng et al., 2002; Pikkujämsä et al., 1999; Stergiou, Moraiti, Giakas, Ristanis, & Georgoulis, 2004; Thurner, Mittermaier, & Ehrenberger, 2002; Yang et al., 2013). The deterioration of the dynamics is suggested to be exacerbated when an individual is advanced in age and has a pathological condition or injury (Manor et al., 2010; Roerdink et al., 2006). There are even several studies that have used a within-subject design to observe how certain pathological conditions change dynamics or are predictive of survival (Buzzi & Ulrich, 2004; Ho et al., 1997; Ho, Lin, Lin, & Lo, 2011; Mäkikallio et al., 1997, 1999; Norris, Stein, & Morris, 2008; Vikman et al., 1999). Interestingly, several interventions have successfully altered the dynamics of physiological systems through the use of resistance training, aerobic exercise, pharmacological intervention, sub-sensory vibrations, Wii Fit balance training, Tai Chi, and auditory/visual metronomes with several observing functional improvements associated with such changes (Castiglioni et al., 2011; Collins et al., 2003; Cone et al., 2016; Heffernan, Fahs, Shinsako, Jae, & Fernhall, 2007; Hove, Suzuki, Uchitomi, Orimo, & Miyake, 2012; Huisinga, Filipi, & Stergiou, 2012; Jartti, Kuusela, Kaila, Tahvanainen, & Välimäki, 1998; Kanaley et al., 2009; Lepoluoto et al., 2005; Lough et al., 2012; Millar, Levy, McGowan, McCartney, & MacDonald, 2013; Priplata et al., 2002; Priplata et al., 2006; Rhea, Kiefer, D'Andrea, Warren, & Aaron, 2014; Tulppo et al., 2001).

There is only limited direct evidence presented on the relationship between dynamical systems analyses and adaptability thus far due to the invasive nature of most physiological systems in the human body. Within the dynamics literature, direct evidence would be observed by measuring a system's dynamics and then immediately perturbing the system to observe how system dynamics relates to the system's ability to revert back to a healthy state of behavior. To date, only studies investigating this relationship in the postural control system have reported results that support this theory (Cone et al., 2016). However, there are limitations in the functional applications of the postural control system (typically measured in the context of fall-risk) and how it is perturbed (validity of laboratory-based perturbations to the system) (Berg, Alessio, Mills, & Tong, 1997; Cone et al., 2016; Norton, Campbell, Lee-Joe, Robinson, & Butler, 1997). Studying the locomotor system, on the other hand, is an ideal physiological system to provide direct evidence on the relationship between physiological dynamics and adaptability.

The Argument for the Locomotor System

There is ample empirical and theoretical support that the locomotor system is the ideal system to identify an individual's relationship between nonlinear measures and adaptability. Beforehand, it is important to note that outside of motor behavior tasks, other physiological systems (i.e. cardiovascular, breathing, central nervous, endocrine) have thus far been deemed too invasive to be perturbed safely in a live human to test such a relationship directly. For this reason, motor behavior-based methodology appears to be ideally situated to directly observe this relationship with minimal risks to an individual's health. Within motor behavior, the most common physiological signals measured with dynamical systems analyses have been metrics derived from the postural control and locomotor systems. The reasons for this are numerous, but include the clinical usefulness of the signals, strength of background literature, strength of mechanistic-based theoretical models, and standardization of equipment available in laboratories.

The argument for using the locomotor system as an indication of adaptability is best addressed through Newell's Constraints model (Newell, 1986). Within the model, all movement (including its variability) is affected by the constraints placed through the individual, task, and environment. First, an individual's constraints (both structural and functional capabilities of the body) have an impact on the ability to adapt to perturbations during ambulation (locomotion), which has clinical significance. Unintentional falls are the number one cause of non-fatal and fatal injuries in older adults ("CDC Press Releases," 2016). Furthermore, medical costs associated with unintentional fall-related injuries costs over $31 billion dollars annually in the United States alone (Burns, Stevens, & Lee, 2016). The fall literature has consistently reported a greater percentage of unintentional falls occur during ambulation (Berg et al., 1997; Bergland, Pettersen, & Laake, 1998; Kelsey, Procter-Gray, Hannan, & Li, 2012; Nachreiner, Findorff, Wyman, & McCarthy, 2007; Talbot, Musiol, Witham, & Metter, 2005). From a biomechanical perspective, this is due to the consistent displacement of the body's center of mass (COM). As a person ambulates through an environment, their COM is constantly fluctuating outside of their base of support (BOS), whereas during postural control tasks the COM remains within the BOS. Concurrently, more degrees of freedom (systematic complexity) are involved in ambulation, providing more opportunity for fluid coordination or system dysfunction to emerge, depending on the system's adaptive capacity, which ultimately influences fall-risk (Assaiante, 1998; Winter, 2009).

Second, the actual task of perturbing the locomotor system in a laboratory setting is conceptually closer to real-world environmental disturbances. The majority of falls during ambulation occur due to either a slip or trip (Berg et al., 1997; Kelsey et al., 2012; Nachreiner et al., 2007). Furthermore, overground and treadmill induced perturbations (slips and trips) have been observed to produce similar kinematic consequences in young and older adults (Grabiner, Koh, Lundin, & Jahnigen, 1993; Owings, Pavol, & Grabiner, 2001; Pavol, Owings, Foley, & Grabiner, 1999; Pavol, Owings, Foley, & Grabiner, 2001). Due to the limitation of space in most laboratories, the ability to use a motorized treadmill to measure complexity and perturb the locomotor system within the same task and environment is conceptually ideal.

Another reason to use locomotor tasks over postural control tasks is that the latter is typically measured during upright stance, where fewer real-world perturbations are currently accessible in a laboratory. Nevertheless, the first direct evidence of the relationship between complexity and adaptability was been observed in a postural control task. The Sensory Organization Test on the NeuroCom Balance Master challenges the postural control system through six separate conditions (three trials each) consisting of various tasks including sway-referenced motion of the surrounding and force plate (Cone et al., 2016). Raw data from the NeuroCom Balance Master allows for quantitative analysis of the center of pressure readings from all trials to calculate complexity metrics. It was observed that a balance training program increased center of pressure complexity and also increased vestibular function (Cone et al., 2016), providing some of the first direct evidence linking complexity with function. The normative values of each trial are quantified by the following Natus algorithm that is based off of the range of anterior-posterior (AP) sway:

$$SOT\ score = 100\{12.5 - [\theta(A) - \theta(P)]\}/12.5$$

Unfortunately, this measure has not consistently been able to detect differences in changes to the postural control system of several pathological or injured populations, limiting its potential utility to measure adaptability (Cavanaugh et al., 2005; Di Fabio, 1995). Currently, there is no reported methodology that can validly and reliably measure the postural control system's responses to perturbations in the various aging, pathological, and injured populations. Also, similar to previous findings in motor tasks, there is a conflict in the literature regarding how postural complexity compares between healthy and aging/pathological populations (Duarte & Sternad, 2008; Newell, 1998; Seigle, Ramdani, & Bernard, 2009; Sosnoff & Newell, 2008; Thurner et al., 2002; Vaillancourt & Newell, 2002, 2003). This leaves room for debate on the most appropriate postural control task to measure adaptability in a variety of populations.

Finally, the environmental constraints (world around us) between postural control and locomotor tasks can be very similar or different depending on the context of the situation or study design. Differences in equipment and surroundings can have a variety of effects on any individual's performance due to their cultural background, possible condition, or physiological function. The most important aspect of this constraint is to be mindful of this so that consistency is possible with each participant in a research study to mitigate any possible environmental effects that could alter the results of the study. With all of the possible constraints of human movement in perspective, it is clear that there is a greater likelihood of finding expected outcomes from measuring this relationship in the locomotor system.

Dynamical Components of the Locomotor System

The locomotor system is a more complex system then once theorized. In order to ambulate around varied environments, researchers have established more lifelike models comprised of a neuro-muscular-skeletal network. The use of passive walking models has established that adaptive ambulation requires the interaction of the nervous and musculoskeletal systems' dynamics (Shik, Severin, & GN, 1966; Taga, 1995). Furthermore, the locomotor system appears to be influenced by, and even couple with peripheral systems such as the sensory and cardiorespiratory systems to influence locomotor dynamics under certain task constraints (Hove et al., 2012; Hunt, McGrath, & Stergiou, 2014; Nakamura et al., 1997; Niizeki, Kawahara, & Miyamoto, 1996; Novak, Hu, Vyas, & Lipsitz, 2007; Phillips & Jin, 2013; Rhea, Kiefer, D'Andrea, et al., 2014; Takeuchi, Nishida, & Mizushima, 2014). In addition, certain neuropsychological factors such as the focus of attention, depression, and confidence may influence an individual's dynamics (Dingwell, Robb, Troy, & Grabiner, 2008; Herman, Giladi, Gurevich, & Hausdorff, 2005). Thus, in order to measure the adaptive capacity of the locomotor system, it is imperative to consider the interaction occurring between the various components of several systems at different temporal and spatial scales. Hausdorff et al. (2001) introduced a theoretical model describing the factors affecting locomotor dynamics (Hausdorff, 2005; Hausdorff et al., 2001). However, further research is still required to better understand how these various components interact together to create dynamic behavior in the locomotor system.

Prominent Measures of Locomotor Dynamics

It is important to note that there are two main categories of analyses to measure the behavior of the locomotor system: the interval method and continuous method (Rhea & Kiefer, 2014). Interval method analyses examine a discrete time interval, such as stride time (amount of time between heel strikes on same foot), and capture the dynamics of the system over multiple time scales (Hausdorff et al., 1995, 1996, 1997, 2000; Rhea et al., 2014; West & Griffin, 1999; West & Scafetta, 2003). This approach may require trials to last up to 10-20 minutes to capture enough data points to reliably conduct dynamical analyses. The continuous method can capture the dynamics of continuous movements (e.g. joint angles), and depending on sampling frequency, can capture the same amount of data points in a few strides (Buzzi, Stergiou, Kurz, Hageman, & Heidel, 2003; Buzzi & Ulrich, 2004; Kurz & Stergiou, 2003; Labini, Meli, Ivanenko, & Tufarelli, 2012; Lockhart & Liu, 2008; Myers, Stergiou, Pipinos, & Johanning, 2010). However, capturing data over fewer strides diminishes the capacity of the analysis to interpret dynamical behavior over various time scales. Thus, careful consideration must be placed on the study design and analysis depending on the research question and limitations within the population of interest.

Detrended Fluctuation Analysis

Detrended fluctuation analysis (DFA), originally developed to measure the structure of variation in DNA, was quickly identified as a possible index of multiscale dynamical behavior during gait (Hausdorff et al., 1995; Peng et al., 1994). The "detrended" process added to the original analysis was developed in order to handle the nonstationary behavior of physiological signals (Peng, Buldyrev, & others, 1992; Peng et al., 1994). The first step to calculate the DFA value is to subtract the mean from each point as demonstrated with the following equation:

$$y(k) = \sum_{i=1}^{k} [S(i) - S_{ave}]$$

In this equation, y(k) is the time series, $S(i)$ is the ith step, and S_{ave} is the average step (Hausdorff et al., 1995; Rhea & Kiefer, 2014). Next, the data is separated into equal-sized windows, and a trend line is fitted to the individual windows. Finally, the trend line within each window is removed and the absolute sum of the remaining fluctuations is quantified with the following equation:

$$F(n) = \sqrt{\frac{1}{N} \sum_{k=1}^{N} [y(k) - y_n(k)]^2}$$

This process is repeated through multiple time scales by increasing the window size two-fold in each subsequent calculation (Hausdorff et al., 1995; Rhea & Kiefer, 2014). Finally, the average amount of fluctuation across the time scales [F(n)] is graphed on a log-log plot as the y coordinate against the window size (n) as the x coordinate, and a least-squares line is fitted to determine the slope of the data (Hausdorff et al., 1995; Rhea & Kiefer, 2014). The slope represents the DFA *alpha exponent* (α), a measure of a physiological signal's fractal nature, also known as the strength of long-range correlations. Typically, human stride interval time series' α ranges between .5 and 1.0, with .5 indicating low strength of long-range correlations/fractality (random noise) and 1.0 revealing a high strength of long-range correlations/fractality (structured noise).

Healthy locomotor behavior has been observed to exist around $\alpha \approx .75$, suggesting a combination of random and structured behavior, as theorized by the loss of adaptability and optimal movement variability models (Hausdorff et al., 1995; Hausdorff et al., 1996; Stergiou & Decker, 2011; Vaillancourt & Newell, 2002, 2003). Similar to previous observations on physiological fractals, the aging process appears to diminish the fractality of the locomotor system as observed by DFA (Hausdorff, Mitchell, et al., 1997).

Approximate, Sample, and Multiscale Entropy

Approximate entropy (ApEn) was introduced in 1991 to study the patterned behavior of system dynamics using shorter data sets (Pincus, 1991). Since then, ApEn (and its derivative measures) have been utilized to observe the dynamics of a variety of physiological signals (Bravi et al., 2011). First, a template length (*m)* and level of tolerance (*r*) are determined for the time series. Previous literature has suggested that *m*=2 and *r*=.2 of the standard deviation are appropriate parameters to analyze locomotor patterns with ApEn (Georgoulis, Moraiti, Ristanis, & Stergiou, 2006; Moraiti et al., 2009). Once the parameters are established, the ApEn algorithm will match all *m*-length templates of consecutive data points throughout the time series and calculate how many identical patterns within radius *r* exist. Then, it calculates the ratio of *m*-length repeated patterns observed throughout the time series to the number of possible *m*-length repeated patterns within the time series. This procedure will be repeated with a template of *m* + 1 and the following equation will determine the conditional probability of new pattern generation:

$$\mathrm{ApEn}(S_n,m,r)=\ln\left[\frac{C_m(r)}{C_{m+1}(r)}\right]$$

From this equation, a higher probability of *m*-length repeated patterns (numerator) indicates increased dynamical behavior, with the opposite true for the probability of *m* + 1 pattern repeatability (denominator). Typically, ApEn values from movement-based time series range from 0 to 2, with 0 indicating patterned dynamics and 2 indicating more complex dynamics (Arif, Ohtaki, Nagatomi, & Inooka, 2004; Buzzi & Ulrich, 2004; Cavanaugh et al., 2006; Vaillancourt & Newell, 2000). While ApEn has not been observed to change due to aging, studies have reported significantly lower entropy in older adults at higher-risk of falling (Karmakar, Khandoker, Begg, Palaniswami, & Taylor, 2007; Khandoker, Palaniswami, & Begg, 2008). A more robust version of ApEn called Sample Entropy (SE) has been developed to handle the noisy, short time series typically available in many physiological signals. SE improves on ApEn by taking away a bias towards patterned behavior through discarding self-matched patterns (Richman & Moorman, 2000). These single-scale entropy measures, as well as a multiscale version of SE (MSE) have been suggested to have utility at reporting the underlying dynamics (Costa, Peng, Goldberger, & Hausdorff, 2003; IJmker & Lamoth, 2012; Lamoth et al., 2011; Liao, Wang, & He, 2008; Rhea, Wutzke, & Lewek, 2012; Riva, Toebes, Pijnappels, Stagni, & van Dieën, 2013; van Schooten et al., 2015). Similar to DFA, MSE measures entropy at multiple time scales by taking the average value of various window sizes (data points), calculating the conditional probability of $m/m+1$, and plotting each entropy value as a function of its scale factor (Costa, Goldberger, & Peng, 2002).

