Nonlinear Measures for Biomechanical Assessment of Movement Health and Postural Complexity

by

Jacob Stuart Larson, B.S.

A dissertation submitted to the Graduate Faculty of
Auburn University
in partial fulfillment of the
requirements for the Degree of
Doctor of Philosophy

Auburn, Alabama
August 6, 2022

Keywords: Nonlinear Dynamics, complexity,
posture, biomechanics, health

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Approved by

Michael Zabala, Chair, Assistant Professor of Mechanical Engineering
Chad Rose, Assistant Professor of Mechanical Engineering
Jaimie Roper, Assistant Professor of Kinesiology
Edmon Perkins, Assistant Professor of Mechanical Engineering

Abstract

The focus of this dissertation is on using nonlinear dynamics to analyze traditional biomechanical movements. The benefit of this approach is that nonlinear dynamics may be used in the future to help athletes avoid injury and rehabilitate more effectively than they could with current protocols. The local dynamic stability (LDS) is a robust nonlinear metric which has been used previously to understand a mechanical system's ability to adapt to small perturbations. Although the LDS has a history of use in mechanical systems, recent biomechanical studies have suggested that the LDS can also be used effectively to assess human movement patterns. Due to the relatively recent emergence of the LDS in the field of biomechanics, this dissertation aims to broaden the limited scope of understanding by analyzing younger athletes with different movement patterns to build the foundation for future nonlinear dynamics studies in biomechanics. The studies comprised in this dissertation involve two basic experimental approaches: 1) motion capture to gather kinematic profiles of the lower extremity, 2) verbal semantic fluency tests to place greater cognitive load on participants.

The first of the three studies in this dissertation gathers data from elite level collegiate women's athletes during a maximum vertical hopping task and makes group comparison between participants with previous ACL injury and participants without previous ACL injury. This study showed that lower extremity LDS can be used to effectively categorize individuals based on prior injury status in a post-hoc screening, and that lower extremity LDS can be measured in non-gait

movements. Additionally, this study did not find evidence that there was a relationship between lower extremity LDS variables and variables measured at MKF during a jump. These findings suggest that LDS measures unique movement information which could allow for more accurate injury screenings, and that lower extremity LDS should be further analyzed in future studies.

The second study used semantic fluency to investigate the impact of cognitive load on motor control. This study found that lower extremity LDS decreases by a larger magnitude during a dual-task as the speed of the dual-task increases, and that subjects compensate during gait by both increasing and decreasing LDS in different degrees of freedom of the lower extremity. This study did not find evidence of limb dominance affecting the change in LDS during a dual-task while walking or jogging. These findings reveal where healthy adults compensate for simple movement patterns while multitasking. It has been demonstrated that different tasks evoke different, movement-specific compensations and that the difficulty of these tasks can impact the degree of compensation required by the user to complete both a movement and cognitive task.

Finally, the third study measured the relationship between lower extremity motor control (as quantified using LDS) and balance control (as quantified using multiscale entropy (MSE)). Multilevel modeling was used to find a relationship between MSE during a single legged balance and lower extremity LDS during various movement tasks. This study showed that postural complexity does not appear to be directly related to lower extremity neuromuscular control.

Additionally, there were significant interaction effects in lower extremity LDS variables, which suggests that lower extremity LDS is prone to significant changes depending on movement task, lower extremity joint, and movement plane. Finally, the normality of LDS residuals was improved by the design variables included in this study, although future studies could aim to further improve normality by the inclusion of other explanatory variables such as limb dominance, gender, or injury history.

Acknowledgments

I would like to thank my advisor, Dr. Michael Zabala, for his continual help and guidance throughout my Ph.D. study. Michael took a chance on me when not many other advisors chose to, and I remain thankful for the opportunity that I was given. While most other research in our lab was firmly grounded in biomechanics, Michael was forced to hear about my abstract signal processing techniques for the last few years, and maintained a positive attitude through it all. His patience and wisdom have been invaluable for me as I navigated this field of study, and I greatly appreciate the time that we've spent together.

I'd like to thank my AUBE lab mates who have made my four years at Auburn an enjoyable and fruitful academic experience. Graduate school is so much more than data collection and writing, and the memories that I've made during my studies have greatly enriched my well-being.

I would like to thank my thesis committee members, Dr. Edmon Perkins, Dr. Chad Rose, Dr. Jaimie Roper, and my university reader Dr. Mark Schall for their career advice, expertise, and insight into the work which I have produced.

In addition, my friends and family have been bastions of support during my studies. My mom helped me keep a level head through the highs and lows of the last 4 years, and my dad always knew how to give me advice and make me laugh when I needed it the most. My sisters provided a constant supply of funny stories and energy through their many group texts, and generally helped keep me grounded in reality when I spent too much time in a lab with no windows. My friends have helped me make some lifelong memories, and my life has been so greatly improved because of their presence in my life. I'm truly grateful for the people that I've been able to surround myself with.

Finally, I am most grateful to my cat Morris and my wife Lydia for their constant support throughout my graduate studies. Morris, because he is dumb and funny, and Lydia because her love and support have been truly priceless throughout my Ph.D. studies. Lydia's work ethic and passion for her veterinary studies have been a true inspiration when I have doubted myself throughout this process, and I am truly blessed to have had her support and encouragement.

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List of Abbreviations

LDS	Local Dynamic Stability
MSE	Multiscale Entropy
ACL	Anterior Cruciate Ligament
D1	Division 1
ROC	Receiver operating characteristic
DOF	Degree of freedom

1 Introduction

1.1 Dissertation Overview

The focus of this dissertation is on using nonlinear dynamics to analyze traditional biomechanical movements. The benefit of this approach is that nonlinear dynamics may be used in the future to help athletes avoid injury and rehabilitate more effectively than they could with current protocols. . Local dynamic stability (LDS) is a robust nonlinear metric that has been used previously to understand a mechanical system's ability to adapt to small perturbations[1–3]. Although the LDS has a history of use in mechanical systems, recent biomechanical studies have suggested that LDS can also be used effectively to assess human movement patterns[4–6]. Due to the relatively recent emergence of LDS in the field of biomechanics, this dissertation aims to broaden the limited scope of existing literature which focuses primarily on gait tasks in elderly populations[4,5,7]. By analyzing younger athletes with different movement patterns, the goal of this dissertation is to build the foundation for future nonlinear dynamics studies in biomechanics.

The studies comprised in this dissertation involve two basic experimental approaches: 1) motion capture to gather kinematic profiles of the lower extremity, and 2) verbal semantic fluency tests to place a greater cognitive load on participants. The first of the three studies in this dissertation gathers data from elite level collegiate women's athletes during a maximum vertical hopping task and makes a group comparison between participants with previous ACL injury and participants without previous ACL injury. The second and third studies use semantic fluency to investigate the impact of cognitive load on motor control (as quantified using LDS) and explore the connections between balance control (as quantified using multiscale entropy (MSE)).

The remainder of Chapter 1 is focused on background information relating to injury epidemiology, lower extremity injury risk factors, injury screening techniques, nonlinear dynamics, dual-task techniques to be used during testing, as well as the utility of multi-level modeling in biomechanics.

1.2 Epidemiology of Lower Extremity Injuries and Occurrence in Collegiate Athletes

Although it is difficult to track injury data for varied populations and injury types in the United States, collegiate athletes provide a specific and compelling pool of individuals to study due to their elite athleticism, consistent age range, and oversight as provided by the National Collegiate Athletic Administration (NCAA). The NCAA collects standardized injury and exposure data for 16 collegiate sports through the Injury Surveillance System, which allows researchers to gain insight into injury mechanisms from elite level athletes. One study in particular compiled data over 16 years from 1988 - 2004 and found that lower extremity injuries were by far the most common, with over 50% of injuries being attributed to the hip, knee, or ankle[8]. Of the lower extremity injuries, ankle ligament sprains and anterior cruciate ligament (ACL) injuries were the most common, accounting for 15% and 3% of all injuries, respectively.

Although ACL injuries have a much lower incidence than ankle sprains, 88% of ACL injuries resulted in more than 10 days of lost playing time, whereas only 20% of ankle sprains caused injuries of similar severity[9]. In addition to the immediate risk of lost playing time, knee injuries come with high financial costs (estimated between ~$13,000 and $17,000 for ligament repair[10]) and decreased quality of life as well as an increased risk of developing chronic osteoarthritis[10–12]. Of an estimated 8.6 million annual sports injuries, many occur at the lower extremity (50% to 66%), and a great deal of those injuries occur at the knee (30% to 45%)[13]. Due to the high incidence of lower extremity injury and long-lasting physical and financial consequences, it is important to have robust metrics to measure the risk of knee injury to allow for preventative measures to be taken before injuries occur.

1.3 Lower Extremity Injury Risk Factors

Several biomechanical studies have identified ACL risk factors such as landing mechanics, neuromuscular factors, anatomical features, and physiological factors[14]. A classic indicator of future injury risk is having sustained a previous injury. Prior non-dominant leg injury has been shown to increase the risk of contralateral ACL injury[15,16♀], just as previous ACL and ankle sprain history were also shown to be significant risk factors for future ACL injury[17,18]. Sex also plays a large role in determining risk factors, and the above-listed risk factors may affect men, women, or both equally[14]. Therefore, risk factors will be categorized in this dissertation by sex when applicable.

1.3.1 Landing Mechanics

There are a variety of risk factors based on landing mechanics. The most commonly studied are increased knee abduction moments and angles during landing, as well as increased knee valgus at landing[19–21♀]. Abnormal knee positioning and movement patterns have been shown to place greater strain on the ACL during dynamic movements, which is a large contributor to this injury risk. Additionally, decreased hip external and internal rotation[22♂] have also been shown to increase ACL injury risk.

1.3.2 Neuromuscular Factors

Neuromuscular risk factors typically refer to the patterns of muscular control that an individual exhibits. Abnormal muscle firing patterns can lead to excessive strain on surrounding ligaments and soft tissues causing an increased risk for premature injury[23♂], which is common for many reported neuromuscular risk factors. Two key neuromuscular injury risk factors are decreased resistance to fatigue and increased hamstring stiffness[24♀]. Additionally, decreased core stability[25♀], and decreased iliotibial band flexibility[17♀] are also risk factors for ACL injury. Finally, decreased knee abductor strength, decreased hip external rotation strength, and decreased hamstring strength[26,27] have been found to significantly increase the risk of ACL injury.

♀ Indicates that studies only tested or found significance for females
♂ Indicates that studies only tested or found significance for males
♀ Indicates that studies only tested or found significance for females

1.3.3 Anatomical Features

Anatomical features are one of the most studied risk factors for ACL injury and typically refer to either non-modifiable aspects of the muscular or skeletal systems. These factors include increased joint laxity[17,28], decreased ACL width[29], increased ACL length[29], and decreased ACL volume[30,31]. In addition to properties directly impacting the ACL, femoral properties also play a large role in how forces are transferred through the ACL. These include decreased femoral notch width or notch width index[28,31–40], increased tibial tuberosity to trochlear groove distance[41], increased medial tibial plateau depth[42–44], increased lateral or posterior tibial plateau slope[37,39,43–49], and increased medial tibial slope[50].

1.3.4 Physiological Factors

Physiological risk factors for ACL injury tend to be more specific to females due to being mostly grounded in hormonal imbalance. The two most common factors are associated with increased body weight or BMI[15,28♀] as well as hormones released due to the menstrual pre-ovulatory phase[51–54♀].

1.4 Injury Screening Procedures

Although there are many risk factors for ACL injury, this does not necessarily mean that there are corresponding screening tests for each established risk factor. There is an important distinction that exists between risk factors and injury screenings. Some studies highlight this distinction effectively[55], noting that a risk factor is typically found by analyzing subjects after a data

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♀ Indicates that studies only tested or found significance for females collection and noting long term outcomes. In a hypothetical study with 100 subjects, a researcher may have participants perform several tasks and measure several outcome variables. Then, the researcher would track the injury status of all 100 participants throughout the next year and note any participants which sustained an ACL injury. If 10 subjects sustained an ACL injury, then the researchers would look for differences in measured variables of the 10 participants that became injured with the 90 participants that were not injured. If a significant difference is noted in self-selected walking speed between two groups, this would suggest that walking speed could be a risk factor that should be further explored in future studies. In this way, a risk factor is dependent on the group being studied, the variables being measured, and the task being performed.

The important distinction between a risk factor and an injury screening is that instead of waiting until after data is collected to determine variables, tasks, and populations to study, a screening must commit to these selections before data is collected. Additionally, an injury screening must commit to a specific threshold of a variable to determine whether a participant is at risk for injury or not. So while there are plenty of risk factors listed in section 1.3, many of these factors have not been validated, and some may be expected to lose reported significance when expanded to large-scale injury screenings[55]. Nonetheless, many published injury risk factors are performed in small-scale laboratory environments due to the resources required to validate screening tests on a large scale[14]. In this way, researchers can effectively investigate new metrics for injury screening with fewer resources.

1.5 Interventions after Injury Screening

After injury screenings are established, researchers may take one further step to create follow-up studies to investigate how to reduce and/or modify the risk of injury if an individual is found to display certain risk factors as a result of an effective injury screening. Although there are a substantial number of ACL injury risk factors, not all factors are useful to screen for since not all factors can be readily changed. For example, anatomical features such as femoral notch width or tendon length would not be useful to measure in widespread studies due to the cost of determining these features and the impracticality of surgically altering these factors[55].

There are several widely used methods to reduce the risk of ACL injuries, such as neuromuscular warm-up and exercise regimens[56,57]. In the broader context of lower extremity injuries outside of the ACL, some studies indicate that “neuromuscular control” may be the most modifiable risk factor with regards to broadly reducing lower extremity injury risk[19,58]. Moreover, a study assessing 24 systematic reviews of multicomponent lower extremity injury prevention regimens found that interventions incorporating lower extremity muscle strengthening and balance training were most commonly implemented in effective injury prevention programs[59]. Overall, most researchers acknowledge that neuromuscular control is a highly important component of injury risk, but most programs tend to implement traditional strength and balance training protocols to reduce the risk of lower extremity injury.

1.6 Local Dynamic Stability

One effective method of comprehensively evaluating nonlinear movement patterns is the Maximum Lyapunov Exponent (MLE), where the MLE quantifies the rate of divergence of a cyclic kinematic trajectory such as knee flexion or ankle rotation[60]. Because of the somewhat abstract nature of the MLE as a variable, it is important to contextualize the MLE depending on the task to which the MLE is being applied. The MLE can be interpreted as a measure of Local Dynamic Stability (LDS), which is consistent with other literature in this field[61–64]. An increased LDS is typically associated with a lower risk of injury due to the increased ability of a system to successfully adapt to perturbations[65]. This can be seen in previous studies where the LDS has been used to determine fall risk in elderly participants[4–6,66], identify varied movement patterns in amputees and previously injured subjects[61,67–70], and applied broadly to understand neuromuscular control in human systems[71–74].

1.6.1 Local Dynamic Stability Calculation

The LDS has several steps of calculation which are: 1) calculating the time delay, 2) calculating the minimum embedding dimension, 3) reconstruction of the signal, and 4) evaluating the resulting signal to determine LDS.

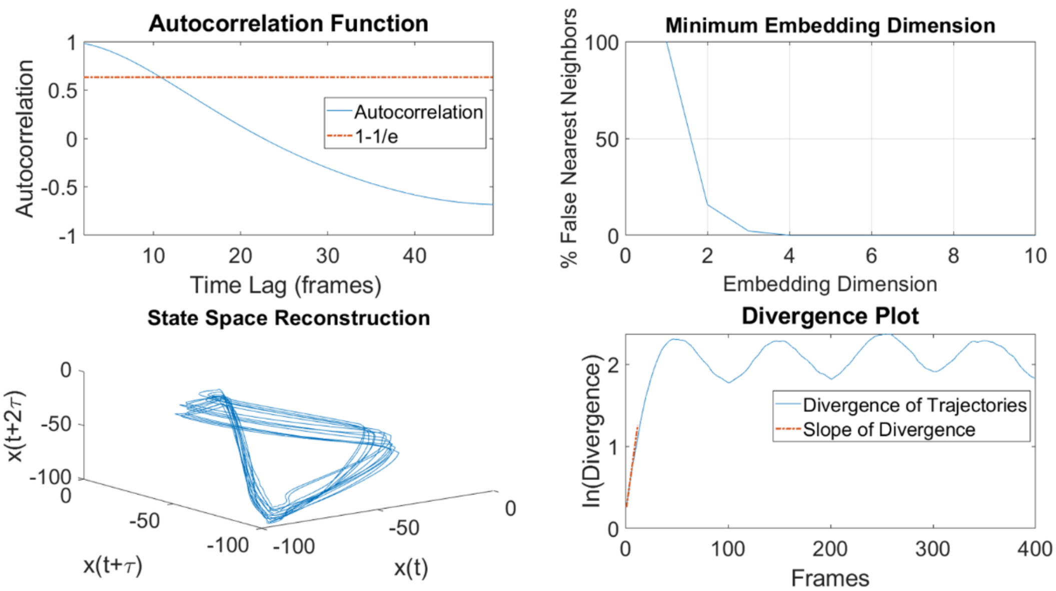

Figure 1: The steps for calculation of the LDS. Top-Left) First, a time delay is calculated using the crossing point between the autocorrelation function and 1–1/e. Top-Right) Next, the embedding dimension is calculated by finding when the percentage of false nearest neighbors goes to zero. Bottom-Left) The signal is reconstructed with the given time delay and embedding dimensions. Bottom-Right) Finally, the initial slope of the natural log of the divergence is calculated and used as the LDS.

1.6.1.1 Signal Preprocessing

Although it is standard practice to smooth and filter kinematic/kinetic data in the field of biomechanics[75], preprocessing data before calculating LDS is still somewhat controversial due to concerns that filtering data before processing through nonlinear analyses will affect the outcome of the LDS[76–78]. However, preprocessing kinematic signals to remove noise before LDS processing has become more widely accepted in the last five to ten years[79–81], with several studies using both first and second-order, low-pass Butterworth filters between 6Hz and 10Hz.

1.6.1.2 Time Delay

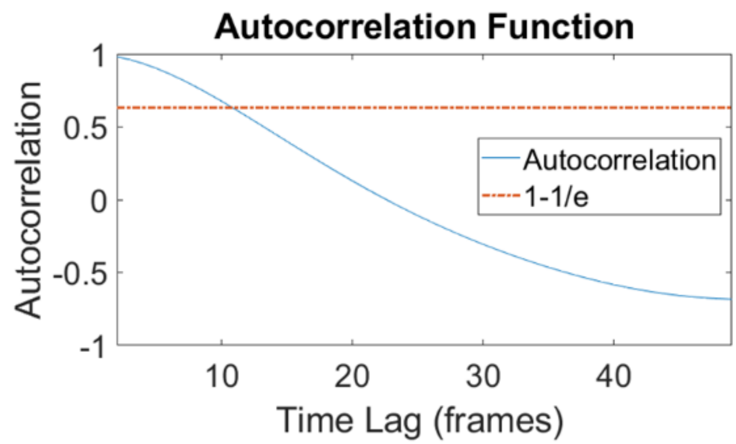

Figure 2: Example of an autocorrelation function on a signal. The chosen time delay is where the autocorrelation intersects with the 1-1/e line, which indicates where the signal likely shares the least information with itself upon time delay. In this case, the original signal should be delayed ~10 frames.

The first step to calculating the LDS is determining the best way to separate signals to ensure that as little information as possible is shared between signals. There are two primary methods used to determine a signal's time delay: the autocorrelation function[82] (Figure 2) and average mutual information[83]. Both calculation techniques compare the similarity of the original signal and a copy of the original signal which is progressively delayed until it shares as little information with the original as possible. There are significant differences between the two techniques, however, which are important to consider before applying to a biomechanical study.

The autocorrelation technique calculates a correlation between a signal and the same signal delayed over several time intervals as shown in Equation (1).

$$\boldsymbol{r_k} = \frac{\sum_{t=k+1}^{n}(\boldsymbol{y_t} - \overline{\boldsymbol{y}})(\boldsymbol{y_{t-k}} - \overline{\boldsymbol{y}})}{\sum_{t=1}^{n}(\boldsymbol{y_t} - \overline{\boldsymbol{y}})^2}$$

(1)

In this equation, y_t represents a data point of function y at time t, and k represents the additional frames that a signal is progressively delayed up to n iterations. $\bar{y}$ represents the average signal over a window of reference, which is then compared to y_t. The result of an autocorrelation can range from +1 to -1, where +1 indicates a perfect positive linear correlation, and -1 indicates a perfect negative linear correlation. In LDS applications, the time delay is chosen when the autocorrelation is equal to 0, which is the point at which there is theoretically no correlation between the original signal and its time-delayed self, or below 1/e, which is the standard error of the autocorrelation function.