Lyapunov Exponents and Floquet Multipliers

Stability analyses, such as Lyapunov exponents (LyE) and Floquet multipliers, are dependent on the theory that the locomotor system is a multidimensional system with dynamic components. Taken's theorem suggests that there is enough information that can be observed in a one-dimensional time series to reveal a system's underlying dynamics. Thus, by using a time-delayed approach it is possible for both analyses to reconstruct the original time series within a multidimensional state space to quantify the underlying dynamical behavior of the locomotor system (Lockhart & Liu, 2008; Takens, 1981). This is done by creating time-delayed copies of the original time series determined by the mutual information and false nearest neighbors approach (Abarbanel & Kennel, 1993; Cao, 1997; Lockhart & Liu, 2008; Rhea & Kiefer, 2014). With an initial dimension time series $x(t)$, the state space $X(t)$ can be constructed through this equation:

$$X(t) = [x(t), x(t+T), x(t+2T,\ldots,x(t+d_e\text{-}1)\mathrm{T})]$$

The LyE value is considered a measure of local dynamic stability that tracks the average divergence of the nearest neighbors in the state space. The nearest neighbors are revealed by calculating the data points from different strides that are closest together in state space. This function is reiterated for all data points. This distance between data points is then tracked throughout time. Thus, LyE is tracking the average amount of divergence as a function of time (Lockhart & Liu, 2008; Rhea & Kiefer, 2014). The LyE equation is as follows:

$$\lambda(i) = \langle \ln\{D_j(i)]\rangle/\Delta t$$

“where $D_j(i)$ is the Euclidean distance between the jth pair of nearest neighbors after i discrete steps, Δt is the length of the time series data and $\langle\cdots\rangle$ calculates the average over all values of j” (Lockhart & Liu, 2008). By placing a linearly fitted slope on the rate of divergence over time it is possible to measure the effects of local perturbations affecting the locomotor system (Abarbanel, 2012; Lockhart & Liu, 2008; Rhea & Kiefer, 2014).

Floquet multipliers, in contrast, are considered to be measures of orbital stability, indicating that the measurement of convergence or divergence is observed in two-dimensional slices of the state space that are perpendicular to the motion of the system. These are known as Poincaré sections (Bruijn, van Dieën, Meijer, & Beek, 2009). Because Floquet theory assumes that the system is periodic, each cycle (e.g. stride) must be normalized to 101 samples (0-100%). Thus, 101 Poincaré sections can be created (Dingwell & Kang, 2007).

The first equation to calculate Floquet multipliers assumes that "the state of a system after one cycle is a function of its current state" as calculated in this equation:

$$S_{k+1}=\mathrm{F}(S_k)$$

Then, the second equation two "follows the limit cycle trajectories to correspond to fixed points" as follows:

$$S^{*}=F(S^{*})$$

Finally, a linearization of the previous equation by showing the rate of convergence/divergence:

$$[S_{k+1}-S^{*}]=J(S^{*})[S_k-S^{*}]$$

The fixed points across each Poincaré section are then averaged together to determine the mean Floquet multipliers. Then, magnitudes of the largest Floquet multipliers can be calculated for each % of the cycle. The largest of these is considered to represent the most unstable in the cycle. Both the mean and max values of the Floquet multipliers have been used to describe the stability of the locomotor system (Bruijn et al., 2009; Dingwell & Kang, 2007; Granata & Lockhart, 2008).

Recurrence Quantification Analysis

Recurrence Quantification Analysis (RQA) measures the repeatability within a dynamical system's behavior by measuring the original time series against time-delayed copies as they cycle through a multidimensional state space. As with the local dynamic stability measures, this is conceptualized using Taken's theorem and optimized with the mutual information and false nearest neighbors approaches (Abarbanel & Kennel, 1993; Cao, 1997; Takens, 1981). Next, a radius must be set to ensure that the proper sensitivity of recurrence is observed. Typically, it is best to have a lower radius so that the plot is not over saturated. A 5% recurrence within the plot is suggested as a baseline (Pellecchia & Shockley, 2005; Webber Jr & Zbilut, 2005). From this, a multitude of variables can be calculated, including: percent recurrence, determinism, max line length, and Shannon entropy. Recurrence (REC) quantifies the ratio of shared recurrent points in the state space between the original time series and its time-delayed copies divided by the possible amount of recurrent points in the state space (Rhea & Kiefer, 2014; Webber Jr & Zbilut, 2005). Determinism (DET) quantifies the ratio of recurrent points that are part of a pattern (2 or more sequential points) divided by the total number of recurrent points (Rhea & Kiefer, 2014; Webber Jr & Zbilut, 2005). Shannon entropy (ENT) quantifies the probability of the line lengths within the plot being equal in length (Pellecchia & Shockley, 2005; Rhea & Kiefer, 2014). Max line length (MAX) quantifies the longest pattern observed in the recurrence plot. While RQA has potential utility for the study of locomotor dynamics, it has only sparingly been used to help address questions related to the adaptive capacity of the locomotor system (Labini et al., 2012; Riva et al., 2013).

General Observations from Measuring Locomotor Dynamics

The study of locomotor dynamics is still in its infancy, with observations beginning just over 20 years ago (Hausdorff et al., 1995). Due to the complex nature of studying a system with so many interacting components, there are still many unanswered questions regarding the underlying mechanisms and clinical relevance of using a dynamical systems approach to measure or improve the function of the locomotor system. However, enough empirical evidence has been compiled in the literature to make some general observations on the utility of dynamics-based measures.

Population Comparison

To date, the bulk of the literature on locomotor dynamics has focused on the comparison of dynamics between healthy and clinical populations. It has been suggested that locomotor dynamics can be used to detect the maturation and/or deterioration of the central nervous system via multiple studies observing differences throughout the lifespan (Hausdorff, Zemany, Peng, & Goldberger, 1999; Hausdorff, Mitchell, et al., 1997). For example, Hausdorff and colleagues reported different locomotor dynamics in children (<15 years old), young adults (20-30), and in older adults (>70 years old) (Hausdorff et al., 1999; Hausdorff, Mitchell, et al., 1997). These initial studies were conducted by measuring the dynamics of stride intervals through foot switches detecting heel strikes. Locomotor dynamics can also be used to discriminate between older adult fallers and non-fallers (Granata & Lockhart, 2008; Hausdorff, Rios, & Edelberg, 2001; Karmakar et al., 2007; Khandoker et al., 2008; Lockhart & Liu, 2008; Paterson, Hill, & Lythgo, 2011; Riva et al., 2013; Toebes, Hoozemans, Furrer, Dekker, & van Dieën, 2012). Furthermore, locomotor dynamics are altered due to various neurodegenerative conditions, such as Huntington's disease, Parkinson's disease, and amyotrophic lateral sclerosis (Hausdorff, Mitchell, et al., 1997; Hausdorff et al., 2000; Hausdorff, Cudkowicz, Firtion, Wei, & Goldberger, 1998). A deterioration of locomotor dynamics has also been observed in hypovestibular individuals (Labini et al., 2012; Sloot et al., 2011; van Schooten et al., 2011). LyE and entropy measures have also been able to differentiate dynamics between healthy populations and populations with lower extremity injury or diabetic neuropathy (Dingwell et al., 2000; Georgoulis et al., 2006; Lamoth, Ainsworth, Polomski, & Houdijk, 2010; Manor, Wolenski, Guevaro, & Li, 2009; Moraiti et al., 2007). Finally, there is building evidence that locomotor dynamics can be used to detect differences between individuals with altered neuropsychological factors such as attentional focus, depression, cerebral blood flow, fear of falling, confidence in physical functioning, and/or cognition change (Dingwell et al., 2008; Hausdorff, Nelson, et al., 2001; Hausdorff, Rios, et al., 2001; Herman et al., 2005; Lamoth et al., 2011; Nakamura et al., 1997).

Association to Functional Measures

While there are no current observations on the direct relationship between locomotor dynamics and adaptability, there is limited evidence of such a relationship through associations to functional measures. Functional measures are those that specifically relate to a person's ability to perform activities of daily living—termed as functional mobility—or are clinical assessments/neuromechanical factors that are suggested to indicate a person's susceptibility to an unintentional fall. Such associations further suggest that locomotor dynamics are indicative of adaptive capacity.

Hausdorff et al. (2001) found that changes in older adults' locomotor dynamics following a six-month home-based strength and balance intervention were associated with knee extension strength and endurance, exercise capacity, as well as ankle and back range of motion (Hausdorff, Nelson, et al., 2001). Another study by Hausdorff et al.

found associations between locomotor dynamics and the Berg Balance Test, Dynamic Gait Index, and Timed Up and Go during dual-task (Hausdorff, Schweiger, Herman, Yogev-Seligmann, & Giladi, 2008). While all three clinical tests mentioned are common assessments of balance and mobility, each have been suggested to have only limited predictive value in fall-risk assessment (Chiu, Fritz, Light, & Velozo, 2006; Lajoie & Gallagher, 2004; Muir, Berg, Chesworth, & Speechley, 2008; Podsiadlo & Richardson, 1991; Whitney, Hudak, & Marchetti, 2000). Finally, there is strong evidence that locomotor dynamics change as a person's gait speed changes, revealing an interesting relationship with a well-tested predictive factor of overall locomotor functionality and fall risk (England & Granata, 2007; Jordan, Challis, & Newell, 2007). That is, a decrease in gait speed is commonly associated with lower functional behavior.

Ability to be Modified

If locomotor dynamics are indicative of adaptability, then it is necessary to understand to what extent the system's dynamics can be modified. This would allow researchers and clinicians to further optimize the effectiveness of interventions on adaptive behavior. As mentioned in the previous section, initial results have suggested that a resistance exercise and balance intervention is able to alter locomotor dynamics in older adults (Hausdorff, Nelson, et al., 2001). While this study used a more conventional paradigm, there have since been more novel interventions that have been suggested to effectively alter an individual's locomotor dynamics.

As noted before, locomotor dynamics and speed are closely related and might be modified together. Rhea et al. (2012) tested the effect of using variable speed sessions on a treadmill to improve locomotor dynamics for stroke survivors. They observed improved locomotor dynamics from the gait-speed training (Rhea et al., 2012). Furthermore, treadmill interventions that progressively increase speed over multiple sessions have also shown improvement of locomotor dynamics in individuals with Parkinson's disease (Herman, Giladi, Gruendlinger, & Hausdorff, 2007).

Most dynamics-based analyses have measured the timing of movement, so it seems intuitive that one of the more established methodologies to modify locomotor dynamics is through external pacemakers, defined as something requiring a certain gait speed (e.g. a treadmill or metronome). Initial results from this branch of locomotor intervention found that walking on a treadmill altered locomotor dynamics in individuals with Parkinson's disease when compared to control subjects (Frenkel-Toledo et al., 2005). When comparing treadmill to overground walking, locomotor dynamics may be altered between the two environments, depending on the variable being used to quantify locomotor dynamics (Chang, Shaikh, & Chau, 2009; Dingwell, Cusumano, Cavanagh, & Sternad, 2000).

Other studies have investigated the effect of rhythmic auditory cuing on locomotor dynamics. Similar to stochastic resonance, rhythmic auditory cuing uses non-correlated timing to which participants attempt to synchronize. In preliminary studies, locomotor dynamics were improved (Herman et al., 2007; Sejdić, Fu, Pak, Fairley, & Chau, 2012; Terrier & Dériaz, 2012; Terrier & Deriaz, 2013). Fractal-based visual and auditory metronomes have been developed to advance this line of study and researchers have observed alterations to locomotor dynamics in healthy, older, and pathological populations (Hove et al., 2012; Kaipust, McGrath, Mukherjee, & Stergiou, 2012; Marmelat, Torre, Beek, & Daffertshofer, 2014; Rhea, Kiefer, Wittstein, et al., 2014; Rhea, Kiefer, D'Andrea, et al., 2014). Alternative to these approaches, there is preliminary evidence that certain pharmaceutical aids may enhance the locomotor dynamics of an individual with Parkinson's disease (Schaafsma et al., 2003).

Locomotor Adaptability

Adaptability of the locomotor system can be defined as the body's ability to remain in a safe upright position while walking, regardless of the constraints placed on the individual. As previously mentioned, the greatest public health concern of locomotor adaptability relates to an individual's fall-risk. This concern currently has a tremendous impact on our society, in particular the older adult population (Burns et al., 2016; "CDC Press Releases," 2016). Slips and trips are the most common causes of falling in older adults, with a growing literature focused on understanding the underlying mechanisms and improving responses to such tasks (Berg et al., 1997; Grabiner et al., 1993; Kelsey et al., 2012; Owings et al., 2001; Pai & Bhatt, 2007; Pavol et al., 2001). While there are some biomechanical factors that have been associated with fall-risk, there seems to be a lack of consensus on how to appropriately test locomotor adaptability (Grabiner, Bareither, Gatts, Marone, & Troy, 2012; Pai & Bhatt, 2007; Pai, Yang, Wening, & Pavol, 2006; Pavol, Owings, Foley, & Grabiner, 1999).

From a mechanical perspective, the ability for an object to remain upright is termed balance. This ability to stay upright is determined by the displacement of the COM to the BOS. When an object's COM leaves the area of the BOS, the object begins to fall (Bell, 1998; Hall, 2014; Kreighbaum, 1996; Pollock, Durward, Rowe, & Paul, 2000). In contrast, stability can be defined as an object's ability to remain balanced as the COM moves closer to the edge of the BOS, as well as to remain balanced when an external force is applied. As slips and trips are considered environmental and/or task constraints, they are considered external forces on the body. Thus, an individual's stability during locomotor tasks is suggested to be synonymous with an individual's ability to adapt to environmental and task constraints. In the dynamics literature, this biomechanical stability has been termed global stability (van Emmerik et al., 2016).

Global Stability Measures

There are currently several measures that have been used to test an individual's global stability from a dynamical systems framework. For each measure, the individual's COM and boundaries of the BOS must be quantified. Typically, these measures were first conceptualized for postural control, but were then adapted for locomotor tasks. Pai and colleagues were the first to quantify global stability from this perspective. They postulated that locomotor stability can be measured as the minimum distance between the COM motion-state, which is its position as a function of its velocity, and a mathematically predicted "feasible stability region boundary" in relation to forward and backward loss of balance (Pai, Wening, Runtz, Iqbal, & Pavol, 2003; Pai & Bhatt, 2007; van Emmerik et al., 2016).

Hof and colleagues developed a similar measure called the margin of stability (MOS) that measures the minimum distance between the extrapolated COM and the edge of the BOS (Hof, Gazendam, & Sinke, 2005; Young & Dingwell, 2012). Such extrapolation occurs through the use of kinematic and/or kinetic data to project the velocity of the COM (Bruijn, Meijer, Beek, & Dieën, 2013). However, there are limitations to earlier versions of this measure, as center of pressure can only be accurately reported in single-limb stance and an individual's ground reaction force is assumed to be kept constant during ambulation. The metric has since been further adapted to theoretically be more sensitive to changes of global stability between populations or during external perturbations (Lugade, Lin, & Chou, 2011; Terry, Stanley, & Damiano, 2014). Other measures, such as time-to-contact, take into account the position, velocity, and acceleration of the COM and the boundaries of the BOS during the swing phase of gait (Remelius, Hamill, & van Emmerik, 2014).

Methods to Improve Global Stability

Pai and colleagues investigated the effects of repeated slip training on global stability in healthy, young subjects and found that proactive mechanisms mitigated the effects of slips after such training, increasing the participants' stability (Bhatt, Wening, & Pai, 2006). Even after one slip, noticeable changes can be observed to the system's adaptive processes (Marigold & Patla, 2002). While not retained after a year, the acquisition of more stable mechanics can be retained for several months, and may be re-learned at a faster rate in a follow-up session (Bhatt & Pai, 2005; Bhatt, Wang, & Pai, 2006). These initial results suggest a potential training mechanism to improve stability using perturbation-based training.

The MOS has also been shown to be modifiable via interventions. In one study, even reducing somatosensory feedback couldn't negate the improvement on individuals' stability after repeatedly walking down a path whose surface had varying stiffness (Höhne, Stark, Brüggemann, & Arampatzis, 2011). Furthermore, dynamic balance training in aging and pathological populations has also been suggested to improve their stability when faced with similar perturbations (Bierbaum, Peper, & Arampatzis, 2013; Fonteyn et al., 2014).

Summary of Gaps in the Literature with Regards to this Dissertation

The current literature lacks direct evidence to link an individual's locomotor dynamics to their ability to recover from an external perturbation. As there is a rich amount of literature that is based on the inference that underlying system dynamics are indicative of adaptability, it is of critical importance to understand if this is observed in the locomotor system, and to what extent. The disconnect between the fields of locomotor dynamics and biomechanical stability appears to be filled with ample opportunity to further explore this relationship. Moreover, while locomotor dynamics and biomechanical stability have both been suggested to be modifiable through acute interventions, no observations have been made on the effect of locomotor dynamics and its relation to biomechanical stability from a trip-training session. Since tripping has been shown to be one of the most common causes of a fall, it is necessary to have a better understanding of novel training methods that health professionals can use to optimize fall-prevention programs.