The average mutual information technique takes the same original signal and delays it by increasing time scales as shown in Equation (2).

$$I_{AB} = \sum_{i,j} P_{AB}(a_i, b_j) log_2 \left[\frac{P_{AB}(a_i, b_j)}{P_A(a_i)P_B(b_j)}\right]$$

(2)

In this equation, P_{AB} represents the probability that a point will lie in the range of probable points for signal A (original) and B (time-delayed), while P_A and P_B represent the probability that a point will lie in the range of probable points for signals A or B, respectively. The average mutual information technique then calculates the probability that the original signal can provide information about the time-delayed signal. In LDS applications, the time delay is chosen at the first local minimum of average mutual information. This is a very different approach from the autocorrelation function, and provides a solution that has been described as a nonlinear generalization of the autocorrelation function[84]

While both autocorrelation and average mutual information functions can be successfully applied depending on the dataset, the differences in calculation technique have been shown to make a statistically significant difference in accuracy for biomechanical applications[85]. The robustness of the average mutual information technique allowed it to determine appropriate time delays more successfully for chaotic time series when compared to the autocorrelation function, which is important to biomechanical studies as most kinetic and kinematic signals, such as flexion of the hip, knee, and ankle, are chaotic to some degree.

1.6.1.3 Embedding Dimension

One of the main strengths of the LDS is that it can take a signal and expand it into as many dimensions as necessary to extract all possible information that may not be readily available in the original signal[86]. The most popular calculation technique to determine the appropriate embedding dimension is the false nearest neighbors technique as is shown below in Equation (3) and shown in Figure 3.

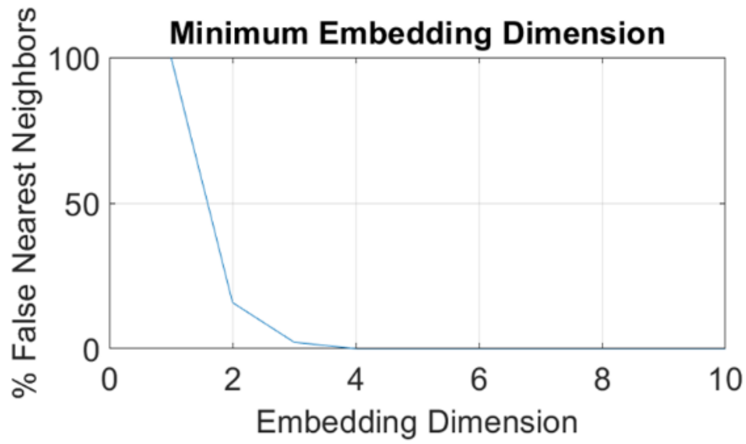

Figure 3: Results from a calculation of false nearest neighbors, where the appropriate embedding dimension is picked when the percentage of false nearest neighbors goes to zero. In this example, the number of embedding dimensions would be 4.

$$\frac{|\hat{s}_{n+kd} - s_{n+kd}|}{R_n(d)} > R_T$$

(3)

In this equation, $\hat{s}_n$ represents the original trajectory with time delay kd, while s_n represents the second trajectory with time delay kd. $R_n(d)$ represents the distance between the two points at a given embedding dimension d, and R_T is the threshold at which the points will be determined to be false nearest neighbors. Anything less than R_T will be considered an appropriate embedding dimension for a time series.

The false nearest neighbors calculation evaluates the appropriate number of dimensions of a signal by plotting a signal against copies of itself using the time delay calculated in the previous step. Starting with the 1-dimensional signal, adjacent points are selected and their distance is measured. Then, the original signal is plotted against the time-delayed version of itself, and the distance between the points is measured again. If the distance between these points increases beyond a certain threshold, these points are determined to be “false neighbors” due to their insufficiently low embedding dimension. As the embedding dimension increases, however, the distance between the original points will plateau, resulting in the optimal embedding dimension to analyze the signal.

1.6.1.4 Lyapunov Exponent Calculation

After determining the appropriate embedding dimension of a signal, the signal must be reconstructed in state space using the number of dimensions previously calculated (Figure 4). Once a signal has been reconstructed, the next step is calculating the divergence between nearby points. There are two popular methods for this calculation, which are Wolf’s method and Rosenstein’s method. Rosenstein’s method is somewhat more straightforward, in that it simply calculates the divergence between two points and follows the two points through the entire length of the dataset. Conversely, Wolf’s method sets a reference trajectory and compares the divergence of a nearby point until it diverges past a certain threshold. Once the secondary trajectory reaches the divergence threshold, a new nearby trajectory is selected and the divergence process is repeated. For biomechanical applications, Rosenstein's method is the more commonly used metric[87], although some recent studies have suggested that Wolf's method may be better suited for small gait data sets[88].

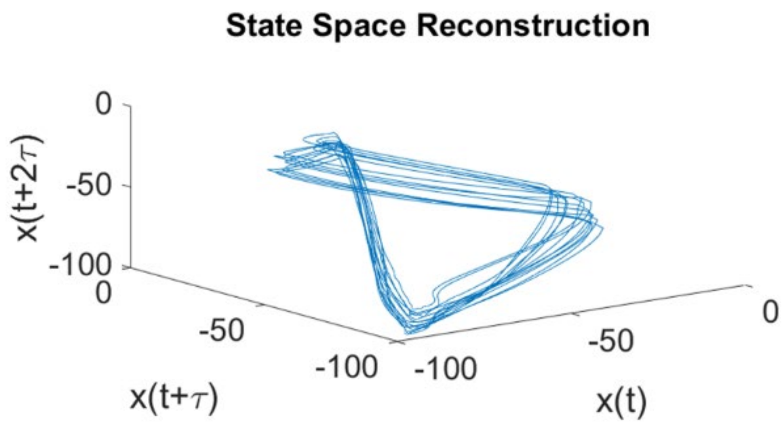

Figure 4: A state space reconstruction of a time-delayed and extrapolated 1-dimensional signal in three dimensions. The three axes indicate that this is the same signal plotted against itself with a time delay on the y-axis, and 2x the time delay on the z-axis.

1.6.1.5 Local Dynamic Stability Calculation

After the Lyapunov exponents have been calculated, the final step is to determine the local dynamic stability, also referred to as the maximum Lyapunov exponent (MLE). In Lyapunov calculations using Rosenstein's method, there are distinct areas to the Lyapunov exponent as shown in Figure 5: a sharply rising section at the beginning of the signal, and a flat section where the divergence signal reaches steady-state. The initial rising portion of the figure is referred to as the short term Lyapunov exponent, while the steady-state portion of the figure is typically referred to as the long-term Lyapunov exponent. In biomechanical applications, the short term Lyapunov exponent is typically used to approximate the LDS.

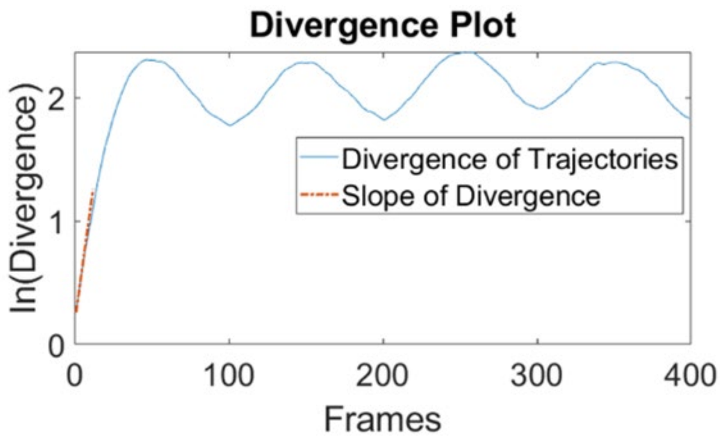

Figure 5: Divergence of the reconstructed trajectories and the short term Lyapunov exponent represented by the orange dashed line.

1.7 Multiscale Entropy

Another effective method of evaluating nonlinear movement patterns is the Multiscale Entropy (MSE). MSE is a technique that quantifies the complexity of a system by calculating the entropy of a signal at different time scales[89,90]. There are many alternative iterations of entropy analysis in human movements such as Approximate Entropy (ApEn), Sample Entropy (SE), and Control Entropy (CE)[91]. While all of these techniques involve entropy in their calculations, the MSE is uniquely suited to analyze human signals due to its ability to analyze various time scales. In practice, this is useful because human neurological conditions may only present themselves as short or long time scales depending on the signal being studied[89]. The MSE has been used in many different applications ranging from evaluating cardiac health[92] and differentiating healthy and unhealthy fetuses at birth[93] to characterizing the dynamics of blood cells[94]. In the field of biomechanics, the MSE has been used to evaluate gait health[90], and most commonly to evaluate the center of pressure (COP) fluctuations in the elderly to determine fall risk[91,95,96]. In all applications, a higher MSE is associated with a more complex system, which typically indicates greater health of the system being studied. These findings are tied to a theory known as the "loss of complexity" hypothesis, in which researchers suggest a more theoretical justification behind healthier systems having higher complexity than unhealthy systems[97,98].

1.7.1 Multiscale Entropy Calculation

The calculation of MSE is comprised of two steps: 1) coarse-graining the input signal to create multiple time series and 2) calculating sample entropy for each time series.

1.7.1.1 Coarse graining input signal

A coarse-graining procedure is a task that involves averaging the data points of a signal within a certain non-overlapping "window" of data. In this case, a "window" is a series of consecutive data points. By increasing the length of the sampling window, the fidelity of the data signal being processed becomes progressively coarser, as shown in Figure 6.

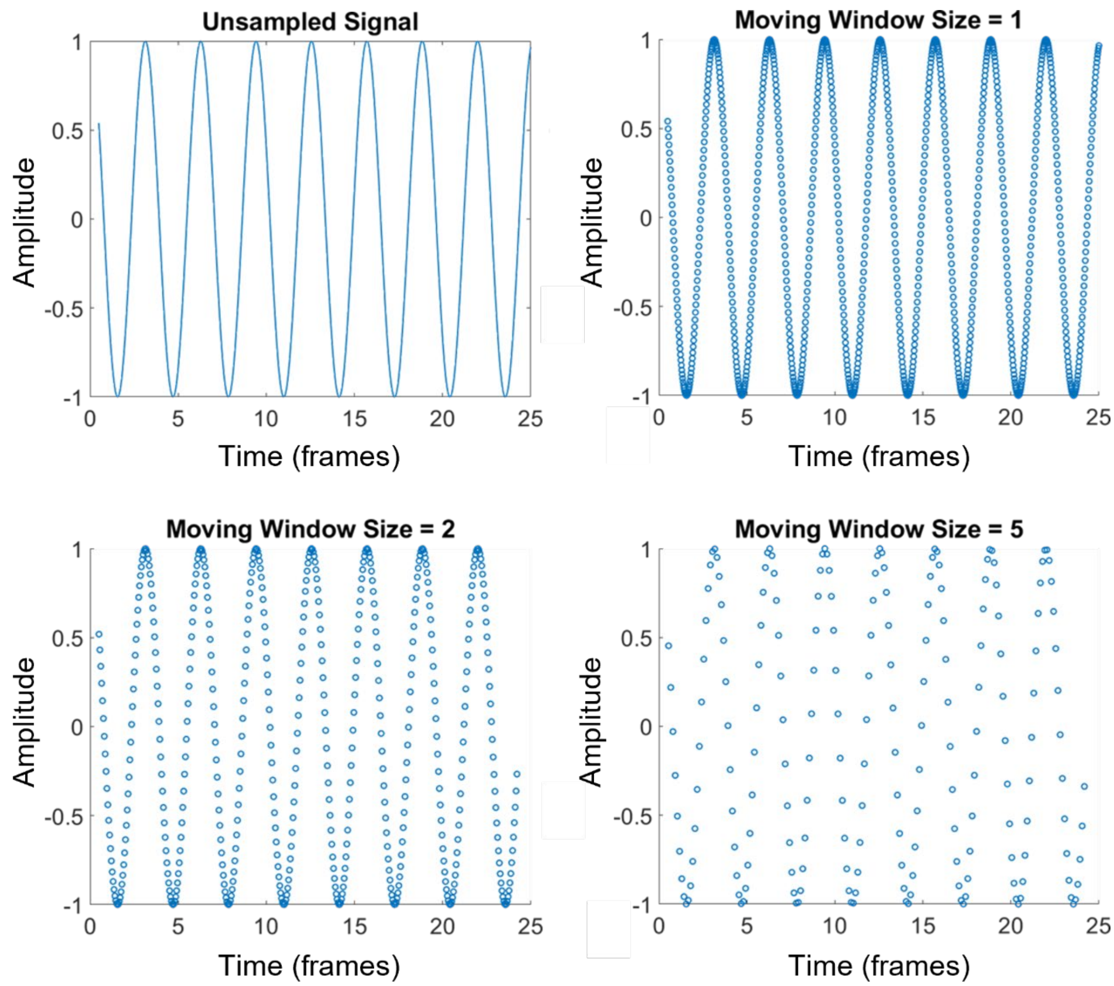

Figure 6: The effect of coarse graining on a signal at 1, 2, and 5 step increments. The top left figure shows a raw sine wave in analog form, which becomes progressively more averaged and down sampled as the moving window size increases. At the maximum moving window size of 5 shown in the bottom right, each plotted point is the average of the previous 5 unsampled data points.

1.7.1.2 Sample Entropy Calculation

Sample entropy is a technique that evaluates a dataset to find instances of repeated consecutive points in different locations of a signal within a certain error tolerance, as shown in Equation (4).

$$SampEn = -ln\frac{A}{B}$$

(4)

In this equation, sample entropy is calculated as the negative natural log of the ratio between variables A and B, where A is a set of vector pairs containing similar points m+1 within a margin of error, and B is a set of vector pairs ontaining similar points m within a margin of error. This concept is also visually demonstrated in Figure 7.

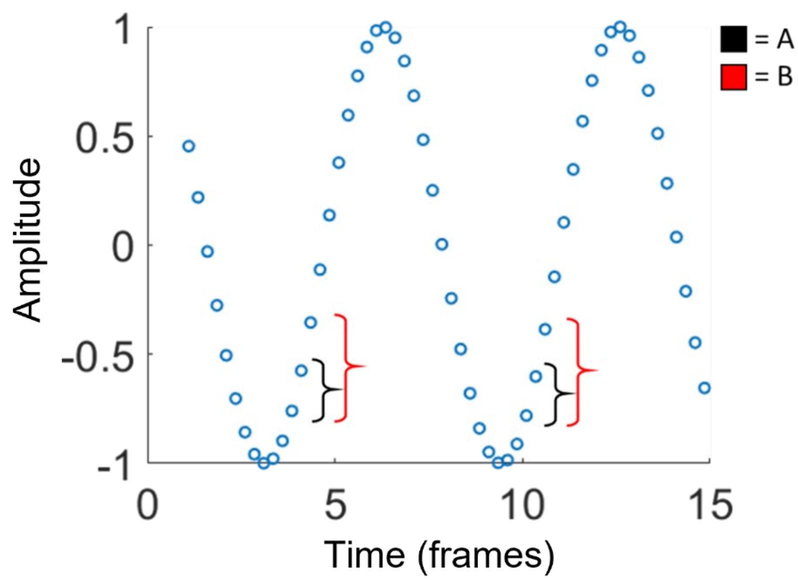

Figure 7: A visualization of the sample entropy calculation in a sine wave. Here, the black brackets represent points belonging to set $\boldsymbol{A}$ and the red brackets represent points belonging to set $\boldsymbol{B}$.

When multiple instances of consecutive points are found, the sample entropy calculates the probability that those matching sets of points will still match after increasing the length of the dataset. As a reference, a sine wave would have a sample entropy of 0, and a purely chaotic motion would have theoretically infinite entropy. After calculating sample entropy for one time scale, the sample entropy is stored and recalculated for all other additional time scales. The MSE is finally created by summing the result of the sample entropy over the preset number of time scales.

1.8 Utility of Dual-Tasking During Gait

A dual-task paradigm requires an individual to perform both a cognitive and motor task simultaneously, and has been used previously to study topics ranging from the postural control of dyslexic children[99] to the effects of talking during gait[100]. The dual-task is a useful tool for a biomechanist as several studies have found that requiring participants to complete multiple tasks at once places a greater strain on the neuromuscular and cognitive functions of an individual[101]. This solves a problem for many biomechanical studies, as the results from studies that do not reflect common daily activities are less effective than those studies which do effectively recreate common daily activities. For this reason, several studies have suggested that utilizing dual-task scenarios during a study can more effectively evaluate behavior[102,103].

1.8.1 Semantic Fluency

One of the most common ways to implement a dual-task scenario in a biomechanical study is by using semantic fluency. Semantic fluency refers to a range of verbal techniques which assess executive function and cognitive processes. These semantic fluency tasks are typically broken into two categories: 1.) tasks that require subjects to name words that start with a specific letter, and 2.) tasks that require subjects to name objects from a group over a present length of time[104]. In both cases, the performance of a semantic task is typically scored based on the number of responses generated over a set period of time[105].

1.9 Multi-Level Modeling in Biomechanics

Multi-level modeling is a technique used to analyze data that is “nested” within other data structures. This can take the form of students in a classroom, employees in a business, or family members within families[106]. In the student/classroom example, a large population sample would result in students being compared to other students within the same classroom, students being compared to students in other classrooms in the same school, students being compared to students in other classrooms in other schools, and so on. The multi-level model allows researchers to effectively analyze these relationships because it does not make assumptions about data points being independent, unlike many other statistical tools. Trying to analyze a nested data set with traditional statistical processes such as a t-test or analysis of variance (ANOVA) could lead to an increased likelihood of type 1 errors, which would indicate potential significance where there should not be.

One of the key reasons for multi-level modeling in biomechanics is due to the highly nested and dependent nature of human variables[107]. Information such as an individual’s physical properties, movement mechanics, and other factors can be interpreted more effectively to better assess the relationships between training load[108], biomechanical patterns[109], and injury prediction[110,111]. There are several useful resources for gathering more information on how to effectively calculate a multi-level model[106]. In an example multi-level model of educational performance, the researcher picks an outcome variable such as the test score for all students. These outcome scores would be deemed the “Null” model, and the level of variance among all scores would be measured. Then, the researcher would introduce potential explanatory variables such as “classroom” or “school” and recalculate the variance of the test scores with the added context of the room and school that a student is in. If the variance of test scores significantly decreases, then the explanatory variables added in the next step of the model would be determined significant, and more variables could be added in additional steps.

1.10 Motivation and Purpose of this Work

Sports injuries are becoming increasingly common, and the assessment tools to reduce the likelihood of lower extremity injuries need to evolve to reduce the likelihood of injuries. Nonlinear dynamics is a powerful field of study which gives researchers a robust and powerful toolset to analyze patterns underlying complex athletic movements. This allows researchers and clinicians to make more informed decisions about what constitutes a safe and unsafe movement. While several preliminary studies are probing the utility of nonlinear dynamics in human movement, much work still needs to be done to understand appropriate applications of the LDS more fully and MSE in human movement studies.

Therefore, the purpose of this dissertation is to explore the relationships between the lower extremity LDS and MSE as they relate to previous injury and neuromuscular control. The hypotheses from three studies are listed below to show the fundamental research questions investigated in this dissertation.

Study 1 Hypothesis: The objective of this study was to determine the ability of LDS variables to categorize previously injured and uninjured subjects in a *post-hoc* classification. The authors hypothesized that lower limb LDS will be a more effective classification metric than standard kinematic variables of the lower limb, measured at maximum knee flexion.

Study 2 Hypothesis: The purpose of this study was to use the LDS to determine compensation strategies in the lower extremity during a dual-task, with additional considerations for limb dominance and gait speed. This hypothesis is based on several previous studies recording trunk variability during gait that found increased variability through various non-LDS measures during a dual-task scenario[112,113]. It is therefore plausible that if a dual-task creates global instability during gait, that variability in the lower extremity LDS during a dual-task should also increase. For this study, the authors hypothesized that the LDS of the lower extremity would increase from a control to a dual-task condition during walking and jogging. The results from this study provide foundational knowledge which gives researchers a better understanding of compensatory mechanics during repetitive tasks.

Additional sub-hypotheses were created to assess the effects of limb dominance and task speed. Previous studies have indicated that while a dual-task disrupts gait stability overall, it should not disrupt limb symmetry [114], and therefore should affect the LDS of both limbs equally. Accordingly, the authors hypothesized that the change in LDS from control to dual-task will not be affected by limb dominance.

Finally, the authors hypothesized that the change in LDS during a dual-task condition will increase as task speed increases. Previous studies have determined that an increase in gait speed is associated with an increase in lower extremity LDS [73], while others have shown that performing a dual-task decreases LDS during a cyclic motion [115]. While these studies explore the effect of dual-tasking and gait speed separately, the authors believe that the effects of gait will outweigh the effects of dual-tasking on lower extremity LDS.

Study 3 Hypothesis: This study aimed to use nested hierarchical modeling techniques to better understand how LDS and MSE interact in a control population during gait tasks. If there were an interaction between these variables, it would improve the depth of interpretation for MSE and LDS studies. Because the metrics of interest in this study were nonlinear, the authors opted to use mixed-effects modeling to account for differences based on various commonly recorded metrics. The authors hypothesized that MSE would significantly explain the variance in lower extremity LDS during gait tasks. This analysis looked at the effect of limb dominance, dual-task conditions, jogging vs walking gait, lower extremity joint, lower extremity plane of motion, and gender.