CHAPTER III

METHODS

Participants

Forty healthy, older adults 70 years or older (75.2±4.9 years) were recruited by convenience from the local community to participate. These participants were randomly assigned to either the control group (n=10, 76.7±6.8 years) or intervention group (n=30, 74.7±4.1 years). Healthy was defined as having no neuromuscular injuries that cause abnormal walking behavior. All participants had to be able to walk 15 minutes on a treadmill without aid. Before arriving at the Virtual Environment for Assessment and Rehabilitation Laboratory, participants were instructed to wear athletic/tennis clothes and shoes. Participants read and signed a consent form before the beginning of the session, as required by the University of North Carolina at Greensboro Institutional Review Board.

Clinical Assessments and Demographic Information

Once consent had been signed, participants' height and mass were obtained. Next, participants filled out demographic, basic health, and physical activity questionnaires. Then, participants completed the Activities-Specific Balance Confidence (ABC) Scale, which rated the individual's confidence of remaining upright while performing 16 separate tasks. The ABC scale ranges from 0% (no confidence) to 100% (total confidence) in ability to remain upright. Afterwards, participants completed 30 trials of a simple reaction time (SRT) test. SRT is defined as the "length of time measured between the presentation of an unexpected stimulus and the onset of a response to that stimulus" (Lajoie & Gallagher, 2004; Schmidt & Debû, 1993). The Deary-Liewald reaction time test was used in order to measure SRT. In this task, the SRT was measured as the number of milliseconds required to move the dominant hand's index finger and strike the space bar on a keyboard after a visual stimulus appeared on a computer screen to signify movement time. This test has been reported to be both a valid and reliable measurement of SRT (Deary, Liewald, & Nissan, 2011). Next, participants completed three trials on each hand to test for maximal hand grip strength using a hand dynamometer. Hand grip strength has been observed to correlate to knee extensor strength, lower-limb strength, overall body strength, mobility, and fall-risk in older adults (Batista et al., 2012; Bohannon, Magasi, Bubela, Wang, & Gershon, 2012; Hoda, Samia, & Ahmed, 2013; Rantanen et al., 1999; Schaubert & Bohannon, 2005). Finally, participants completed the Berg Balance Scale (BBS), which consists of 14 separate tasks to measure an individual's overall fall-risk.

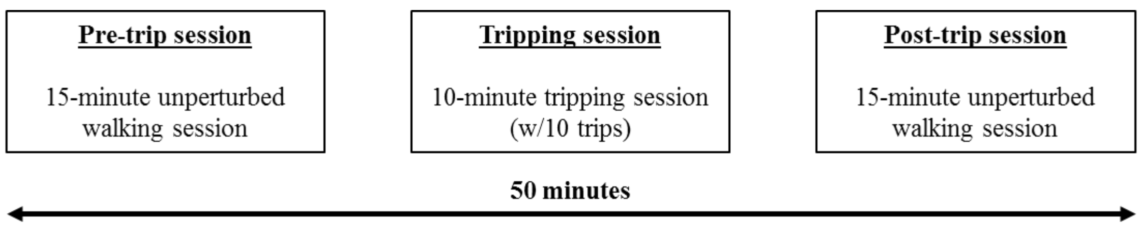
Instrumentation

An Oqus motion capture system (Qualisys, Göthenburg, Sweden) recorded all 3-D kinematic data at 100 Hz while participants walked on an ActiveStep treadmill (Simbex, Lebanon, NH, USA). A safety harness that attaches to an overhead railing was placed on the participants to ensure safety while on the treadmill. A set of 40 markers was placed on the participant's body and head, including: head of second metatarsals, head of first and fifth metatarsals, calcaneus, medial and lateral malleoli of ankle, shank, medial and lateral knee, thigh, ASIS, PSIS, sacrum, C7 vertebra, 3 markers around head, manubrium, acromion, olecranon, radial/ulnar styloid processes, and dorsal third metacarpophalangeal joint. Next, participants were instructed to identify their preferred walking speed on the treadmill. First, the speed of the belt was steadily increased from .5 m/s until an appropriate speed was identified by the participant. Then, the speed was adjusted above the initial preferred speed and steadily decreased until an appropriate speed was identified by the participant. The average of those two speeds was taken as the participant's preferred walking speed, which was consistent throughout the rest of the session.

Experimental Procedures

The entire study took place within a single session (Figure 3.1). During all walking trials, participants were instructed to keep their eyes straight ahead. The first walking session lasted 15 minutes and was unperturbed. Next, participants rested for 5 minutes to reduce fatigue. Then, one of two procedures took place depending on which group the participants were in. Participants in the control group walked for 10 minutes unperturbed. Participants in the intervention group walked for 10 minutes with repeated tripping perturbation, via sudden deceleration and acceleration of the treadmill belt (8 trips total). These trips were spaced out randomly to reduce participants' ability to predict when the next perturbation would occur. The timing of the belt perturbation was determined by the lead investigator. A hand-triggered device was directly connected to the treadmill and sent a signal to begin each perturbation. The investigator randomly ordered trips to each limb so that four trips occurred while both limbs were in single stance. The trips occurred around mid-stance to toe-off of single stance in order to imitate real-world scenarios as closely as possible. After the Tripping session, the participants rested again for 5 minutes to reduce fatigue. Finally, participants walked for another 15-minute unperturbed session. During all three sessions, a researcher asked the participants to give an estimated rating of perceived exertion at five-minute intervals.

Figure 3.1. Experimental Protocol



Data Reduction

Fall-risk was determined by data from the ABC, SRT, and BBS. A percentage of the likelihood of falling was developed by Lajoie and Gallagher (2004) and computed with the following equation:

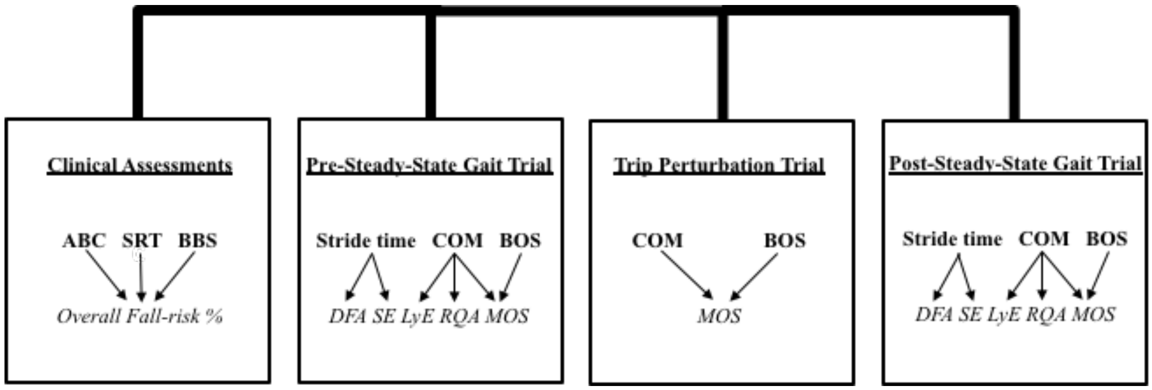
$$\text{Overall Fall-Risk (\%)} = \frac{(\exp(-7.519+0.026(SRT_{ave})-0.071(ABC1)-2.139(BBS14))}{1+\exp(-7.519+0.026(SRT_{ave})-0.071(ABC1)-2.139(BBS14))} \times 100$$

SRT_{ave} is the average of the 30 SRT trials as measured in milliseconds. ABC1 is the score from question 1 from the ABC survey, and BBS14 is the score from question 14 of the BBS. This combination was shown to predict fallers with 93% sensitivity and 95% specificity. To provide a concrete example, a person with a simple reaction time of 625 ms, and ABC1 of 85%, and a BBS 14 of 3 has a 2.4% chance of falling, whereas a person with a simple reaction time of 680 ms, and ABC1 of 65%, and a BBS 14 of 1 has a 96.8% chance of falling.

All kinematic data were reduced via customized Visual3D (C-motion, Germantown, MD, USA) scripts. The heel (calcaneus) markers were used to identify stride time intervals during the undisturbed walking trials due to support of measure in the literature (Hausdorff et al., 1995, 1999; Hausdorff et al., 1997). From there, the data were filtered with a 4th order Butterworth filter and velocity was calculated from the derivative of the anterior-posterior (AP) position data. Heel contact was identified as the time point when the AP velocity crosses from the positive to negative direction (Zeni, Richards, & Higginson, 2008). Stride times of each limb indicated the time interval between consecutive heel contacts of the ipsilateral limb.

The COM position, velocity, and acceleration were calculated from a 15-segment model and were representative of the summative displacements of the body in the AP direction. The anterior boundary of the BOS was defined as the AP position of the second metatarsal marker on the lead foot. DFA and SE of stride time, as well as multiple variables from RQA and LyE of COM were used to measure locomotor dynamics. MOS was used to calculate global stability. All values were calculated from the individual time series from the walking sessions utilizing customized Matlab scripts (Figure 3.2) (Mathworks, Natick, MA, USA). Hand-grip strength and walking speed were controlled for as covariates in all calculations.

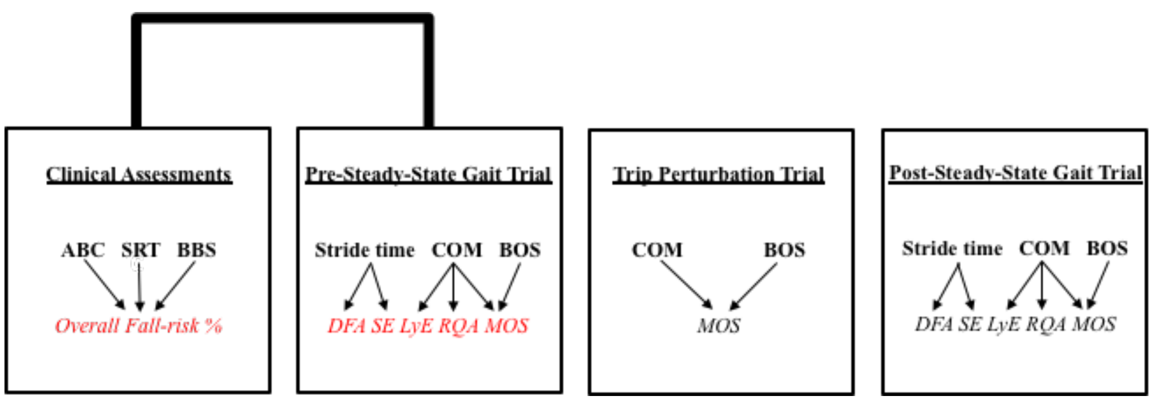
Figure 3.2 Data Reduction Framework



Statistical Analyses

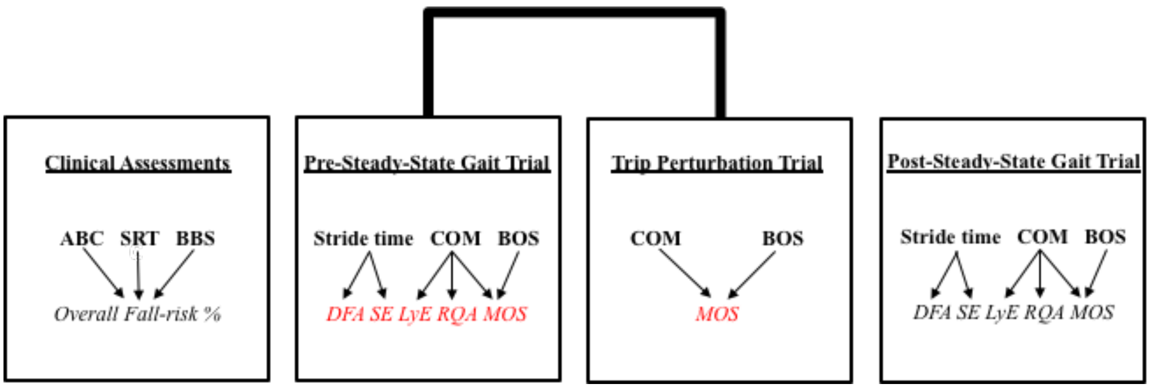
Hypothesis 1: Forward selection multiple regression models were calculated to observe the association between the fall-risk assessment and the various locomotor dynamics (DFA, SE, LyE, RQA) and stability (MOS) measures from the Pre-trip walking trial (regression model 1) (Figure 3.3). Follow-up partial correlations were calculated to further investigate the associations between individual metrics and overall fall-risk.

Figure 3.3 Hypothesis 1 Variables of Interest



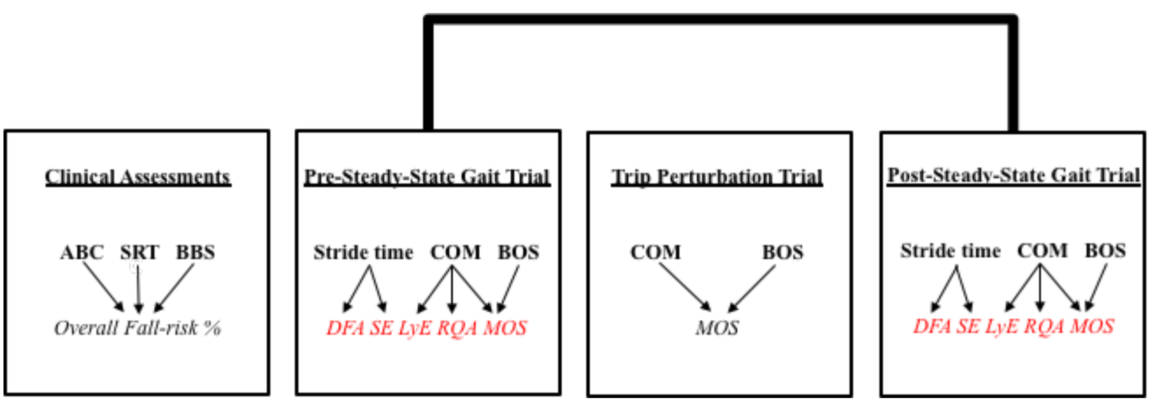
Hypothesis 2: Forward selection multiple regression models were calculated to determine the relationship between the Pre-trip walking session locomotor dynamics (DFA, SE, LyE, RQA) and stability (MOS) measures, with the trip-recovery metric from the Tripping session (Figure 3.4). Follow-up partial correlations were calculated to further investigate the associations between the Pre-trip and Tripping session metrics.

Figure 3.4 Hypothesis 2 Variables of Interest



Hypothesis 3: Mixed analysis of variance models were calculated to determine group differences to the locomotor dynamics (DFA, SE, RQA, LyE) and stability (MOS) metrics between the Pre- and Post-tripping sessions. (Figure 3.5).