2 Methods

2.1 Motion Capture and Instrumentation

The motion capture system used throughout Chapters 3, 4, and 5 was an Optical-Passive reflective marker-based system produced by Vicon (Oxford, UK). Kinematic data was captured with a 10-camera motion capture system (Vicon, Vantage V5 Wide Optics cameras with 22 high-powered IR LED strobes at 85nm, 240Hz), where all cameras were aimed towards the center of the biomechanics laboratory. This camera system allows for reconstruction of reflective marker positioning in three-dimensional space within 2mm[116] of accuracy.

Subjects in Chapters 3, 4, and 5, fitted with 79 reflective markers using the point cluster technique[117] as shown in Figure 8. These markers were affixed to the body using double-sided tape. Reflective markers were placed on bony landmarks and in clusters on the thigh and shank. The placement of reflective markers on bony landmarks allows for a digital model of the body to be created, to allow for measurements to be made regarding limb movement throughout the capture space.

The lower kinematic model was assigned three degrees of freedom for the hip, knee, and ankle by restraining translational movement, as done by Charlton et al.[118]. The International Society of Biomechanics recommendations for coordinate systems were applied to each segment[119].

Data from the Vicon system was collected using Nexus software and then processed and analyzed using Visual 3D (C-Motion, Inc., Germantown, MD). Kinematic data were filtered, as suggested by Visual 3D, using a 6 Hz Butterworth filter[120].

Figure 8: This figure shows a subject during calibration and during phases of the repeated vertical jump. Top-Left) Frontal calibration view. Top-Right) Side calibration view. Bottom-Left) Subject at maximum knee flexion during a vertical jump. Bottom-Right) Subject at peak of vertical jump.

3 Study 1: Local-Dynamic Stability of the Lower-Limb as a Means of Post-Hoc Injury Classification[1]

3.1 Abstract

Since most sporting injuries occur at the lower extremity (50% to 66%) and many of those injuries occur at the knee (30% to 45%), it is important to have robust metrics to measure risk of knee injury. Dynamic measures of knee stability are not commonly used in existing metrics but could provide important context to knee health and improve injury screening effectiveness. This study used the Local Dynamic Stability (LDS) of knee kinematics during a repetitive vertical jump to perform a post-hoc previous injury classification of participants. This study analyzed the kinematics from twenty-seven female collegiate division 1 (D1) soccer, D1 basketball, and club soccer athletes from Auburn University (height = 171 ± 8.9cm, weight = 66.3 ± 8.6kg, age = 19.8 ± 1.9yr), with 7 subjects having sustained previous knee injury requiring surgery and 20 subjects with no history of injury. This study showed that LDS correctly identified 84% of previously injured and uninjured subjects using a multivariate logistic regression during a fatigue jump task. Findings showed no statistical difference in kinematic position

[1] This chapter is presented as published: Jacob Larson et al., "Local Dynamic Stability of the Lower-Limb as a Means of Post-Hoc Injury Classification," *PLOS ONE* 16, no. 6 (June 4, 2021): e0252839, https://doi.org/10.1371/journal.pone.0252839.

at maximum knee flexion during all jumps between previously injured and uninjured subjects. Additionally, kinematic positioning at maximum knee flexion was not indicative of LDS values, which would indicate that future studies should look specifically at LDS with respect to injury prevention as it cannot be effectively inferred from kinematics. These points suggest that the LDS preserves information about subtle changes in movement patterns that traditional screening methods do not, and this information could allow for more effective injury screening tests in the future.

3.2 Introduction

Knee injuries come with high financial costs and decreased quality of life as well as an increased risk of developing chronic osteoarthritis[10–12]. Of an estimated 8.6 million annual sports injuries, many occur at the lower extremity (50% to 66%), and a great deal of those injuries occur at the knee (30% to 45%)[13]. Due to the high incidence of knee injury and long-lasting physical and financial consequences, it is important to have robust metrics to measure the risk of knee injury to allow for preventative measures to be taken before injuries occur.

One of the shared aspects of the metrics commonly used for evaluation of injury risk is that most techniques focus on variables that are only represented at single points in time (e.g., peak knee flexion, maximum knee abduction, knee valgus angle at initial contact, etc.). Although these metrics can provide valuable insights into the characteristics of an individual’s movement, they often fail to provide enough information to understand how a subject moves outside of the point of evaluation. For example, if two subjects both reach 90° of knee flexion during a jump landing, evaluating maximum knee flexion for both subjects will show them to have identical landing mechanics. However, evaluating the entire kinematic trajectory before and after maximum knee flexion could reveal that both subjects have radically different knee flexion movement patterns, which could allow for a more holistic injury risk evaluation.

One effective method of comprehensively evaluating nonlinear movement patterns is the Maximum Lyapunov Exponent (MLE), where the MLE quantifies the rate of divergence of a cyclic kinematic trajectory such as knee flexion or ankle rotation[60]. Because of the somewhat abstract nature of the MLE as a variable, it is important to contextualize the MLE depending on the task to which the MLE is being applied. Because of the design and purpose of this study, the authors will be interpreting the MLE as Local Dynamic Stability (LDS), which is consistent with other literature in this field[61–64]. For this study, the LDS is being used to quantify the sensitivity of an individual to small, intrinsic perturbations during a movement[121]. These cyclic changes can be attributed to neuromuscular noise, slight changes in terrain, or non-uniform kinematics from cycle to cycle. An increased LDS is typically associated with lower risk of injury due to the increased ability of a system to successfully adapt to perturbations or changes due to non-uniformity of motion[65]. This can especially be seen in studies that focus on elderly risk of falls, where it has been demonstrated that subjects at risk for falling exhibited lower trunk LDS than subjects not at risk for falling[7,66].

Several biomechanical studies have identified potential lower extremity injury risk factors such as landing mechanics[122–127], gender[128–131], neuromuscular strategies[19], and anatomical features[132–134]. However, some researchers have challenged the effectiveness of these screening tests when expanded to large scale populations[55]. Because of the resources required to validate screening tests on a large scale, it can be beneficial to identify injury risk metrics using post-hoc methods of analysis between groups with previously known differences. In this way, researchers can effectively investigate new metrics for injury screening with fewer resources. Although LDS has gained popularity as a method of biomechanical analysis[121], no studies to the authors' knowledge directly focus on the LDS as it relates to injury screening—making it a good candidate for potential validation using a post-hoc classification of previous injury. This investigation will analyze a set of athletes via post-hoc classifications based on previous knee injury history to validate the potential for the LDS to be used in future studies. Additionally, few studies have attempted to analyze the LDS of non-gait movements such as jogging or walking. While gait is more easily repeatable and simple to capture, the authors wanted to explore more dynamic movements involving jumping and landing to see if significant differences in LDS could be found. The methods and results described in this paper, although retrospective and not predictive in nature, advance knowledge needed for exploration of new predictive injury screening methods in the future.

The objective of this study was to determine the ability of LDS variables to categorize previously injured and uninjured subjects in a post-hoc classification.

The authors hypothesized that lower limb LDS will be a more effective classification metric than standard kinematic variables of the lower limb, measured at maximum knee flexion.

3.3 Methods

3.3.1 Participants

Study participants included 27 female collegiate division 1 (D1) soccer, D1 basketball, and club soccer players from Auburn University (height = 171.2 ± 8.9cm, weight = 66.3 ± 8.6kg, age = 19.8 ± 1.9yr). Subjects were chosen based on anterior cruciate ligament (ACL) risk assessment, as women in cutting sports, such as soccer and basketball, have been shown to be at the greatest statistical risk for ACL injury[135]. Participants included those who were currently active players who were cleared to participate in their respective sport. Out of 27 recruited athletes, two had bilateral ACL reconstructions, two had unilateral ACL reconstructions, and three had surgical interventions for meniscus or cartilage repair. Each subject signed informed consent forms approved by the Auburn University Institutional Review Board.

3.3.2 Data Processing

Jump trials were recorded for 3 sets of 10 jumps. Kinematic variables were taken at maximum knee flexion and averaged over all 30 jumps to present one value for each subject. LDS data was calculated for each set of 10 continuous jumps (3 total LDS values per subject), and the resulting 3 LDS values were averaged to result in one LDS value per subject. This method of calculation follows convention for working with similar data sets as shown by Sloot et al.[136]. To achieve signals of consistent length for LDS data analysis, kinematic data was normalized from toe-on to toe-on for each individual jump. This method of normalization is considered the most effective for data processing using Rosenstein's method[137].

3.3.3 Movement Tasks

Repetitive Maximum Vertical Height Jumping Task

The subjects performed a repeated jumping task, where they jumped ten times in a row at a self-selected jumping frequency to avoid influencing subject landing mechanics. This task was repeated three times for a total of 30 jumps. The subjects were told to jump to maximal height with their hands on their hips, but they were otherwise given minimal directions to perform the task.

3.4 Lyapunov Analysis

The analysis in this paper follows Rosenstein's method for calculating the MLE[138]. The embedding dimensions used in this study were calculated using the false nearest neighbors method, and the time delay was calculated using the autocorrelation function[139]. Embedding dimensions were calculated individually for each trial and subject, and found to be 5.12 ± 1.85 dimensions. Time delay was similarly calculated, with the delay calculated to be 12.17 ± 4.08 frames for all subjects. Although decimal values are presented in this set of average and standard deviation data, only integer values were used for individual embedding dimension and time delay calculations. LDS was calculated using the slope of the initial divergence data. Steps for the MLE calculation are depicted in Figure 1.

3.5 Data Processing

Jump trials were recorded for 3 sets of 10 jumps. Kinematic variables were taken at maximum knee flexion and averaged over all 30 jumps to present one value for each subject. LDS data was calculated for each set of 10 continuous jumps (3 total LDS values per subject), and the resulting 3 LDS values were averaged to result in one LDS value per subject. This method of calculation follows convention for working with similar data sets as shown by Sloot et al.[136]. To achieve signals of consistent length for LDS data analysis, kinematic data was normalized from toe-on to toe-on for each individual jump. This method of normalization is considered the most effective for data processing using Rosenstein's method[138].

Statistical analysis was performed using SAS software version 9.4 (SAS Institute Inc., Cary, NC, USA). A bivariate correlation was performed between variables calculated at maximum knee flexion and their corresponding LDS calculations. Additionally, two multivariate logistic regressions were run for post-hoc sorting based on previous injury status with one using only LDS variables and the other only using kinematic variables recorded at maximum knee flexion. For logistic regression analysis, previously injured subjects were given a value of "1" and previously uninjured groups were given a value of "0". The multivariate logistic regression had stepwise entry conditions of $P < 0.2$ and removal conditions of $P > 0.1$. Finally, a set of two-sided t-tests were performed between injured and uninjured subjects for kinematic and LDS variables to explore potential differences between groups.

3.6 Results

Table 1 shows the results from the bivariate correlation between the kinematic variables at maximum knee flexion and the same kinematic variables processed using the LDS. These results show a significant but weak correlation between ankle internal/external rotation measured at MKF and LDS.

Table 1: Correlation between LDS and corresponding kinematic variables evaluated at MKF for previously injured and uninjured subjects. Bold value indicates significance at the P < 0.05 level.

	r	P
Hip Flexion/Extension	**0.297**	**0.040**
Hip Ab/Adduction	-0.031	0.825
Hip Internal/External Rotation	0.178	0.198
Knee Flexion/Extension	-0.024	0.864
Knee Ab/Adduction	-0.213	0.121
Knee Internal/External Rotation	0.100	0.472
Ankle Flexion/Extension	-0.120	0.462
Ankle Ab/Adduction	-0.120	0.433
Ankle Internal/External Rotation	**0.324**	**0.018**

Figure 9 shows the results of the multivariate logistic regression when using the LDS of lower body kinematics. The LDS variables were able to successfully perform a post-hoc categorization of injured subjects with a receiver operating characteristic (ROC) of 0.8407, with ankle rotation LDS being the primary variable in this logistic regression. While a second multivariate logistic regression was performed on the kinematic variables at maximum knee flexion, there were no variables able to meet the entry and exit conditions outlined in the statistical analysis section.

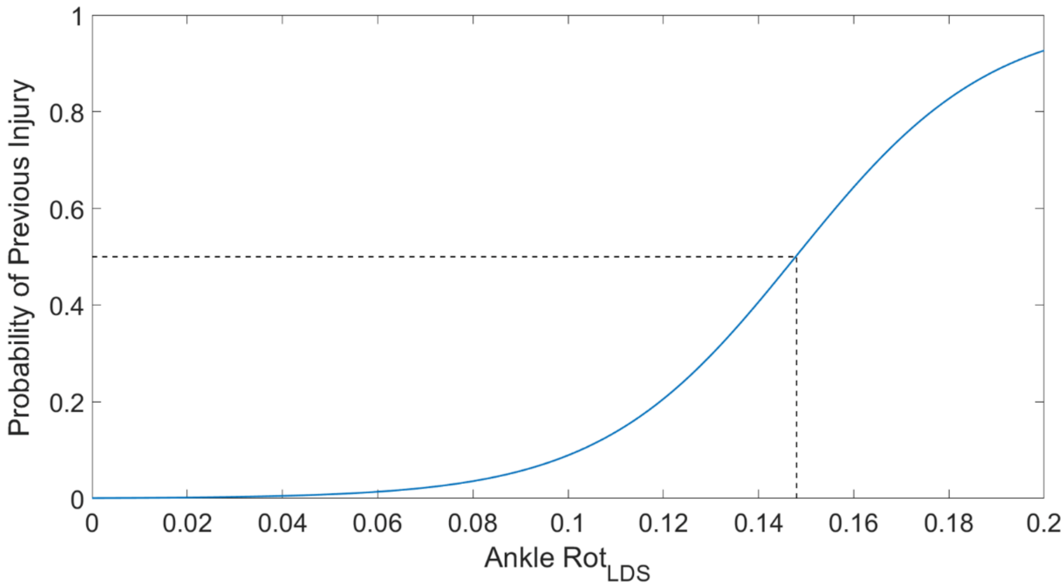

Figure 9: Logistic regression as a function of ankle internal/external rotation LDS. This figure shows the likelihood of belonging to the previously injured subject group based on ankle internal/external rotation LDS. The dotted lines show the approximate values at which the probability of being classified to belonging to the previously injured population is 50%. This would represent a very basic method by which the ankle internal/external rotation LDS could be used as a screening metric, and the approximate threshold at which subjects would be considered “at risk” for belonging to a previously injured group. The ROC for this figure was calculated to be 0.8407.

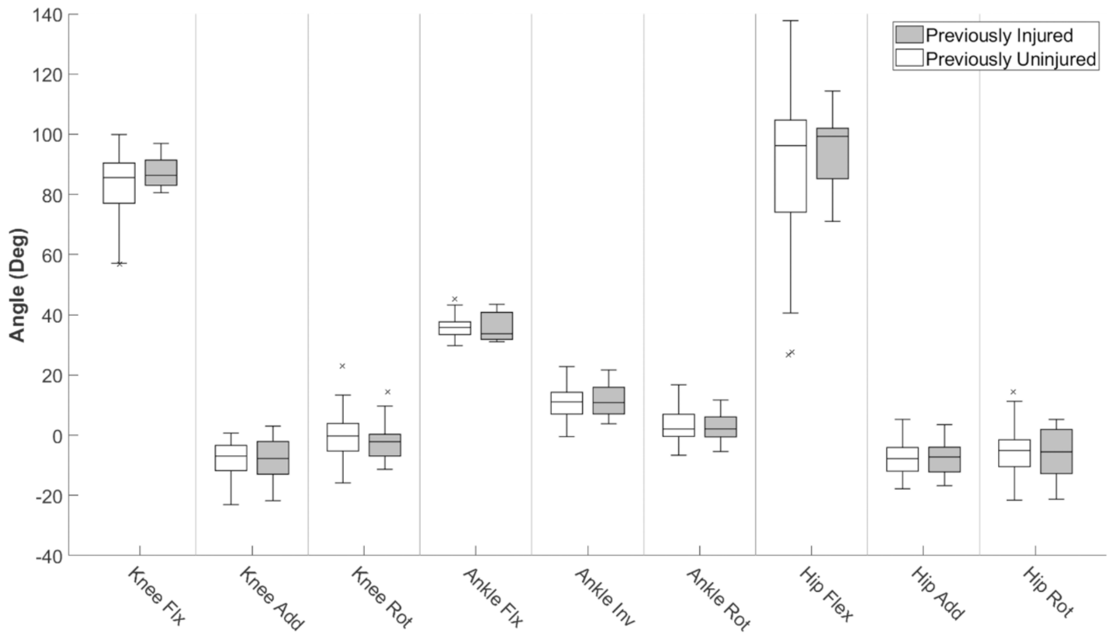

Figure 10: Kinematics of lower extremity at maximum knee flexion during repetitive jumps. Normative values of kinematics at MKF during a fatigue jump and their distributions. * indicates a significant difference between injured and uninjured subject groups with P < 0.05.

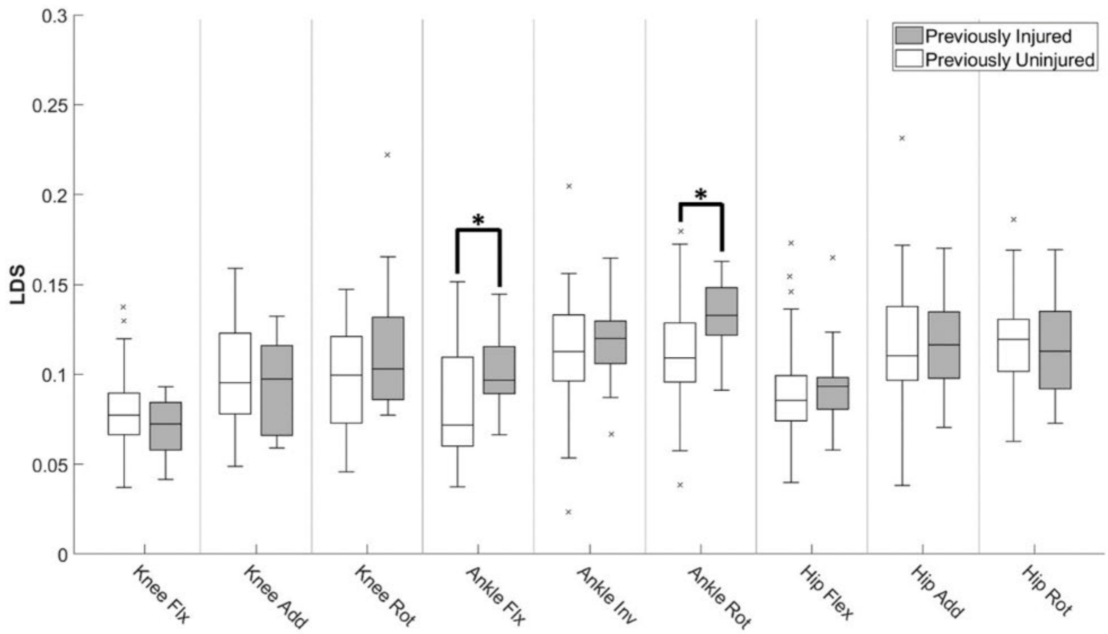

Figure 11: Local dynamic stability of lower extremity during repetitive jumps. Normative values of LDS during a fatigue jump and their distributions. * indicates a significant difference between injured and uninjured subject groups with P < 0.05.

Figure 10 and Figure 11 show the differences between injured and uninjured groups for the kinematic and LDS variables respectively. There are no significant differences found for the kinematic variables, while significant differences were found for both ankle internal/external rotation and ankle flexion/extension between previously injured and uninjured groups.

3.7 Discussion

The purpose of this study was to determine the ability of LDS variables to categorize previously injured and uninjured subjects in a post-hoc classification. The main finding was that the LDS did indeed categorize previously injured subjects at a high rate of success using a multivariate logistic regression. Conversely, the multiple traditional lower body kinematics measured at maximum knee flexion were unable to pass through the entry and exit conditions of the logistic regression.

Figure 10 shows that the lower limb kinematics at maximum knee flexion were not significantly different between previously injured and uninjured subjects, which suggests that lower limb kinematics at maximum knee flexion provides an incomplete assessment of landing strategy differences between subject groups. Furthermore, the lack of difference between groups in Table 1 shows that minimal insight to LDS can be gained through traditional kinematic analysis at maximum knee flexion during a fatigue jump. This finding shows that subjects can display similar kinematics at the bottom of a jump but still display unique movement characteristics that can be characterized with the LDS.

While the logistic regression shown in Figure 9 performed well when using LDS variables compared to the kinematic variables measured at maximum knee flexion, Figure 10 shows that there was a significant difference in ankle flexion/extension LDS between previously injured and uninjured groups as well. The increased ankle LDS for previously injured subjects indicates that a significant degree of ankle instability exists within this group, which is consistent with previous studies that identified ankle compensation as a popular movement strategy after knee injury[140–142].