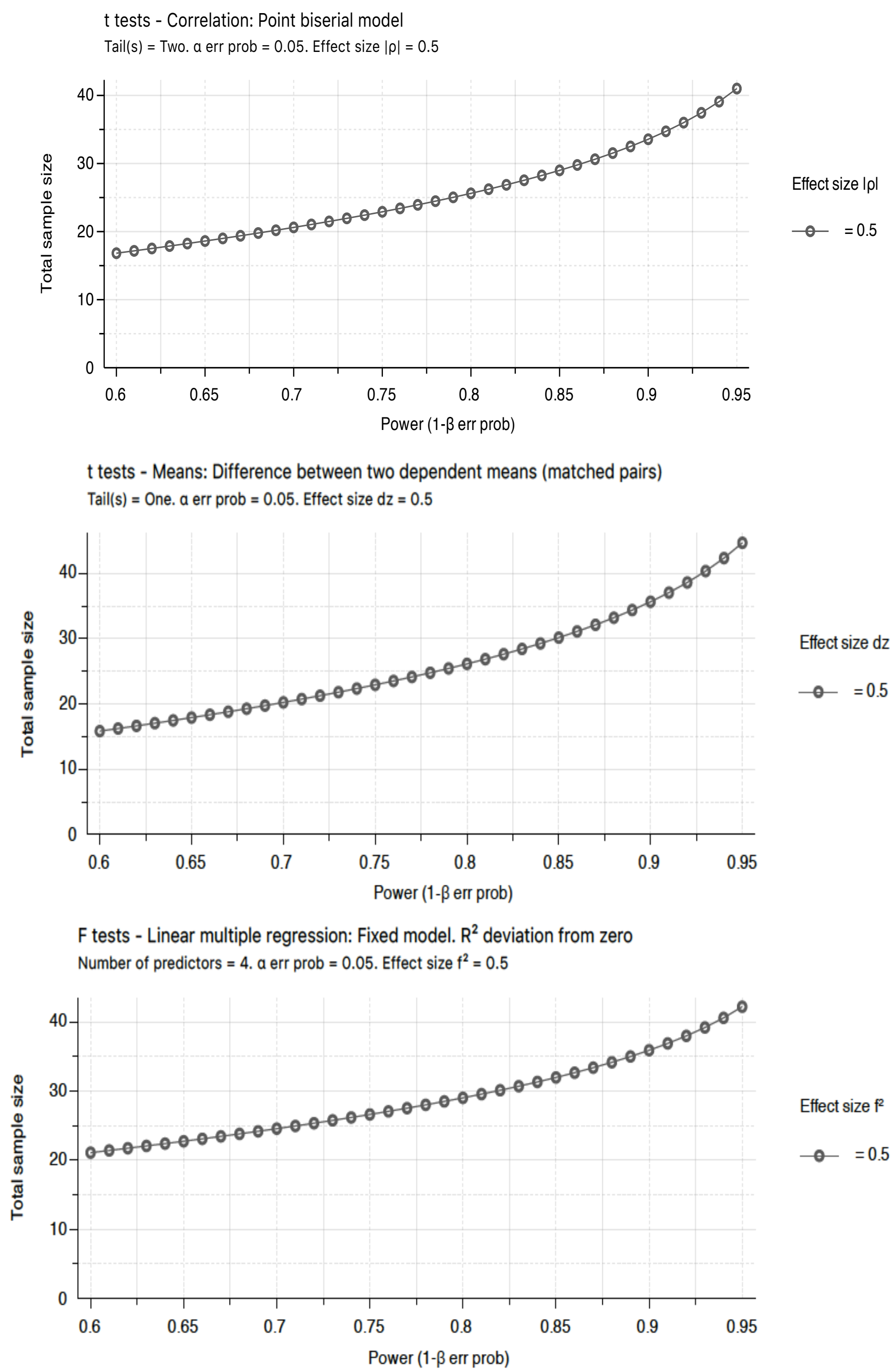
Figure 3.5 Hypothesis 3 Variables of Interest



Power Analysis

An *a priori* power analysis was conducted with pilot data on G*Power software (Version 3.1) for all hypotheses. Five older adults performed the Pre-trip, Tripping, and Post-trip sessions similar to as outlined in this proposal. LyE of the estimated COM (via the sacrum marker) was calculated for this power analysis to determine the extent to which it is modifiable after an acute trip-training session. LyE decreased from the Pre-trip session (1.112±.201) to the Post-trip session (1.059±.171), indicating an improvement in dynamics. Next, the values of the LyE were correlated to the participants' overall fall-risk from a predictive model. Correlations between Pre-trip LyE and fall-risk (.398) and Post-trip LyE and fall risk (-.581) were observed. These data were used for the separate power analyses and indicated a sample size of 30 should be sufficient to address hypotheses 1 and 3 (Figure 3.6). Pilot data to run a power analysis for hypothesis 2 have not been collected/analyzed. However, our power analysis is consistent with sample sizes from previous literature examining similar older adult fall-risk questions (Herman, Giladi, Gruendlinger, & Hausdorff, 2007).

Figure 3.6 Power Analyses



CHAPTER IV

MANUSCRIPT I

Introduction

The rapidly increasing population of adults aged 65 and over make up ≈15% of the U.S. population (48 million). This is projected to increase to 20% of the population (≈70 million) by 2030, and then to almost 100 million by 2060 (U.S. Census Bureau, 2017; Ortman, Velkoff, & Hogan, 2014). It is estimated that one out of every four individuals in this population fall each year, with one of out every five falls resulting in a serious injury (Alexander et al., 1992; Sterling et al., 2001; Stevens et al., 2012). This has led to unintentional falls becoming the leading cause of both fatal and non-fatal injury in the population with over 800,000 hospitalizations per year ("CDC Press Releases," 2016). Furthermore, this appears to be an increasingly hazardous problem for the population, with the fatality rate increasing year over year ("Important Facts about Falls | Home and Recreational Safety | CDC Injury Center," 2017). One of the main challenges facing health professionals is the ability to identify those who may be at an elevated fall-risk.

As the majority of falls occur during ambulation, assessing an individuals' ability to adapt to perturbations while they walk represents an ecologically valid way to assess fall-risk. In particular, tripping and slipping appear to be the most problematic perturbations for older adults to attempt to recover from (Berg et al., 1997; Bergland et al., 1998; Kelsey et al., 2012; Nachreiner et al., 2007; Talbot et al., 2005). Technological advances have made it possible to mimic the effects of a tripping perturbation using motorized treadmills (Owings et al., 2001; Pavol et al., 2001). This offers health professionals and researchers the opportunity to develop novel assessments that simulate real-world situations, such as observing an individual's ability to recover from a tripping perturbation during ambulation. Such information shows promise to help identify those with increased fall-risk and can also be used as a training modality in fall prevention programs (Gerards, McCrum, Mansfield, & Meijer, 2017; Lurie, Zagaria, Pidgeon, Forman, & Spratt, 2013; Mansfield, Wong, Bryce, Knorr, & Patterson, 2015; McCrum, Gerards, Karamanidis, Zijlstra, & Meijer, 2017; Okubo, Schoene, & Lord, 2016).

The development of fall-risk profiles has long been a focus of researchers. Numerous clinical tests have been developed with cut-off scores that indicate whether a person is at an elevated fall-risk. In an effort to increase the sensitivity and specificity of fall-risk identification, Lajoie and Gallagher (2004) determined that elements from three commonly used tests could be combined to predict fallers with 93% sensitivity and 95% specificity. These tests included the answer from the first question of the Activities-Specific Balance Confidence Scale (ABC), the score from the 14th element of the Berg Balance Scale (BBS), and the participant's simple reaction time (SRT). For example, a person who indicated an 85% on the first question of the ABC, scored a 3 on the 14th element of the BBS, and had a SRT of 625 ms would have a 2.4% chance of falling, whereas a person who indicated a 65% on the first question of the ABC, scored a 1 on the 14th element of the BBS, and had a SRT of 680 ms would have a 96.8% chance of falling.

This advancement helped better identify potential fallers, but there is still a need to understand how gait differs across the fall-risk spectrum so that health professionals can develop programs specifically targeting relevant locomotor deficiencies.

To address this challenge, researchers have adopted advanced mathematical techniques to better understand subtle differences in gait, and these novel paradigms have shown promise in understanding fall-risk due to particular characteristics within locomotor patterns (Beltran, Dingwell, & Wilken, 2014; Beurskens, Wilken, & Dingwell, 2014; Hausdorff, Rios, et al., 2001; McAndrew, Wilken, & Dingwell, 2011; Riva et al., 2013; Young, Wilken, & Dingwell, 2012). The dynamical systems framework is a mathematical approach that measures how a system's variability (i.e., slight differences between each stride in gait) changes over time, also known as the system's structure of variability. Analyses based on this framework are believed to characterize the overall output of a system (i.e., how the system is performing), which is becoming a more commonly used framework in fall-risk and fall-prevention research (Fino et al., 2016; Lipsitz & Goldberger, 1992; Lockhart & Liu, 2008; Manor & Lipsitz, 2013; Riva et al., 2013; Stergiou & Decker, 2011; van Emmerik et al., 2016). This is different than measuring how various inputs (e.g. strength, vision, proprioception, etc.) affect the system, which is a prominent methodology in fall-risk assessment literature (Horak, 2006; Lord, Menz, & Tiedemann, 2003). The dynamical systems approach is theorized to represent the quality of communication/interactions between a system's subcomponents across various time scales. Researchers in the field believe this indicates the system's global health via its adaptive capacity (Hausdorff, 2007; Lipsitz & Goldberger, 1992;

Rhea & Kiefer, 2014; Stergiou & Decker, 2011; Vaillancourt & Newell, 2002). While invasive testing would be required in most physiological systems to test adaptive capacity, movement-based systems, such as the locomotor system, are unique in their ability to be non-invasively tested for adaptive capacity through the use of perturbations during gait and then measuring the response. One way to do this is through the use of the aforementioned specialized treadmill that can provide a near instantaneous slip or trip while the participant is harnessed, allowing researchers to probe the adaptive capacity of the locomotor system in a relatively safe manner. Currently, a dynamical systems theory approach has only been adopted when studying perturbation responses in static postural control tasks (Cone et al., 2016; Manor et al., 2010). Adopting this approach in locomotor perturbation tasks will help better define the utility of dynamical systems metrics in the context of fall-risk research.

In addition to metrics derived from dynamical systems theory, another candidate metric to identify fall-risk during locomotion is the margin of stability (MOS). MOS is a stability metric that is similarly thought to indicate an individual's overall adaptive capacity during gait and posture, with adaptive capacity defined as the ability to remain upright regardless of task or environmental demands (Balasubramanian, Clark, & Fox, 2014). Stability, in the biomechanical sense, refers to a person's ability to stay balanced as their center of mass (COM) approaches the edge of their base of support (BOS), as well as their ability to remain upright when an external force is applied. Thus, MOS values are theorized to determine how well an individual adapts to various situations by measuring the minimal distance between the COM and BOS boundaries in the anterior-posterior (AP) and medial-lateral (ML) directions (Young et al., 2012). Dynamical systems metrics, by definition, measure patterns in the system and thus require a finite amount of data points to allow the pattern to emerge. Thus, they are commonly measured during steady-state gait. However, MOS can be measured at each step, allowing for a more acute characterization of biomechanical stability. Therefore, MOS can be measured during steady-state gait and directly after a perturbation.

Due to limited research, it is unclear the extent to which dynamical systems and/or stability metrics relate to locomotor adaptive capacity. If they are, it would lay the foundation to use these metrics to measure and monitor populations at higher risk of falling, and potentially use these metrics to help prescribe treatment plans, as has been suggested in previous literature (Manor & Lipsitz, 2013; Rhea, Kiefer, Wittstein, et al., 2014). However, evidence-based practice dictates that a relationship must exist between dynamical systems and/or stability metrics with fall-risk metrics before clinical practice can be transformed. The gaps in the literature could be addressed by: 1) assessing a person's fall-risk profile, 2) determining whether there is an association between fall-risk and locomotor dynamics/stability, and then 3) examining how these locomotor system characteristics relate to the ability to recover from a trip (i.e. locomotor adaptive capacity). Addressing these gaps would help researchers better understand which metrics have the strongest potential to identify adults with an elevated fall-risk, as well as their potential to indicate the locomotor system's adaptive capacity. For this study, it was decided *a priori* to use four dynamical systems metrics that represent the most common methodologies in human movement research (Bravi et al., 2011). These include detrended fluctuation analysis (DFA), sample entropy (SE), lyapunov exponent (LyE), and recurrence quantification analysis (RQA).

The objectives of this study were broken up into two separate experiments. Experiment one examined the relationship between dynamical systems (DFA, SE, LyE, and RQA) and stability (MOS) metrics during steady-state gait to fall-risk in older adults using a method similar to the Lajoie and Gallagher (2004) approach. We hypothesized for this experiment that all aforementioned metrics would significantly associate to fall-risk. Experiment two examined the extent to which dynamical systems/stability metrics and the locomotor system's adaptive capacity were related through the use of a series of unexpected perturbations provided while walking on a treadmill. For experiment two we hypothesized that all metrics would significantly correlate to trip-recovery performance. An outline of each experiment's methods and results follows.

Experiment 1 – Examining the Relationship between Analyses during Steady-state Gait and Fall-Risk

This experiment was designed to address the first two aforementioned gaps in the literature by assessing a person's fall-risk profile and then determining the extent to which there is an association between fall-risk and locomotor dynamics/stability during steady-state gait.

Methods

Participants

Forty healthy, older participants (75.2±4.9 years; 20 females, 20 males) were recruited via convenience sampling. Healthy was defined as having no neuromuscular injuries that cause abnormal walking behavior. All participants were required to have the ability to walk 15 minutes unaided on a treadmill. Prior to arriving, participants were instructed to wear athletic/tennis attire. Prior to the research session, participants read and signed a consent form. The study protocol and consent form was approved by the Institutional Review Board at the University of North Carolina at Greensboro.

Experimental Procedure

After consent was given, investigators collected the participants' height and mass. Participants then completed a set of demographic, basic health, physical activity, and fall history questionnaires. Next, participants completed a series of tests that were used in the fall-risk calculation published by Lajoie and Gallagher (2004). This included the Activities-specific Balance Confidence (ABC) scale, simple reaction time (SRT) test, and the Berg Balance Scale (BBS). A global strength test was also administered. The ABC rates an individual's confidence of remaining upright during 16 separate tasks (Powell & Myers, 1995). The scale ranges from 0% (no confidence in remaining upright) to 100% (total confidence in remaining upright). Afterwards, participants were brought into a separate office to complete 30 trials of the SRT test. SRT measures the time between the unexpected presentation of a visual stimulus and the appropriate movement response (Schmidt & Debû, 1993). We used the Deary-Liewald SRT test, which has been shown to be a reliable and valid measurement of SRT (Deary et al., 2011). Specifically, this SRT method measured the number of milliseconds it took the participants' to move their dominant hand's index finger and strike the space bar on a keyboard after a visual stimulus appeared on the computer screen. The SRT method used in this study differs from the one used by Lajoie and Gallagher (2004) due to equipment limitations. Following the SRT test, participants completed three trials of maximal hand grip strength on each hand using a hand dynamometer. The average of the stronger hand was used to measure the participants' hand grip strength, which has been observed to correlate to knee extensor strength, lower-limb strength, overall body strength, mobility, and fall-risk in older adults (Batista et al., 2012; Bohannon et al., 2012; Hoda et al., 2013; Rantanen et al., 1999; Schaubert & Bohannon, 2005). Finally, participants completed the BBS, which measures an individual's balance ability through the completion of 14 discreet tasks (Berg, Wood-Dauphine, Williams, & Gayton, 1989).

Next, participants were instructed to identify their preferred walking speed on a motorized treadmill over two walking trials at the start the walking session. In the first trial, the speed of the belt was steadily increased from .5 m/s until their preferred walking speed was identified by the participant. During the second trial, the speed was quickly adjusted above the initial identified preferred speed and steadily decreased until their preferred walking speed was again identified by the participant. The lead investigator then averaged those two speeds to calculate the participant's preferred walking speed, which remained consistent throughout the rest of the session. The data collection phase consisted of a 15-minute unperturbed, steady-state walking trial on the motorized treadmill. During the trial, participants were instructed to keep their eyes and head straight ahead. To control for fatigue, a Borg Rating of Perceived Exertion Scale was administered every five minutes during the trial (Borg, 1985, 1998) and no changes were observed throughout the trail.

Instrumentation

An Oqus motion capture system (Qualisys, Göthenburg, Sweden) recorded all 3-D kinematic data at 100 Hz. An ActiveStep treadmill was used for the walking trial (Simbex, Lebanon, NH, USA). Participants were required to wear a safety harness when on the treadmill. A set of 40 markers was placed on the participants' body and head. The marker locations included the head of second metatarsals, head of first and fifth metatarsals, calcaneus, medial and lateral malleoli of ankle, shank, medial and lateral knee, thigh, ASIS, PSIS, sacrum, C7 vertebra, three markers around head, manubrium, acromion, olecranon, radial/ulnar styloid processes, and dorsal third metacarpophalangeal joint.