Although the post-hoc design of this study does not allow for a direct comparison between other previously attempted pre-hoc injury screenings as discussed in the study by Bahr[55], it is encouraging to see that this study produced a metric with ROC = 0.84 in comparison to eccentric hamstring loading (ROC = 0.56) and medial knee displacement (ROC = 0.60). The potential for a 25–30% improvement in screening ability as well as the ability to test a wider array of non-gait movements provide a strong foundation for the authors to suggest that the LDS should be utilized in future injury screening and classification studies when possible.

3.8 Limitations

Regarding the findings of this study, it is important to note that the data collected from the 7 previously injured subjects was gathered after the injury was sustained. Because of this, it is unclear if the findings indicate that increased LDS put subjects at a higher risk of sustaining future ACL injuries or if the decreased LDS is a result from surgery and/or rehabilitation.

Any interpretations from this dataset should be tempered when concerning populations other than women's collegiate soccer players and a repetitive vertical jump. Because there is a limited body of work in this area, the findings presented in this paper are intended to serve as a foundation for the possibility of using the LDS as a screening metric.

3.9 Conclusions

This study showed that LDS categorized previously injured subjects at a high rate of success using a multivariate logistic regression during a fatigue jump task. Although standard kinematics at maximum knee flexion were unable to identify any statistically significant differences between previously injured and uninjured subjects, the LDS was able to quantify significantly higher ankle instability for previously injured subjects. When compared with traditional screening measures, the LDS was able to correctly identify previously injured and uninjured subjects at a rate 25–30% higher than traditional screening measures. These results suggest that the LDS provides unique movement information that could allow for more effective injury screening tests, and should be critically analyzed in future studies.

4 Study 2: Cognitive dual-task alters Local Dynamic Stability of lower extremity during common movements[2]

4.1 Abstract

Lower extremity injuries account for more than 50% of all injuries suffered by collegiate athletes, and the rates of lower extremity injury are increasing. To address these issues, researchers have established that injury rates of the lower extremity can be decreased through neuromuscular warm-up and exercise regimens. Despite the importance of improving neuromuscular control, there are still questions of how to most effectively quantify neuromuscular aspects of biomechanical movements. The Local Dynamic Stability (LDS) is most commonly used in this regard, but there are still several unknown effects of this metric with varied task conditions and cognitive demands. Therefore, this study used motion capture to collect biomechanical data from 28 healthy collegiate participants during a walk, jog, and hopping task both with and without a semantic fluency task to investigate the effects of task speed, limb dominance, and semantic

[2] This chapter is presented as published: Jacob Larson et al., "Cognitive Dual-Task Alters Local Dynamic Stability of Lower Extremity during Common Movements," *Journal of Biomechanics*, April 2022, 111077, https://doi.org/10.1016/j.jbiomech.2022.111077.

fluency on LDS. This study showed that lower extremity LDS decreased during a dual task as the speed of the dual task increased, that subjects compensate during gait by both increasing and decreasing LDS in different degrees of freedom of the lower extremity, and that compensation strategies may be determined by limb dominance during a hop. These findings reveal where healthy adults compensate for simple movement patterns while multitasking. Future work should further explore the role and relationship between trunk movement and lower extremity compensation, and could help give further context to how the LDS can be interpreted by researchers and clinicians alike.

4.2 Methods

4.2.1 Participants

Study participants included 28 currently enrolled Auburn University students (height = 173.18 ± 9.83 cm, age = 23.64 ± 4.67 yrs, weight = 68.81 ± 11.93 kgs, male = 14, female = 14). Subjects were chosen based on current enrollment status, and were taken as a sample of convenience. Activity level (Activity Level 1 (n = 1), Activity Level 2 (n = 9), Activity Level 3 (n = 4), Activity Level 4 (n = 14)) was also recorded for each participant, with activity level 1 being least active and activity level 4 being most active[143].

4.2.2 Movement Tasks

This study recorded 2 separate movement tasks in 30 second intervals with both a control and dual-task trial for: treadmill walking at a self-selected speed and treadmill jogging at a self-selected speed. While all movement tasks were completed in the same order, conditions (starting limb, control vs dual-task) were randomized by a MATLAB script before each data collection.

Walking

Subjects were instructed to find a comfortable walking pace on a treadmill, and notified researchers when they had reached and acclimated to their self-selected speeds. Subjects were then tasked to perform 30 seconds of walking at this speed during a control and dual-task condition.

Jogging

Subjects were instructed to find a comfortable long distance jogging pace on a treadmill, and notified researchers when they had reached and acclimated to their self-selected speeds. Subjects were then tasked to perform 30 seconds of jogging at this speed during a control and dual-task condition.

4.2.3 Cognitive Dual-Task

Subjects performed a semantic fluency task concurrently with the 2 preselected movement tasks, following the standard set forward by Tombaugh et al.[144] with letters randomly selected from the following options which were determined to be of approximate recall difficulty: H, D, M, W, A, B, F, P ,T, C, and S. Subjects were read the following prompt before each dual-task:

"I'm going to ask you to say as many words as possible beginning with the same letter in 30 seconds. Don't say proper nouns or numbers, or the same word with a different ending and try not to repeat yourself. I will count down from 3 and name your letter in place of the number 0. At that time, you will start jumping and naming words simultaneously. Are you ready? 3, 2, 1, (randomly selected letter)"

Each semantic fluency task was 30 seconds long for walking and jogging. Baseline measures of semantic fluency were recorded while seated.

4.2.4 Local Dynamic Stability Analysis

The main variables of interest in this study were LDS values for each rotational DOF (e.g. flexion, rotation, abduction) for the ankle, knee, and hip. The analysis in this paper follows Rosenstein's method for calculating the maximum Lyapunov exponent[138]. This study used 30 second trials at self-selected gait speeds, which resulted in 23.38 ± 4.58 strides per limb during both the jogging and walking task. These stride counts are in agreement with previous studies showing this length of data to sufficiently estimate local dynamic stability[145]. The embedding dimensions used in this study were calculated using the false nearest neighbors method, and the time delay was calculated using the autocorrelation function[139]. Embedding dimensions were calculated individually for each trial and participant. This study used standard LDS measures which can be further referenced at the previous publication[80].

4.2.5 Data Processing

All data was normalized from foot strike to foot strike, as determined by the minimum vertical position of heel markers[146]. Data before the first full movement cycle and after the last full movement cycle was removed from analysis. A simple percentage difference calculation was performed between the control and dual-task scenarios when statistically significant differences were found to give context to the relative change in mean LDS values, where DT = Dual-Task LDS, and C = Control Task LDS.

1. (DT - C) / C x 100 = %Diff

4.2.6 Statistical Analysis

Three statistical tests were performed on this data. First, a paired t-test was used to determine the effect of the semantic task on the LDS of each limb. Second, a two-sided t-test was used to determine the effect of limb dominance on the change in LDS of each limb from control to dual-task. Finally, a bivariate correlation was used to determine the effect of self-selected movement task speed vs change in LDS from control to dual-task for each limb. For each test, significance was determined as $p < 0.05$. Due to the exploratory nature of these tests, adjustments for multiple comparisons were not made to the effect of the semantic task on the LDS of each limb or the effect of limb dominance[147,148]. However, a Bonferroni adjustment was made for multiple comparisons for the effect of self-selected speed vs change in LDS from control to dual-task due to previously existing literature in this field.

4.3 Results

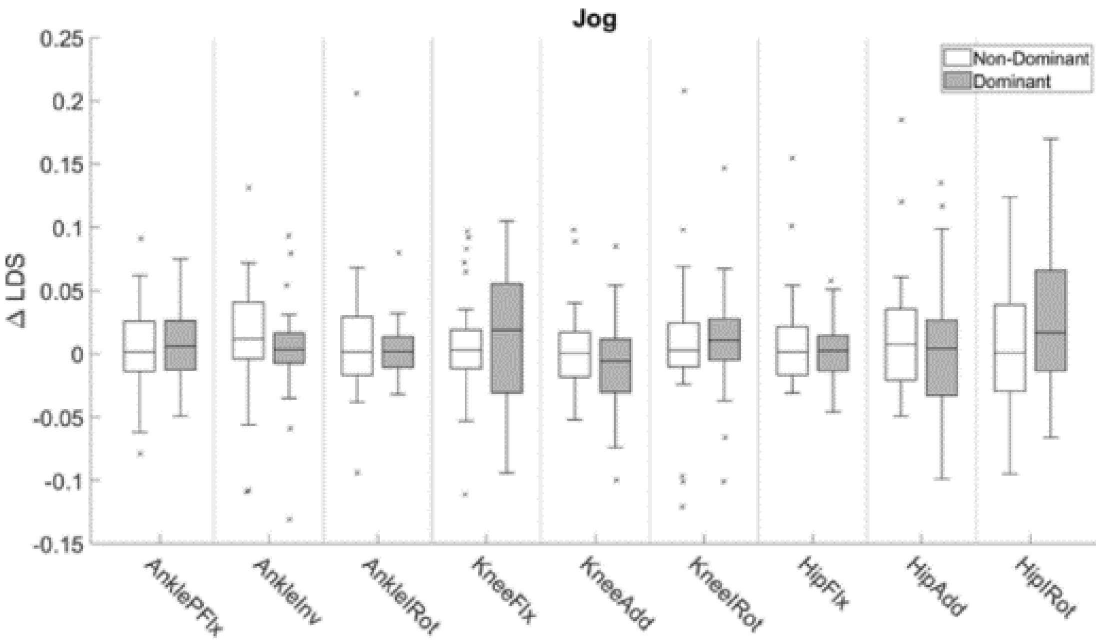

Figure 12: This figure shows the LDS during the control and dual-task for the lower extremity during a walk task. Significance was found for hip adduction (%Diff = -11.80%, p = 0.047) and hip internal rotation (%Diff = +14.85%, p = 0.005). * indicates a significant difference in LDS of the lower extremity during a control and dual-task with p < 0.05.