Data Reduction

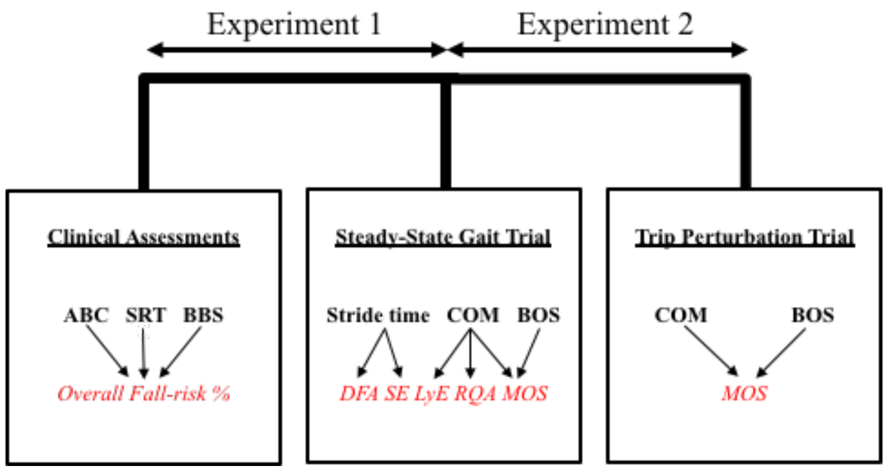
A visual representation of the data reduction framework for Experiments 1 and 2 can be found in Figure 4.1. Overall fall-risk was determined by data from the ABC, SRT, and BBS. A percentage of the likelihood of falling was developed by Lajoie and Gallagher (2004) and computed with the following equation:

$$\text{Overall Fall-Risk (\%)} = \frac{(\exp(-7.519+0.026(SRT_{ave})-0.071(ABC1)-2.139(BBS14)}{1+\exp(-7.519+0.026(SRT_{ave})-0.071(ABC1)-2.139(BBS14))} \times 100$$

where SRT_{ave} is the average SRT score measured in milliseconds, ABC1 is the score from question 1 from the ABC scale, and BBS14 is the score from element 14 of the BBS.

All kinematic data were reduced via custom Visual3D (C-motion, Germantown, MD, USA) scripts. Data were filtered with a 4th order Butterworth filter and velocity was calculated from the derivative of the AP position data. Based on previous research, the data of interest for this study was DFA and SE of the stride time series, RQA and LyE of the center of mass (COM) time series, and MOS, which is derived from the COM and base of support (BOS) time series (Costa et al., 2003; Hausdorff et al., 1995; Hof et al., 2005; Lamoth et al., 2011; Lockhart & Liu, 2008; Lugade et al., 2011; Riley, Balasubramaniam, & Turvey, 1999; Riva et al., 2013). Stride time was defined as the duration between each heel strike (HS) on the same limb. This was measured by identifying the time point when the velocity of the heel marker crossed from positive to negative in the AP direction (Zeni et al., 2008) for each stride, with the stride interval time series representing the subtle stride-to-stride variability observed in steady-state gait. The same methodology was used to identify toe off (TO) with the toe marker (head of the second metatarsal) for the MOS metrics. COM position and its derivatives (velocity and acceleration) were calculated from a 15-segment model that represented the summative displacements of the body in the AP direction. The anterior boundary of the BOS was defined as the AP position of the toe marker on the lead foot. All values were calculated from individual time series using custom Matlab scripts (Mathworks, Natick, MA, USA).

Figure 4.1. Data Reduction Framework



Data Analyses

All dependent variables were calculated from individual time series using custom Matlab scripts (Mathworks, Natick, MA, USA). While DFA and SE were calculated from all strides throughout the trial, LyE and RQA used the acceleration of the COM during the final 40 steps for analysis. Choosing to measure the acceleration of the COM (instead of position or velocity) and the number of steps was based off of previous research on LyE that was able to differentiate between fallers and non-fallers (Lockhart & Liu, 2008). Detailed descriptions of the mathematical processes to calculate the analyses has been previously described (Abarbanel, 2012; Hausdorff et al., 1995; Lake et al., 2002; Lockhart & Liu, 2008; Marwan et al., 2007; Rhea & Kiefer, 2014; Richman & Moorman, 2000; Webber & Zbilut, 1994; Webber Jr & Zbilut, 2005) and are briefly outlined below. The MOS values are the means of all MOS values observed at HS and TO, respectively.

DFA

DFA creates an index of long-range correlations across multiple time scales (Hausdorff et al., 1995; Peng et al., 1994). The slope calculated from the DFA calculation measures the strength of long-range correlations, with human stride interval time series' typically ranging between .5 and 1.0. A slope of .5 indicates low strength of long-range correlations (random noise) and 1.0 revealing a high strength of long-range correlations (structured noise). This measurement has previously been able to differentiate healthy and clinical populations at higher risk of falling (Hausdorff et al., 1997).

SE

SE, based off of approximate entropy, measures the patterned behavior of system dynamics using shorter data sets, with the difference being that SE removes self-matching patterns from the calculation (Lake et al., 2002; Pincus, 1991; Richman & Moorman, 2000). Previous literature has suggested that an template length m =2 and radius r=.2 of the standard deviation are appropriate parameters to analyze locomotor patterns (Georgoulis et al., 2006; Moraiti et al., 2009). SE values from movement-based time series typically range from 0 to 2, with 0 indicating patterned dynamics and 2 indicating more complex/random dynamics, however, previous gait research showed slightly higher values (Arif et al., 2004; Buzzi & Ulrich, 2004; Cavanaugh et al., 2006; Costa et al., 2003; Vaillancourt & Newell, 2000). Recent research reported the potential of SE to predict fall-risk (Fino et al., 2016).

LyE

The LyE value measures the rate of a signal's divergence by placing a linearly fitted slope over short-term (LyE_ST) and long-term (LyE_LT) time scales to measure the effects of local perturbations affecting the locomotor system (Abarbanel, 2012; Lockhart & Liu, 2008; Rhea & Kiefer, 2014). LyE estimates the local dynamic stability of a person, which is theorized to indicate how well a person adapts to minute variability being produced by a state of behavior during a specific task (van Emmerik et al., 2016). Such analyses have been suggested to predict specific pathological behavior via fall-risk in the older adult population (Granata & Lockhart, 2008; Lockhart & Liu, 2008).

RQA

RQA measures the patterned behavior within a dynamical system by measuring the original time series against time-delayed copies of itself within a multidimensional state space (similar to LyE) (Marwan et al., 2007; Webber & Zbilut, 1994; Webber Jr & Zbilut, 2005). From this, a multitude of variables can be calculated, including: percent recurrence (REC), determinism (DET), max line length (MAX), and Shannon entropy (ENT). REC measures percentage of recurrent points between the original and time-delayed copies over the possible amount of recurrent points in the state space (Rhea & Kiefer, 2014; Webber Jr & Zbilut, 2005). DET calculates the percent of recurrent points that are part of a pattern (2 or greater consecutive points) (Rhea & Kiefer, 2014; Webber Jr & Zbilut, 2005). ENT quantifies the probability that the pattern line lengths are equal in the state space (Pellecchia & Shockley, 2005; Rhea & Kiefer, 2014). MAX determines the longest pattern of consecutive recurrent points observed in the plot. Limited research has investigated RQA as it relates to adaptive capacity of the locomotor system, but initial results are promising (Labini et al., 2012; Riva et al., 2013).

MOS

MOS measures the minimum distance between the extrapolated COM (projected on the ground) and the boundary of the BOS at specific points in the gait cycle (Hof et al., 2005; Young & Dingwell, 2012). The use of kinematic and/or kinetic data allows the position and velocity of the COM to be extrapolated as a single value (Bruijn et al., 2013).

Statistical Analysis

A forward selection multiple regression model was used to compare the various metrics calculated from the steady-state-gait trial to the participants' fall-risk. Follow-up partial correlations were calculated to further observe the associations between individual metrics and fall-risk. Outliers defined as >3 SD away from the mean were removed (N=2). Preferred walking speed and strength were controlled for in the statistical analysis based off of previous results in the literature (England & Granata, 2007; Jordan et al., 2007; Karamanidis, Arampatzis, & Mademli, 2008). Alpha level was set *a priori* at p=.05. SPSS Version 25 (IBM, Armonk, NY, USA) was used for all statistical analyses.

Results

Table 4.1. Participant Demographics (Experiment 1). Values [mean±standard deviation (SD)], including: age, height, mass, preferred walking speed (PWS), hand grip strength (HGS).

Age (yrs)	Height (cm)	Mass (kg)	PWS (m/s)	HGS (kgf)
75.2±4.9	171±10	73.1±13.7	.891±.198	28.4±8.6

Table 4.2. Average Metric Scores (Experiment 1). Values (mean and SD) for all dependent variables in this study.

Metric	Mean	SD
ABC1	99.3	2.7
BBS14	3.40	0.93
SRTave (ms)	323	28
Fall-Risk (%)	.0051	.0237
DFA	.810	.093
SE	1.96	.35
LyE_ST	1.76	.41
LyE_LT	.03	.02
REC	5.57	3.40
DET	99.4	.4
ENT	4.93	.54
MAX	2390	355
MOS_HS (m)	.36	.048
MOS_TO (m)	.26	.06

Regression Model

A forward selection multiple regression model was calculated with the overall fall-risk metric as the dependent variable and preferred walking speed/strength variables enter selected in block one to control for variance. The following variables were included in block two and forward selected into the regression model: DFA, SE, LyE_ST, LyE_LT, REC, DET, ENT, MAX, MOS_HS, MOS_TO. The entry point for forward selected variables was set at .05.

One regression model was extracted from the initial model. The model contained the first block of entry selected control variables and produced non-significant results

(*Adjusted* R^2=.0490, *F* $Change_{2,27}$=1.95, *p Change*=.157). Follow-up partial correlations revealed no significant associations between individual metrics and fall-risk.

Experiment 2 – Determining the Relationship between Analyses and Adaptive Capacity

The findings of Experiment 1 highlight the challenge of using a fall-risk metric to quantify a relatively healthy older adult population, making it difficult to determine the utility of steady-state locomotor dynamics relative to fall-risk. In Experiment 2, rather than relying on performance on a series of tests to derive fall-risk, we sought to directly perturb participants with a series of unexpected trips while walking and measure their biomechanical response. Doing so helps us address the second and third aforementioned gaps in the literature by assessing locomotor dynamics/stability during steady-state gait (from Experiment 1) and determining the extent to which those characteristics are associated with the ability to recover from a trip (i.e. locomotor adaptive capacity) (from Experiment 2). Regarding the latter, the MOS variable was used as an indicator of trip recovery, as it provides a way to measure biomechanical stability by comparing the position of the COM within the BOS. This approach helped us determine whether variables derived from steady-state gait are useful in predicting performance when a person is exposed to an unexpected trip.

Methods

Experiment 1 enrolled 40 participants, 10 of which served as control participants and did not participate in Experiment 2. Thus, Experiment 2 enrolled 30 healthy, older participants (74.7±4.1 years; 15 females, 15 males) who also participated in Experiment

1. Each participant read and signed a consent form before beginning the research session, as required and approved by the Institutional Review Board at the University of North Carolina at Greensboro.

The same motion capture system/setup and treadmill described in Experiment 1 was used in Experiment 2. After completing the 15-minute steady-state walking trial described in Experiment 1, participants rested for 5 minutes to minimize fatigue. Next, participants completed a 10-minute unexpected locomotor perturbation trial, during which eight tripping perturbations were unexpectedly provided via sudden a deceleration and acceleration of the treadmill belt. On average, a trip was provided once every 75 seconds, but the actual time interval between each trip was spaced out at random intervals to reduce preparation from participants. All tripping perturbations were executed via a custom hand-triggered device connected to the treadmill. The lead investigator randomly ordered which limb would be in single stance for all trips, with four trips occurring with each limb in single stance per participant. All trips occurred between the mid-stance to toe-off phases of the gait cycle. This was done in order to best imitate real-world trips. As in Experiment 1, a Borg Rating of Perceived Exertion Scale was administered every five minutes during Experiment 2 to control for fatigue and no changes were observed throughout the trail. The same data reduction approach as defined in Experiment 1 was used in Experiment 2. Specific to this experiment, only the MOS variable was derived during the locomotor perturbation trial in order to measure biomechanical stability after the unexpected trips.

Data Analyses

Data derived from the dynamical systems and stability metrics in the initial, unperturbed steady-state gait trial from Experiment 1 were used to address the research question in Experiment 2. Unique to Experiment 2, the MOS values reported during the tripping trial are an average of the eight MOS values in the AP direction that were measured when HS and TO occurred on the subsequent step after each trip. A higher MOS at HS is ideal, as it represents how far back the COM is from the anterior boundary of the BOS. The opposite is true of the MOS at TO, as it indicates how far forward the COM is past the anterior boundary of the BOS. These measures are theorized to be indicative of the locomotor system's adaptive capacity, as they reveal the participants' ability to control their COM within their BOS and remain upright when an external force.

Statistical Analysis

A forward selection multiple regression model compared the various metrics calculated from the unperturbed walking trial to the trip-recovery metrics (MOS at HS and TO). Separate regression models were run for MOS at HS and TO. Follow-up partial correlations were calculated to further observe the associations between individual metrics and locomotor adaptive capacity. Preferred walking speed and strength were again controlled for in the analysis based off of previous results in the literature (England & Granata, 2007; Jordan et al., 2007; Karamanidis et al., 2008). Alpha level was set *a priori* at p=.05. SPSS Version 25 (IBM, Armonk, NY, USA) was used for the analysis.

Results

Table 4.3. Participant Demographics (Experiment 2). Values [mean±standard deviation (SD)], including: age, height, mass, preferred walking speed (PWS), hand grip strength (HGS).

Age (yrs)	Height (cm)	Mass (kg)	PWS (m/s)	HGS (kgf)
74.7±4.1	171±10	74.2±14.5	.913±.204	28.2±9.0

Table 4.4. Average Metric Scores (Experiment 2). Values (mean and SD), including: DFA, SE, LyE_ST, LyE_LT, REC, DET, ENT, MAX, MOS_HS, MOS_TO, MOS_HS_Trip, MOS_TO_Trip.

Metric	Mean	SD
DFA	.819	.076
SE	1.91	.27
LyE_ST	1.78	.44
LyE_LT	.025	.024
REC	5.85	3.59
DET	99.4	.5
ENT	4.96	.58
MAX	2370	389
MOS_HS (m)	.364	.051
MOS_TO (m)	.26	.06
MOS_HS_Trip (m)	.229	.056
MOS_TO_Trip (m)	.067	.101

Figure 4.2. Average MOS_HS Values Across Eight Trips

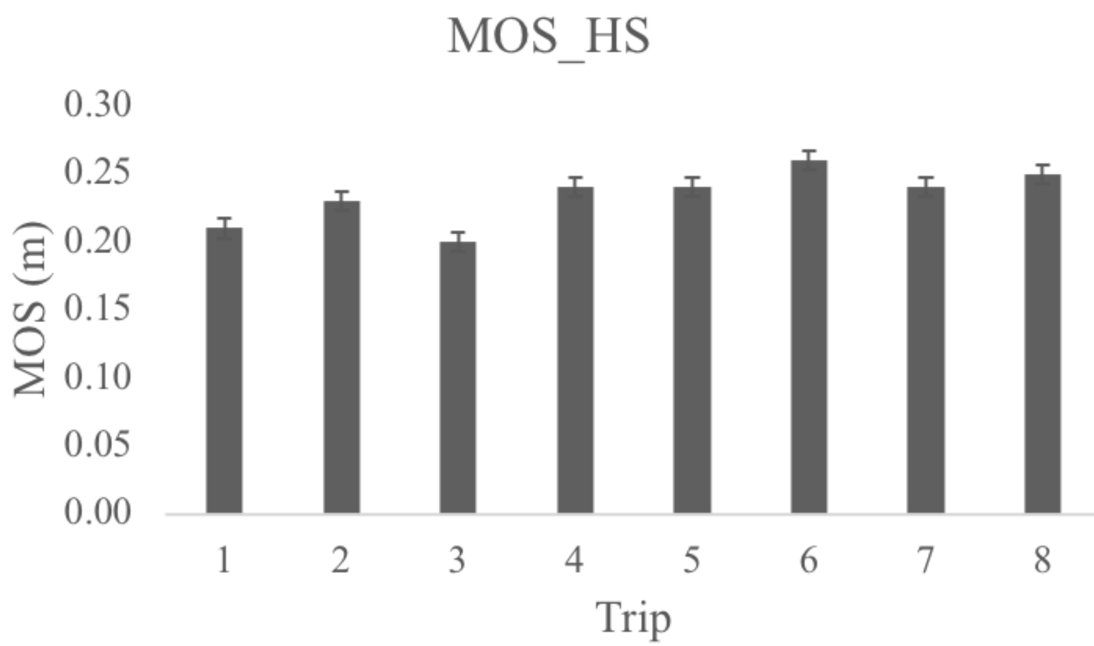
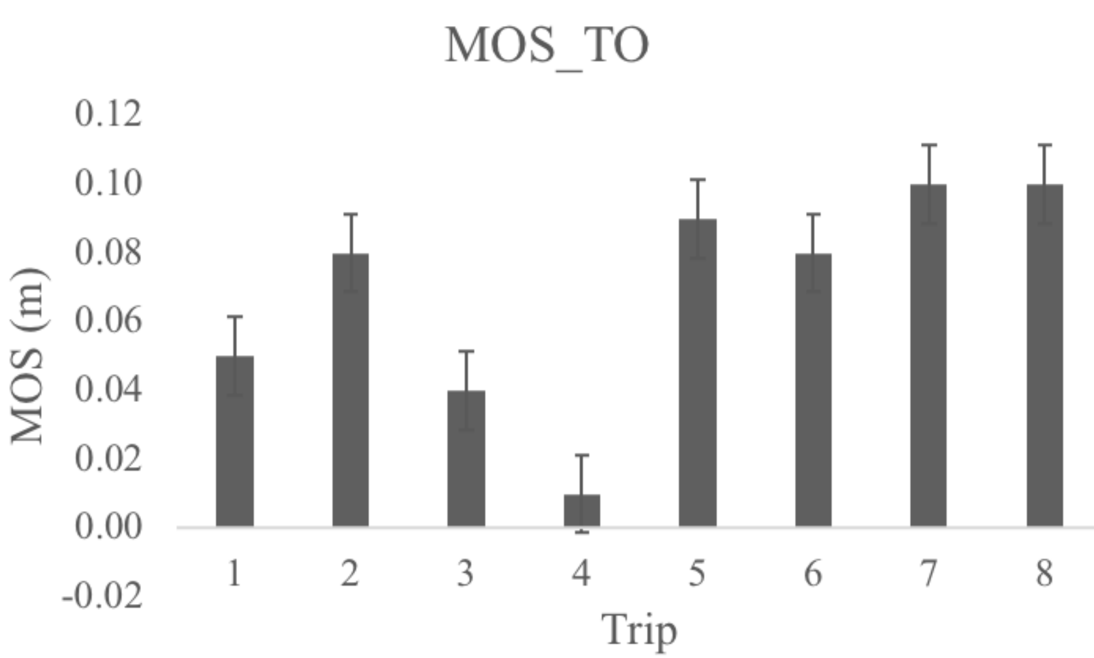


Figure 4.3. Average MOS_TO Values Across Eight Trips



Regression Model #1

A forward selection multiple regression model was calculated with the MOS_HS_Trip variable as the dependent variable and preferred walking speed/strength variables enter selected in block one to control for variance. The following variables were included in block two and forward selected into the regression model: DFA, SE, REC, DET, ENT, MAX, LyE_ST, LyE_LT, MOS_HS, MOS_TO. The entry point for forward selected variables was set at .05. Two separate regression models were extracted from the initial model. The first regression model contained the first block of entry selected control variables and produced non-significant results (*Adjusted* R^2=.100, $F\ Change_{2,27}$=2.61, *p Change*=.092). The second regression model inserted the second block of forward selected independent variables and found that a significant amount of variance in the trip-recovery metric can be explained by DFA (*Adjusted* R^2=.283, $F\ Change_{1,26}$=7.89, *p Change*=.009) when controlled for by preferred walking speed and strength. Follow-up partial correlations, controlling for preferred speed and strength, revealed a significant relationship between DFA (r=.416, p=.031) and the trip-recovery metric (Figure 4.4), as well as a near-significant relationship between MAX (r=.376, p=.053) (Figure 4.5).

Figure 4.4. DFA and MOS_HS_Trip Relationship.

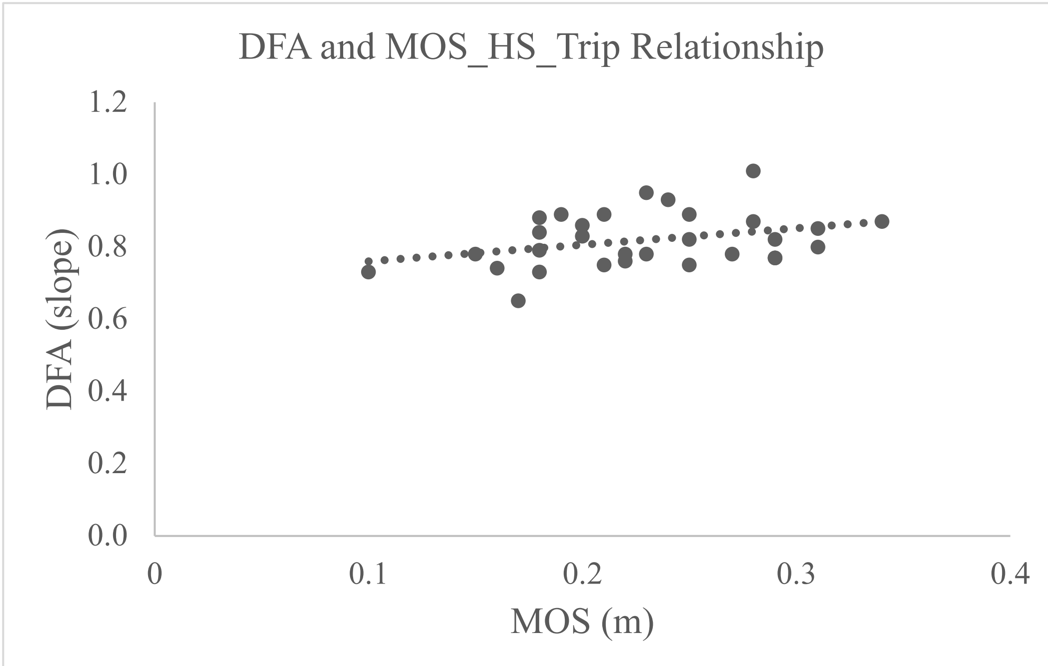
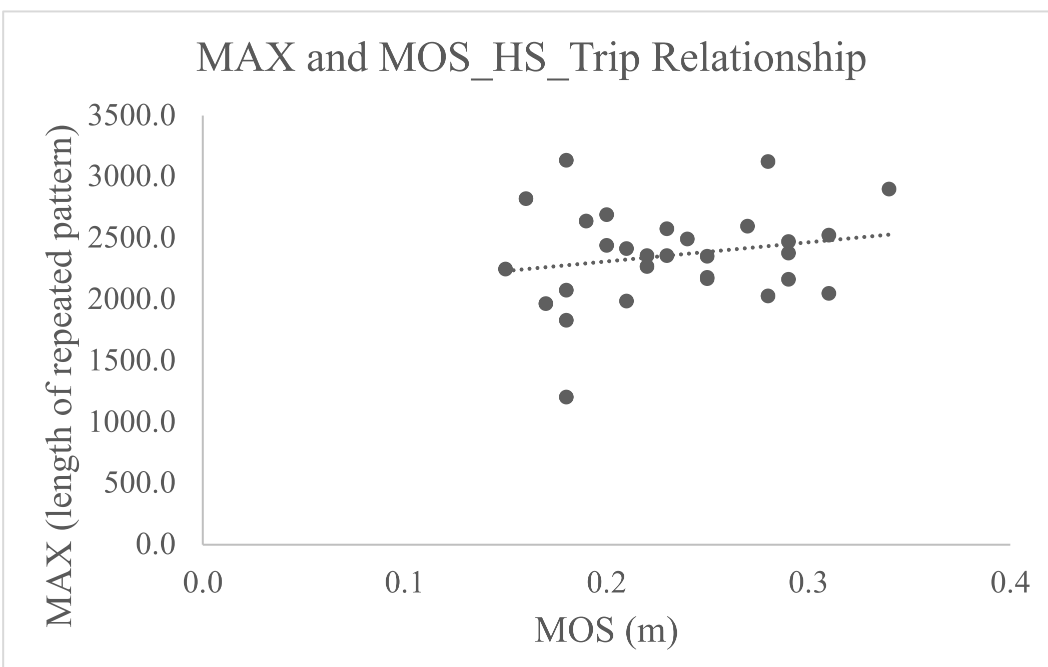


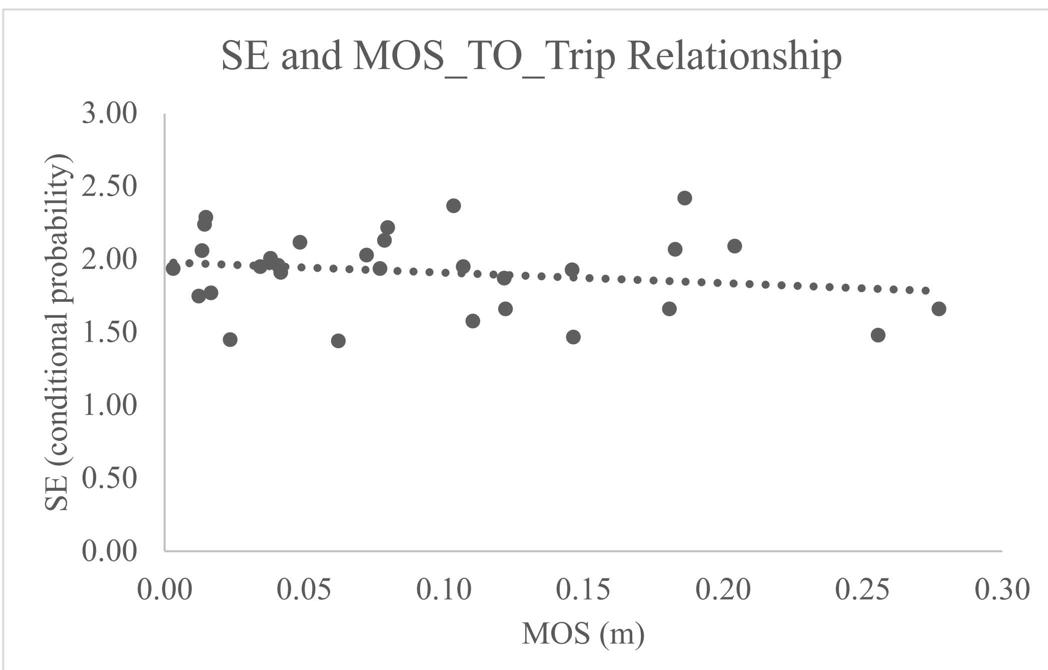
Figure 4.5. MAX and MOS_HS_Trip Relationship.



Regression Model #2

A second forward selection multiple regression model was calculated with the MOS_TO_Trip variable and controlling factors in the first block. The same metrics were entered into block two and forward selected into the regression model. The entry point for both forward selected variables was again set at .05. One regression model was extracted from the forward selection model, replicating the previous results observed for the variance explained by the control variables (*Adjusted* R^2=.064, $F\ Change_{2,27}$=1.96, *p Change*=.161). Follow-up partial correlations revealed a near-significant relationship between SE and the trip-recovery metric (r=-.377, p=.052) (Figure 4.6).

Figure 4.6. SE and MOS_HS_Trip Relationship.



Discussion

This study was composed of two separate experiments. Experiment 1 examined the relationship between dynamical systems (DFA, SE, LyE, and RQA) and stability (MOS) metrics during steady-state gait to a measure of fall-risk in healthy older adults. We hypothesized for this experiment that the dynamical systems and stability metrics would significantly predict fall-risk. The hypothesis of Experiment 1 was not supported, as no significant relationships were observed between the individual metrics and fall-risk. In light of this finding, Experiment 2 sought to determine the extent to which dynamical systems and stability metrics derived from steady-state gait predict one's ability to recover from an unexpected perturbation. The hypothesis of this study was partially supported, as significant or near-significant relationships were observed between two of the predictive measures and a trip-recovery metric. Collectively, these studies provided insight into the relationship between steady-state gait characteristics relative to adaptive locomotor capacity, which could help future researchers better design fall-risk and fall-prevention studies.

Experiment 1 showed no relationship between characteristics of steady-state gait and fall-risk. This observation is antithetical to current thought that postulates that the adaptive capacity of the locomotor system is related to subtle changes from stride-to-stride (Hamacher, Singh, Dieën, Heller, & Taylor, 2011; Hausdorff, 2007; Moon, Sung, An, Hernandez, & Sosnoff, 2016; Rhea & Kiefer, 2014; Stergiou & Decker, 2011). However, to our knowledge, we are the first researchers to empirically test the relationship between so-called "adaptive capacity" gait metrics to an evidence-based metric of fall-risk. This fall-risk metric is based on a person's perceived adaptive capabilities (from the ABC survey), their ability to balance on a single leg (from the BBS), and their reaction time (from the SRT test). It is possible that adaptive capacity in the context of trip recovery is not accurately assessed with the ABC, BBS, and SRT—none of which directly test the ability to recover from a trip. Thus, the constructs of trip recovery and fall-risk (as assessed with the ABC, BBS, and SRT) could be independent, as our results showed. It is also possible that the manner in which SRT was assessed in the current study compared to the original Lajoie & Gallagher (2004) study differed enough to make the fall-risk metric less sensitive and specific. Evidence for this postulate can be found by comparing the average SRT values in the current study (323±27.5 ms) to the SRT values in the original study (~500 ms in non-fallers and ~700 ms in fallers) (Lajoie & Gallagher, 2004). One reason for this difference could be adoption of different protocol for the SRT test. Lajoie and Gallagher (2004) used a SRT test that required a verbal response as soon as the participant heard an auditory stimulus. Further, the participant was instructed to maintain their posture as straight as possible during the SRT test while they were standing on a force plate. This made their SRT test a secondary task (as defined by the authors), which would account for the higher SRT values (i.e., slower) relative to our current study. Although the construct of SRT is the same, the manner in which it was assessed in the original study may be related to their high sensitivity and specificity, and at least partially account for the lack of an association between steady-state gait characteristics and fall-risk in the current study.

Experiment 2 allowed us to directly perturb gait via a series of unexpected trips and then measure the participants' biomechanical response. Such an approach provided a more ecologically valid way to determine the potential utility of steady-state gait characteristics. Both DFA and MAX (from RQA) were found to predict to trip recovery (via MOS at HS). DFA has a long history of being used to understand locomotor dysfunction and fall-risk (Hausdorff, Mitchell, et al., 1997; Hausdorff, Nelson, et al., 2001; Hove et al., 2012; Rhea et al., 2012). Thus, it was not surprising that DFA predicted trip recovery.

As discussed previously, DFA measures how well a physiological system's patterns correlate to each other over an extended period of time. This correlation is thought to indicate how well the different sub-systems are interacting to allow for structured, yet flexible behavior. It is this scale of behavior that is key to understanding why it is thought that a moderate value of DFA (typically .75) is thought to be indicative of healthy behavior. The increased DFA values of this study are in line with previous research observing gait when measured on a treadmill versus overground walking, with the higher DFA values of this study similar to that of young, healthy adults on a treadmill. It has also been observed that active older adults have similar DFA values to young, healthy adults (Chang et al., 2009; Hausdorff, Mitchell, et al., 1997; Stout, Wittstein, LoJacono, & Rhea, 2016). As older adults in general have been observed to have diminished long-range correlations in their stride time as assessed with DFA, (Hausdorff, Mitchell, et al., 1997), our findings indicate that those with higher DFA values will likely respond better to a tripping perturbation. This is the first direct evidence showing DFA can be used as an objective metric that reflect the adaptive capacity of the locomotor system. A recent study by Ducharme et al. (2017) did not show an association between DFA and perturbation response. The perturbation in this study was an asymmetric walking task and it was conducted with young (28.5±4.7 yrs), healthy adults—two factors that may partially account for the different observations. Thus, it remains unresolved whether DFA provides the same meaningful information across the lifespan.

The second variable that was associated with the tripping response was MAX, described the longest pattern the COM repeated at least once over the last 40 steps of the unperturbed walking trial (Webber & Zbilut, 1994; Webber Jr & Zbilut, 2005; Zbilut & Webber, 2006). A similar mechanism as DFA may explain the association to the trip-recovery metric, as the more patterned individuals (defined by a larger MAX value) may be individuals with greater structure in their coordination. Previous work has associated a larger MAX value to stability in a static posture task, but this is the first study to show the extent to which MAX is related to adaptive capacity in the locomotor system (Riley & Clark, 2003). Interestingly, there is a non-significant association between the MAX and DFA variables. This may indicate that there might be different types of coordination that can help individuals recover from a tripping perturbation. This would make sense, as the scales are vastly different between the two metrics, and MAX measuring at the level of COM dynamics, whereas DFA measuring at the level of stride time dynamics.

As SE is measuring the patterned behavior of a system through conditional probability, the association observed with the trip-recovery variable is in line with the previous results. While it is typically believed that an increased SE value is indicative of more adaptability, in this case the increased SE might reveal discoordination due to random behavior (Lipsitz & Goldberger, 1992). Thus, the lower values that represent more patterned behavior might support our rationale that the individual's with more structured coordination were able to better adapt. This observation fits within other theoretical models of locomotor dynamics that suggest a moderate amount of structure indicates higher adaptability than very little or too much structure in the global behavior (Stergiou & Decker, 2011; Vaillancourt & Newell, 2002, 2003).

This is the first study to measure MOS during both HS and TO, with MOS typically only measured at HS (Beltran et al., 2014; Terry et al., 2014; Young et al., 2012). We decided to add TO, as this was the first study to use MOS to investigate performance after a discreet perturbation. While MOS at HS observes how close the COM is getting to the anterior boundary of the BOS, MOS at TO indicates how far forward the COM was beyond the anterior boundary within the first step. We believe that further investigation of MOS will benefit from additional knowledge of the interaction between COM and BOS throughout the gait cycle (Lugade et al., 2011). Collectively, Experiment 2 provided insight into how subtle changes between strides in steady-state gait may reflect locomotor adaptive capacity.

A limitation of this study was the homogenous nature of the participants. All were healthy and able to walk for at least 15 continuous minutes of the treadmill despite having an average age of ≈75 years old. Further, all were willing and able to come to campus for testing, a requirement that not all participants who were initially contacted were willing to do. Thus, we ended up with a sample population of rather fit and motivated older adults. Evidence to support this notion is observed in the DFA values from Experiment 1 (0.81±0.09), which are more in-line with what would be expected in young healthy adults than older adults. However, this observation isn't unprecedented, as previous work has shown that fit older adults exhibit similar DFA values in gait as younger adults (Stout et al., 2016). Relative to the current study, this limitation may have affected the range of behaviors observed in both the clinical assessments and walking trials. On the other hand, this homogeneity of healthy older adults is also a strength, as it is common to see greater differences in a more diverse group. Adding greater diversity should increase the ability of these measures to both associate with fall-risk, as well as trip-recovery ability. Thus, future research should focus on more diverse groups of older adults, and other high fall-risk populations. One way to enhance recruitment is to focus on analyses that require fewer strides, thus reducing participant burden. Analyses that require fewer strides will also be more practical for translation to the clinical realm. Developing other adaptive capacity metrics (for various perturbations) is also needed in order to test the robustness of the analyses. Another important line of investigation needs to focus on the ability of both the predictive and adaptive capacity measures to be modified by intervention. These tools will be much more useful if they can be used to gauge the impact of specific fall-prevention programs.

In summary, when fall-risk was indirectly measured using a previously published method, fall-risk was not associated with dynamical systems and stability analyses measured during steady-state gait in a homogenous older adult population. However, when the response to a perturbation was directly tested using an unexpected trip paradigm, DFA and MAX were associated with the ability to maintain balance after the perturbation, indicating their reflection of adaptive capacity in the locomotor system. This study sets up a novel framework for further research to develop more evidence-based ways to reduce fall-risk and enhance fall-prevention programs.

CHAPTER V

MANUSCRIPT II

Introduction

Falls in older adults have been deemed a public health issue, leading to much time, effort, and resources being devoted to developing fall-prevention programs (Handelsman, 2011). However, recent reviews and meta-analyses have shown that these programs have only been mildly successful at curbing fall rates (Choi & Hector, 2012; Hill-Westmoreland, Soeken, & Spellbring, 2002; Oliver, Hopper, & Seed, 2000). This is especially problematic, as the Centers of Disease Control shows that the fatality rate per 100,000 in the older adult population who have fallen continues to rise every year. Thus, we have a growing public health problem with no real solution. It has been suggested that fall-prevention programs could be enhanced by a better understanding the components of balance control and how movement strategies are derived (Horak, 2006).

Researchers have traditionally proposed that the issue with most fall-prevention programs is that they do not address the specific deficits observed at the individual level. Deficit-specific fall-prevention programs are beginning to be designed to more effectively handle such a diverse population (Conradsson, Löfgren, Ståhle, Hagströmer, & Franzén, 2012; Lord et al., 2003; Mancini & Horak, 2010). These programs focus on the specific balance and gait deficits that have been associated with falling. Unfortunately, these programs are missing critical information regarding how balance systems, such as the locomotor system, function at a global level. Novel fall-prevention programs have recently emerged that intervene on the balance system as a whole, instead of its specific deficits, by using perturbation-based training to reduce fall risk. This approach is more intuitive to diminish an individual's fall-risk, as it simulates the real-world scenarios that are the most common causes of unintentional falls (e.g., slips and trips). Furthermore, a recent analysis suggested that the overall fall-rate of participants was lower after a perturbation-based fall-prevention program when compared to general balance training programs for older adults (Mansfield et al., 2015). Trip-training (repeated tripping in a safe environment), in particular, appears to be effective at improving biomechanical indicators of fall-risk in older adults (Bieryla, Madigan, & Nussbaum, 2007). Similar to the weaknesses associated with deficit-specific fall-prevention programs, traditional assessments (e.g., strength, reaction time, flexibility, etc.) lack the ability to show how altering one deficit might affect the interactions between other inputs (e.g., biomechanical properties) that govern the system's abilities to respond appropriately to perturbations. Thus, there is a need to assess the global behavior of gait.

While the control of gait is a seemingly trivial motor skill, it is actually deceptively complex. The body is made up of 206 bones, over 600 muscles, and millions of nerves and neurons. The act of walking requires the coordination of multiple systems within the body (e.g. muscular, nervous, skeletal, etc.), which have sub-systems that contribute to movement, and most of these sub-systems work at different scales (in both magnitude and duration). It is the interaction of these systems and sub-systems that allows gait behavior to emerge, and ultimately, whether a person is going to recover from a perturbation or not. While these countless interactions are essential to predicting adaptive behavior (i.e., adequate recovery and no fall) or maladaptive behavior (i.e., inadequate recovery leading to a fall), it would be impossible to monitor each sub-system and system individually to determine their relation to recovery.

One solution to measuring such a complex system is to observe the patterns of variation (i.e., the structure of variability) within the system, which quantifies the interaction of multiple sub-systems at an appropriate scale. Thus, the interacting components are accounted for via a more global variable. This approach has recently been suggested as a plausible way to measure physiological complexity in the context of aging and balance control (Wayne et al., 2013). A potential reason that current training programs have only had a minimal impact on fall-risk is because they are not intervening at the right level of behavior. Gait complexity (a measurement of locomotor dynamics) is a plausible, yet untested variable that could be the appropriate behavioral level in which to intervene.

Measurements of gait complexity quantify the variability patterns that emerge over time, rather than the average behavior. Specifically, they calculate characteristics of the variability structure. While there are many ways to quantify gait patterns, detrended fluctuation analysis (DFA), sample entropy (SE), maximum lyapunov exponent (LyE), and recurrence quantification analysis (RQA) are four of the most commonly used techniques that have been inferred to be an index of adaptability for gait (Beurskens et al., 2014; Hausdorff, Mitchell, et al., 1997; Herman et al., 2005; Lockhart & Liu, 2008;

McAndrew et al., 2011; Riva et al., 2013). This means that an individual with inadequate gait complexity would not possess the ability to appropriately respond to perturbations, whereas someone with adequate gait complexity would respond more appropriately. Empirical data to support this notion mostly consists of comparisons between younger and older adults, as well as fallers vs. non-fallers (Granata & Lockhart, 2008; Hamacher, Singh, Dieën, Heller, & Taylor, 2011; Hausdorff, Mitchell, et al., 1997; Hausdorff, Edelberg, Mitchell, Goldberger, & Wei, 1997; Herman et al., 2005; Lockhart & Liu, 2008).

However, gait complexity has been shown to be modifiable through training, so evidence-based training programs could be developed to target a variable that is directly related to fall-risk. Indeed, gait complexity metrics have been monitored before and after a variety of direct and indirect interventions, with direct interventions' primary objective to alter gait complexity. This has typically been achieved through a variety of acoustic and/or visual metronomes that give a degree of structure for the participants' to step in time with (Herman et al., 2007; Hove et al., 2012; Kaipust et al., 2012; Marmelat et al., 2014; Rhea, Kiefer, Wittstein, et al., 2014; Rhea, Kiefer, D'Andrea, et al., 2014; Rhea et al., 2012; Schaafsma et al., 2003; Sejdić et al., 2012; Terrier & Deriaz, 2013; Terrier & Dériaz, 2012). One indirect intervention study found strong associations between gait complexity and functional task outcomes after an exercise-based intervention (e.g. balance, gait, mobility) (Hausdorff, Nelson, et al., 2001). However, no literature to date has directly related the strength of gait complexity before and after a perturbation-based fall-prevention program.

Another approach to measuring the locomotor system as a whole is by observing its stability. Metrics based on this paradigm are thought to indicate an individual's overall adaptive capacity during ambulation, with adaptive capacity defined as the ability to remain upright during various tasks (Balasubramanian et al., 2014). In this framework, stability refers to a person's ability to remain upright when their center of mass (COM) approaches the boundaries of their base of support (BOS), and also their ability to stay balanced when an external force is enacted on them. For example, a stability-based variable such as the margin of stability (MOS) is theorized to determine how well an individual adapts to various tasks by measuring the minimal distance between the COM position and the boundaries of their BOS. This can be measured in both the anterior-posterior (AP) and medial-lateral (ML) directions (Young et al., 2012). Thus, both gait complexity and stability metrics are believed to be indicators of the global behavior of the locomotor system.

Our long-term goal is to design individualized fall-prevention programs using novel methods centered on altering a person's global locomotor system via gait complexity and stability. Currently, there is limited information on how perturbation-based fall-prevention programs impact gait complexity and stability. Treadmill technology is able to produce realistic perturbation-based training, allowing researchers to investigate how an acute trip-training session affects gait complexity and stability in individuals in a controlled environment (Grabiner et al., 1993; Owings et al., 2001).

The purpose of this study is to examine the effects of a novel trip-training session on the gait complexity of healthy, older adults. We hypothesized that the gait complexity would significantly change following a single trip-training session.

Methods

Forty healthy, older participants (75.2±4.9 years; 20 females, 20 males) were recruited from the local community. Participants had no neuromuscular injuries resulting in abnormal walking behavior. All participants were also required to have the ability to walk 15 minutes unaided on a motorized treadmill. Participants were randomly placed in either a control (76.7±6.8 years; 5 females, 5 males) or an intervention (74.7±4.1 years; 15 females, 15 males) group. Prior to arriving, the lead investigator instructed participants to wear athletic clothes and shoes. Before data collection, participants read and signed a consent form. The study protocol and consent form was approved by the Institutional Review Board at the University of North Carolina at Greensboro.

An 8-camera Oqus motion capture system (Qualisys, Göthenburg, Sweden) recorded all 3-D kinematic data at 100 Hz. An ActiveStep treadmill (Simbex, Lebanon, NH, USA) was used for all walking trials. Participants wore a safety harness when walking on the treadmill. A set of 40 markers was placed on the participants' body and head. These included the head of second metatarsals, head of first and fifth metatarsals, calcaneus, medial and lateral malleoli of ankle, shank, medial and lateral knee, thigh, ASIS, PSIS, sacrum, C7 vertebra, three markers around head, manubrium, acromion, olecranon, radial/ulnar styloid processes, and dorsal third metacarpophalangeal joint.

After consent was given, investigators collected the participants' height and mass. Participants then completed a set of demographic, basic health, physical activity, and fall history questionnaires. Next, participants completed three trials of maximal hand grip strength on each hand using a hand dynamometer. The average of the stronger hand was used to measure the participants' hand grip strength, which has been observed to correlate to knee extensor strength, lower-limb strength, overall body strength, mobility, and fall-risk in older adults (Batista et al., 2012; Bohannon et al., 2012; Hoda et al., 2013; Rantanen et al., 1999; Schaubert & Bohannon, 2005).

Afterwards, participants were instructed to identify their preferred walking speed on the ActiveStep treadmill, over two walking trials, at the start the walking session. In the first trial, the speed of the belt was steadily increased from .5 m/s until an appropriate speed was identified by the participant. During the second trial, the speed was quickly adjusted above the initial identified speed and steadily decreased until an appropriate speed was again identified by the participant. The lead investigator then averaged those two speeds to calculate the participant's preferred walking speed, which remained consistent throughout the rest of the session.

The data collection phase consisted of three walking trials on the ActiveStep treadmill, with five minute breaks administered between each trial. During the trials, participants were instructed to keep their eyes and head straight ahead. A Borg Rating of Perceived Exertion Scale was administered every five minutes during each trial, but no significant fatigue was observed throughout the experiment (Borg, 1985, 1998). The first and third walking trials were identical for both groups, with all participants walking unperturbed for 15 minutes on the ActiveStep treadmill. In the second walking trial, the control group walked unperturbed for 10 minutes. The intervention group, on the other hand, was repeatedly and unexpectedly tripped over their 10-minute trial. During the trial, eight total trips were simulated via sudden deceleration and re-acceleration of the treadmill belt. The timing between the trips was randomized to minimize anticipation and occurred on average 75 seconds apart. Four trips were triggered while each limb was in single stance for all participants in the intervention group. All trips were triggered by a custom-made handheld device connected to the treadmill. The lead investigator triggered each trip while the participants were between the mid-stance and toe-off phases of the gait cycle. The order of which limb would be in single stance during each trip was randomized *a priori*, as well as the timing of the trips during the 10-minute walking trial.

All kinematic data was reduced via custom Visual3D (C-motion, Germantown, MD, USA) scripts. The heel (calcaneus) markers were used to identify stride time intervals due to support of the measure in the literature (Hausdorff et al., 1995, 1999; Hausdorff et al., 1997). From there, the data was filtered with a 4^{th} order Butterworth filter and velocity was calculated from the derivative of the AP position data. Heel strikes (HS) were identified as the time points when the velocity of the heel marker crosses from the positive to negative AP direction (Zeni et al., 2008). Stride times of each limb indicated the time interval between consecutive HS of the ipsilateral limb. The same methodology was used to identify toe off (TO) with the toe marker (head of the second metatarsal) for the MOS metrics. COM position and its derivatives (velocity and acceleration) were calculated from a 15-segment model that represented the summative displacements of the body in the AP direction. The anterior boundary of the BOS was defined as the AP position of the toe marker on the lead foot. DFA and SE of stride times (average of both limbs values), as well as multiple variables from RQA and LyE of COM were used to measure locomotor dynamics during the walking trials. MOS was used to measure the stability of the locomotor system during the walking trials. All values were calculated from individual time series using custom Matlab scripts (Mathworks, Natick, MA, USA).

All dynamical systems analyses were calculated from data collected during the Pre-trip and Post-trip walking trials. While DFA and SE were calculated from all strides throughout both trials, LyE and RQA used the acceleration of the COM during the final 40 steps of the Pre-trip and the first 40 steps of the Post-trip walking trials for analysis. Choosing to measure the acceleration of the COM (instead of position or velocity) and the number of steps was based off of previous research on LyE that was able to differentiate between fallers and non-fallers (Lockhart & Liu, 2008). Detailed descriptions of the mathematical processes to calculate the analyses can be found elsewhere. (Abarbanel, 2012; Hausdorff et al., 1995; Lake et al., 2002; Lockhart & Liu, 2008; Marwan et al., 2007; Rhea & Kiefer, 2014; Richman & Moorman, 2000; Webber & Zbilut, 1994; Webber Jr & Zbilut, 2005). The MOS values are the means of all MOS values observed at HS and TO, respectively.

Two-way mixed analysis of variance (mixed ANOVA) models (Time*Group) were used to compare the metrics calculated from the Pre- and Post-trip walking trials for the control and intervention groups. Preferred walking speed and strength were controlled for in the statistical analysis based off of previous results in the literature (England & Granata, 2007; Jordan et al., 2007; Karamanidis et al., 2008). Alpha level was set *a priori* at p=.05. SPSS Version 25 (IBM, Armonk, NY, USA) was used for all statistical analyses. In addition to the aforementioned gait complexity and stability metrics, summary metrics were included to describe the mean and standard deviation (SD) of the gait variables, including mean stride time (Ave_ST), SD of stride time (SD_ST), mean COM acceleration (Ave_ACC), and SD of COM acceleration (SD_ACC).

Results

Table 5.1. Participant Demographics (Manuscript 2). Values [mean±standard deviation (SD)], including: age, height, mass, preferred walking speed (PWS), hand grip strength (HGS).

Group	Age (yrs)	Height (cm)	Mass (kg)	PWS (m/s)	HGS (kgf)
Control	76.7±6.8	169±11	69.7±10.5	.830±.173	28.9±8.0
Intervention	74.7±4.1	171±10	74.2±14.5	.910±.204	28.2±9.0
T-test (p-value)	.411	.606	.461	.382	.557

Table 5.2. Average Metric Scores (Manuscript 2). Values [mean±standard deviation (SD)] for all dependent variables included in the study.

Metric	Control (Pre)	Control (Post)	Intervention (Pre)	Intervention (Post)	Interaction (p-value)
DFA	.79±.14	.79±.09	.82±.08	.78±.09	.61
SE	2.1±.5	2.02±.30	1.91±.27	1.98±.33	.73
LyE_ST	1.73±.33	1.65±.27	1.78±.44	1.84±.37	.20
LyE_LT	.03±.02	.04±.02	.03±.02	.03±.02	.29
REC	4.71±2.71	6.82±4.63	5.85±3.59	4.33±1.46	.01
DET	99±.232	99±.401	99±.475	99±.351	.89
ENT	4.82±.42	4.91±.51	4.96±.58	4.86±.54	.26
MAX	2470±225	2460±276	2365±389	2290±423	.76
MOS_HS (m)	.34±.03	.35±.03	.36±.05	.38±.05	.86
MOS_TO (m)	.24±.06	.26±.06	.26±.07	.27±.06	.14
Ave_ST (s)	1.14±.05	1.22±.06	1.14±.13	1.18±.14	.02
SD_ST (s)	.04±.02	.04±.02	.03±.02	.03±.02	.87
Ave_ACC (m/s^2)	.45±.11	.47±.11	.49±.15	.49±.15	.21
SD_ACC (m/s^2)	.29±.07	.31±.07	.32±.08	.31±.08	.08

Mixed ANOVA Models

Mixed ANOVA models were calculated between all individual metrics to determine the effects of the acute trip-training session. Only the REC variable had a significant interaction ($F_{1,34}$=8.520, p=.006) (Figure 5.1). There was a significant main effect for time with the MOS_HS ($F_{1,34}$=9.021, p=.005), and near-significant effects with both MOS_TO ($F_{1,34}$=3.444, p=.072) and DET ($F_{1,34}$=3.529, p=.069) variables. No significant main effects for group were observed. Additionally, a significant interaction was observed in the Ave_ST changes between groups ($F_{1,34}$=6.016, p=.019) (Figure 5.2).

Figure 5.1 Interaction between the Control and Intervention Groups' REC

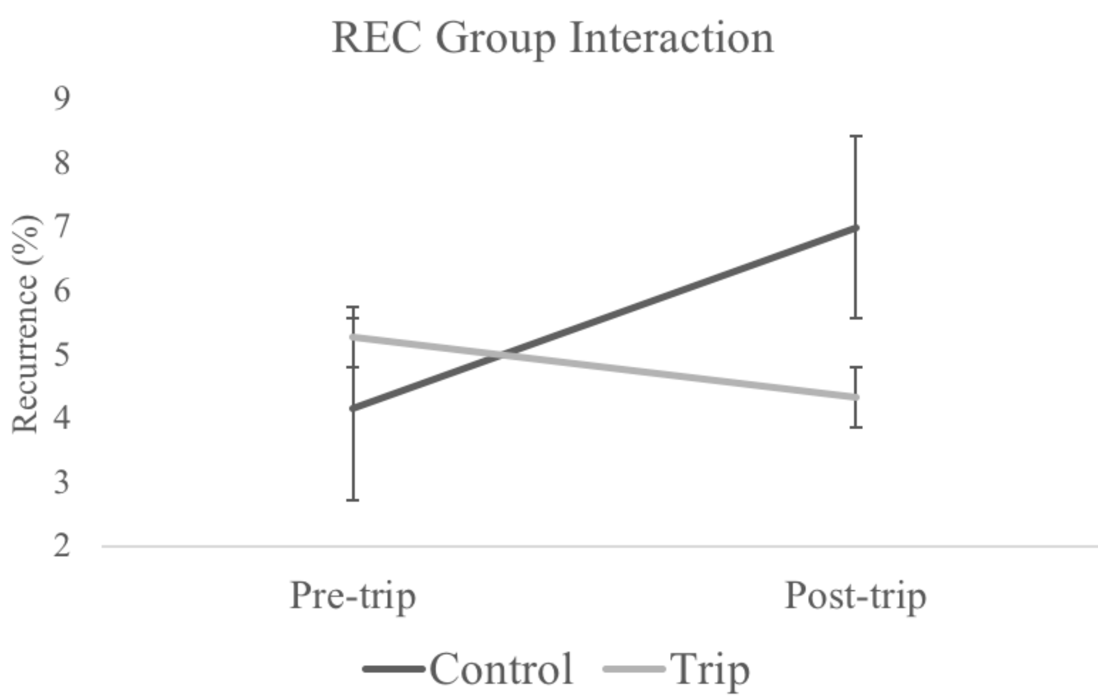
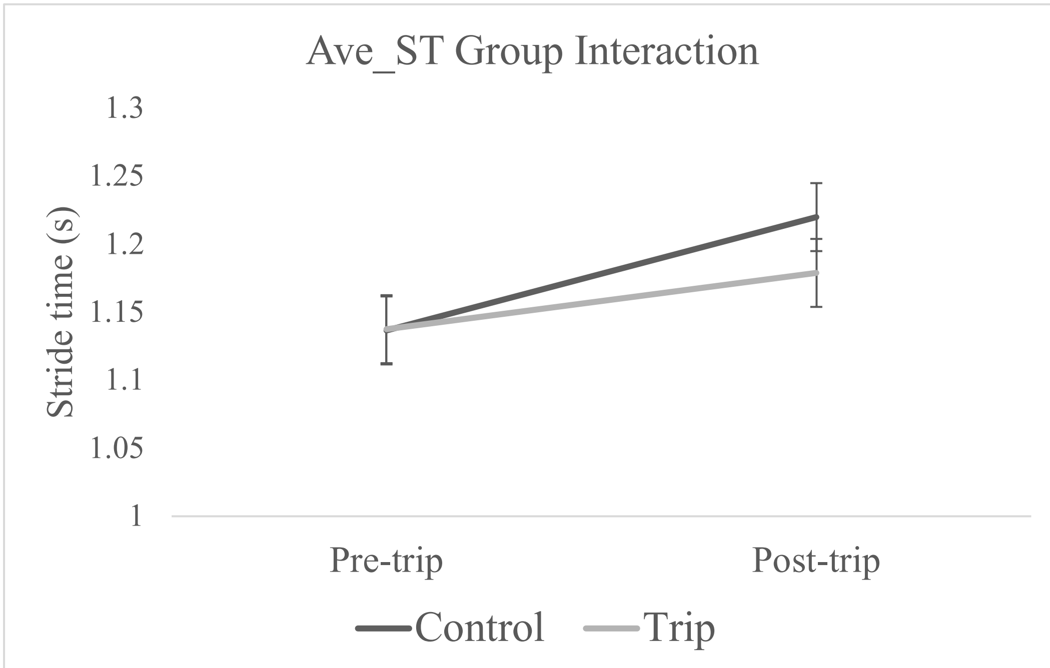


Figure 5.2. Interaction between the Control and Intervention Groups' Ave_St



Discussion

The objective of this study was to examine the effects of an acute perturbation-based training program on dynamical systems (DFA, SE, LyE, and RQA) and stability (MOS) metrics during steady-state gait. We hypothesized that the dynamical systems and stability metrics would significantly change when compared to the control group between the Pre-trip and Post-trip walking trials. The hypothesis of this study was partially supported, as a significant interaction was observed for the REC metric. This study revealed the potential changes in locomotor dynamics associated with a single session of trip training.

REC quantifies the percentage of data points in a state-space that are repeated within a certain radius. Interestingly, the intervention group's REC values significantly decreased compared to the control group, indicating that fewer movements were similar over the first 40 steps of the Post-trip trial. This can be interpreted as the intervention group increased the flexibility of their locomotor system to explore more possible movement strategies while walking, while the control group became more patterned in their behavior as they walked unperturbed on the treadmill over the trials. Previous work has shown that patients with unilateral vestibular hypofunction exhibit lower REC in their trunk during gait compared to healthy controls, providing conflicting evidence that lower REC values reflect a more adaptive behavior in the locomotor system (Labini et al., 2012). Recent research showed that REC is related to the Timed Up and Go and the Two Minute Walk Test, two commonly used clinical measures to measure functional ability (Tamburini, Mazzoli, & Stagni, 2018). Thus, while potential exists, utilizing repeating patterns exhibited in the COM (as assessed with REC) to indicate the adaptive capacity of the locomotor system needs further investigation before conclusions can be made.

The single trip-training session was overall less successful than previous direct and indirect studies relative to the ability to modify gait complexity (Hausdorff, Nelson, et al., 2001; Hove et al., 2012; Kaipust et al., 2012; Rhea, Kiefer, Wittstein, et al., 2014; Rhea, Kiefer, D'Andrea, et al., 2014). In previous studies, gait dynamics were significantly altered in both healthy and clinical populations in a variety of age groups. In hindsight, it appears that eight trips is not enough to significantly reorganize older adults' walking patterns. Given previous studies allowance for numerous practice trials, it appears that further investigation should either extend the number of trips per session, or increase the number of sessions before measuring gait complexity. This indicates that trip-training will likely need to adhere to more rigorous standards of training programs by increasing the duration, frequency, and/or intensity in order to maximize the effects.

The significant interaction between the control and intervention groups in Ave_ST is an interesting observation. It is most likely that minimal fatigue set in to both groups after the first two walking trials, which caused them to increase their stride time as observed in previous studies (Ko, Hausdorff, & Ferrucci, 2010). Although fatigue was not directly assessed, the RPE scale data showed no increases in perceived fatigue. Thus, any fatigue that may have occurred was subthreshold level. The intervention group had an increased average preferred walking speed which most likely did not allow them to take as long of steps as the control group leading to the minimal increase in stride time.

Three variables (MOS_HS, MOS_TO, DET) had significant or near-significant changes for both groups. This may indicate that certain locomotor dynamics and stability variables might be altered simply by walking on a treadmill for a certain duration of time. This is an important finding, as it has potential implications for further research. If variables are being altered similarly between a targeted intervention and walking control group, it will be necessary for researchers to find alternative methodology for control groups. Otherwise, it may be possible that effects observed in further research are not due to the specific intervention of interest. Having a control group will be a necessity in any further investigation of locomotor dynamics and stability, given the large variance between participants, as well as the possibility of significant effects due to confounding factors.

Interestingly, while the requirements of the study (being able to walk on a treadmill for 15 minutes unaided) created limited diversity in the health status of the participants, the ability of these analyses to observe changes due to an acute trip-training session is significant, as greater changes are typically observed in intervention studies monitoring changes in less healthy populations. Especially with the brevity of the intervention (8 trips), these findings may reflect the beginning stages of neuro-motor reorganization.

This supports the need for continued investigation on the potential of perturbation-based fall-prevention programs to alter global locomotor variables. The locomotor dynamics and stability measures appeared to have a large amount of variance between individuals. Even with this limited diversity, the variance appears to have drastically affected the ability of the other measures to exhibit significant differences between groups. This suggests that recruiting a homogenous sample of older adults makes it difficult to fully characterize how a single session of trip-training may reorganize gait complexity and stability.

Adopting a similar approach, but with a wider variety of participants will enhance the ability of future researchers to address this limitation. One way to enhance recruitment for this and other populations is to lower the number of strides required by the analyses, which will increase the number of participants who can participate. Requiring fewer strides for the analysis will also make the eventual translation of this research into the clinical realm more feasible. Conducting similar research with a variety of perturbation-based training methodologies will also help unveil the robustness of such metrics. Further understanding how these metrics fit in with the fall-risk of individuals will also help researchers better understand the utility of such analyses.

In summary, a single session of trip-training modified REC of the COM, reflecting a more flexible walking pattern. However, no other metrics hypothesized to reflect adaptive capacity of the locomotor system were altered after the single trip-training session. This is perhaps not unexpected, as the participants only had eight opportunities to reorganize their gait control, which is rather limited given how much practice is typically required to alter behavior. Nevertheless, a single trip-training session did lead to some altered gait behavior in the postulated direction. This study sets up a potential novel assessment for fall-prevention programs based on perturbation training. Further research is needed to better understand the benefits of such interventions versus more traditional deficit-specific training.

CHAPTER VI

DISCUSSION

The purpose of this dissertation was to examine the direct relationship between locomotor dynamics/stability and adaptive capacity. Currently, researchers in the field of nonlinear physiological variability have assumed with limited direct evidence that physiological dynamics are indicative of adaptive capacity (Cone et al., 2016; Lipsitz & Goldberger, 1992; Manor et al., 2010; Stergiou & Decker, 2011; Vaillancourt & Newell, 2002, 2003). Furthermore, limited evidence suggested that locomotor dynamics and stability change after an acute perturbation-based fall-prevention program, which has been shown previously to reduce fall-risk and improve biomechanical factors (Bieryla et al., 2007; Mansfield et al., 2015). While previous data are promising, evidence-based practice dictates that a relationship must exist between dynamical systems and/or stability metrics with fall-risk metrics before clinical practice can be transformed. The gaps in the literature could be addressed by: 1) assessing a person's fall-risk profile, 2) determining whether there is an association between fall-risk and locomotor dynamics/stability, and then 3) examining how these locomotor system characteristics relate to the ability to recover from a trip (i.e. locomotor adaptive capacity). Addressing these gaps would help researchers better understand which metrics have the strongest potential to identify adults with an elevated fall-risk, as well as their potential to indicate the locomotor system's adaptive capacity.

The first experiment examined the relationship between locomotor dynamics and stability with a previously published fall-risk assessment method. This method utilizes portions of three fall-risk assessments (ABC, BBS, SRT) that individually have been shown to relate to fall-risk in certain populations. None of the individual locomotor metrics collected during steady-state gait significantly related to the fall-risk assessment. The second experiment determined whether locomotor dynamics and stability associated with trip-recovery ability. Several metrics were found to significantly correlate with the trip-recovery metrics, including DFA, MAX, and SE. The last experiment sought to observe the changes to locomotor dynamics and stability due to a trip-training session. The REC metric was shown to change in the postulated direction after a single trip-training session.

Several factors limit the generalizability this research. Most importantly, the health status of the participants seems to have limited the observed behavior of the group. Further research should only use analyses that require fewer strides to allow for a more diverse population. Second, a different SRT assessment was used in this research versus the original study due to equipment limitations. Thus, we cannot be sure to what extent this may have affected the fall-risk assessment values from a correlative perspective. Lastly, it is important to consider that real-world ambulation and perturbations occur overground and not on a treadmill. We did not test for overground transfer differences that might have been observed during the experiments.

Future research should expand the measures of adaptive capacity that can be directly observed on the locomotor system to determine the robustness of these measures.

This includes both perturbations and clinical assessments already verified to predict or associate with fall-risk. Furthermore, numerous clinical populations (e.g. stroke, Parkinson's, cerebral palsy) have a higher fall-risk, thus, similar assessments and interventions should be conducted on such populations to determine how locomotor dynamics and stability might be helpful as an indication of adaptive capacity and/or fall-risk. Lastly, more research is needed on the effects of perturbation-based fall-prevention programs. Current research on the subject is promising considering the complexity of the problem.

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