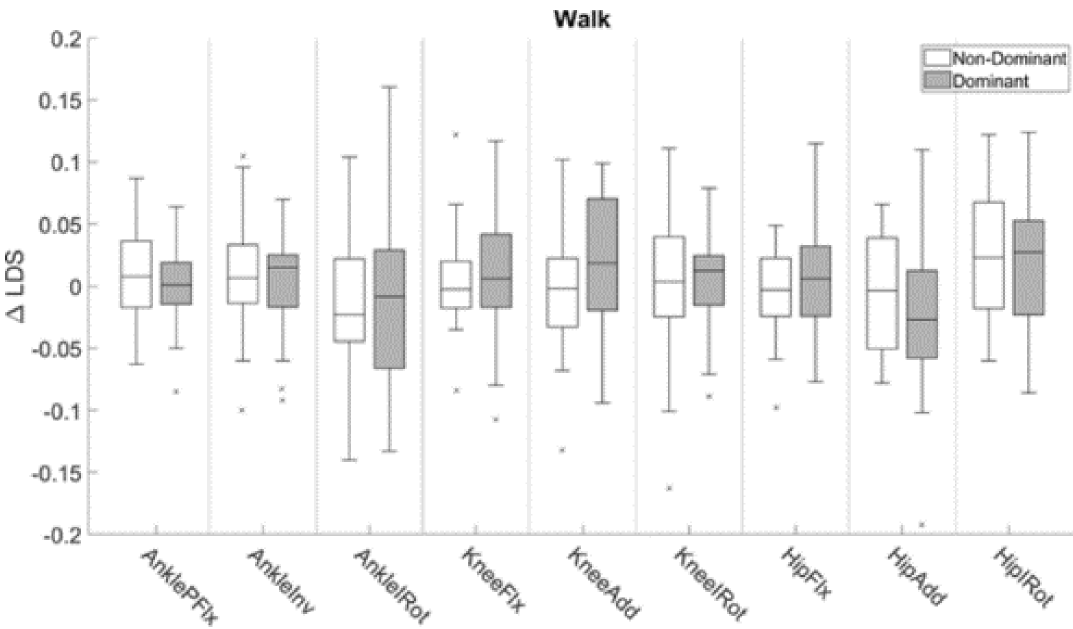

Figure 13: This figure shows the change in LDS from control to dual-task separated by dominant limb for the lower extremity during a walk task. In this figure, a positive Δ LDS indicates an increase in LDS from control to dual-task, and a negative Δ LDS indicates a decrease in LDS from control to dual-task.

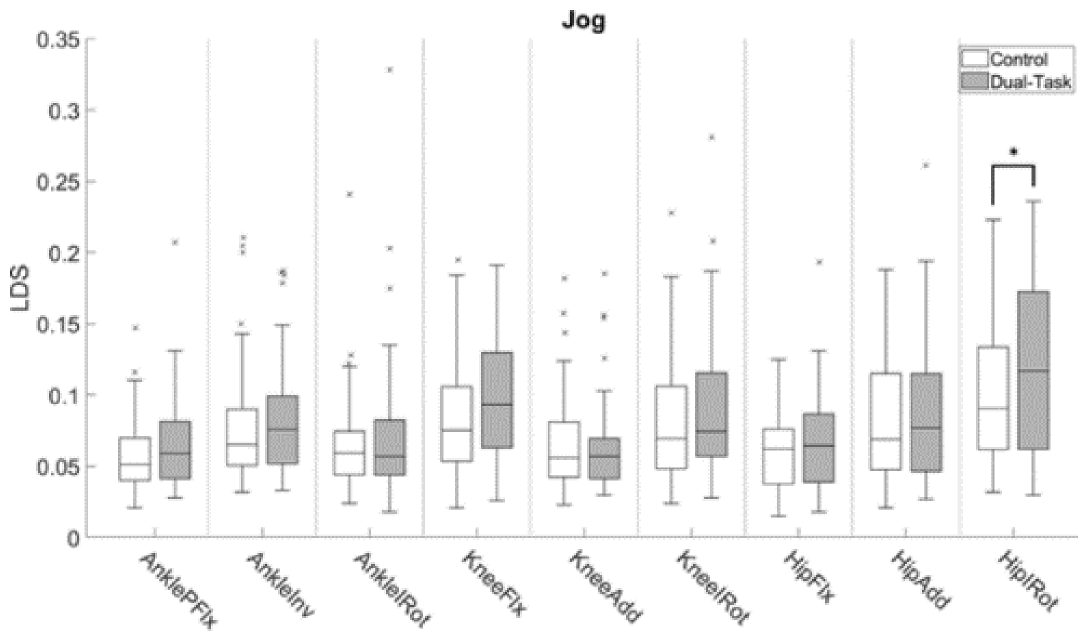

Figure 14: This figure shows the LDS during the control and dual-task for the lower extremity during a jog task. Significance was found for hip internal rotation (%Diff = +16.76%, p = 0.026). * indicates a significant difference in LDS of the lower extremity during a control and dual-task with p < 0.05.

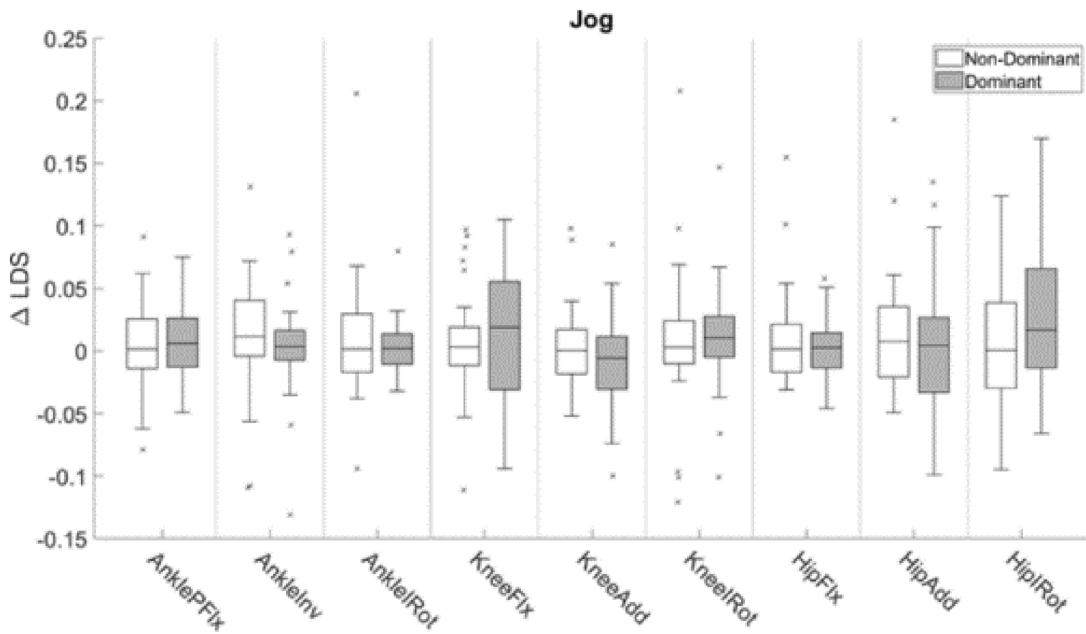

Figure 15: Change in LDS from control to dual-task separated by dominant limb for the lower extremity during a jog task. In this figure, a positive Δ LDS indicates an increase in LDS from control to dual-task, and a negative Δ LDS indicates a decrease in LDS from control to dual-task.

Table 2: This table shows the results of a bivariate correlation between self-selected speeds of walking and jogging vs Δ LDS of the lower extremity for each task respectively.

LDS Change vs Speed					
Walk			Jog		
Δ LDS	Pearson Coeff	Significance	Δ LDS	Pearson Coeff	Significance
Ankle PFlx	-0.219	0.105	**Ankle PFlx**	**-0.393**	**0.003**
Ankle Inv	-0.010	0.940	Ankle Inv	-0.068	0.618
Ankle IRot	0.176	0.194	Ankle IRot	0.068	0.616
Knee Flx	0.139	0.306	Knee Flx	0.096	0.482
Knee Add	0.085	0.532	Knee Add	-0.058	0.670
Knee IRot	0.123	0.369	Knee IRot	-0.113	0.406
Hip Flx	-0.144	0.289	Hip Flx	-0.063	0.643
Hip Add	0.074	0.590	Hip Add	-0.046	0.738
Hip IRot	0.128	0.346	Hip IRot	0.006	0.967

During this study, the authors found that subjects modulated LDS of the lower extremity in varying locations and amounts per each of the three measured tasks. Subjects chose a self-selected speed of 2.30 ± 0.81 m/s while walking, and 4.56 ± 1.15 m/s while jogging. During the walking task, subjects decreased LDS in hip abd/adduction (%Diff = -11.80%, $p = 0.047$), while increasing LDS in hip internal/external rotation (%Diff = +14.85%, $p = 0.005$) during a dual-task (Figure 12). There were no effects of change in LDS and dominant limb (Figure 13) or self-selected walking speed (Table 2). The jogging task also had users increasing LDS of hip internal/external rotation (%Diff = 16.76%, $p = 0.026$) during a dual-task (Figure 14), and there was a statistically significant correlation between self-selected jogging speed and LDS of ankle flexion/extension ($p = 0.027$) (Table 2). The authors did not find evidence of an effect of limb dominance and LDS in the lower extremity during the jogging task (Figure 15).

4.4 Discussion

The purpose of this study was to use the LDS to determine compensation strategies in the lower extremity during a dual-task. This study has two main findings. The first is that ankle flexion LDS decreases as jogging speed increases (Table 2). The second is that subjects seemingly compensate during gait by both increasing and decreasing LDS in different degrees of freedom of the lower extremity (Figures 12-15). This study did not find evidence of limb dominance effecting the change in LDS during a dual-task while walking or jogging. The results of this study show that compensation strategies during a dual-task may be speed and task dependent, which may be useful for future analyses when trying to understand how gait patterns change under dual-task conditions.

The decrease of ankle flexion LDS as speed increases during jogging (Table 2) is partially supported by existing literature, as previous studies have shown that the LDS of the hip, knee, and ankle increase as gait speed increases[73]. Although this finding seemingly conflicts with the results in this study, other studies have shown that a cognitive dual-task decreases LDS during a cyclic movement[115]. The jog findings of this study mirrored those found in the above articles, and added the context that while absolute LDS increased depending on the self-selected speed of a given participant, there was a progressively greater decrease in LDS between the control and dual-task as self-selected speed increased for the jogging task. This finding may help explain why ankle sprains are the most common lower extremity injury[8], as the sharp decrease of ankle plantarflexion LDS while dual-tasking at higher gait speeds may place users at greater risk for injury due to the decreased ability for the ankle to compensate for unexpected perturbations.

This study was unable to find any significant differences between limb dominance and change in Δ LDS for both a walk and a jog (Figure 13, Figure 15). Although no previous studies have examined this paradigm with respect to LDS to the author's knowledge, these findings do seem to be supported by previous studies which suggest that a semantic task will disturb gait equally in both the dominant and non-dominant limb[114]. Due to the highly practiced nature of gait, this seems to be a reasonable finding, although future studies should look further into tasks which may illicit greater differences in movement compensation based on limb dominance such as single-legged landings[149] and changes in direction[150].

The LDS compensation patterns during gait (Figures 12-15) were also notable in that there were significant increases in hip rotation LDS during both walking and jogging during a dual-task, but only significant decreases in hip adduction LDS during the walking dual-task. These findings are somewhat supported by previous literature which show that the gluteus maximus is the greatest force producing muscle at the hip and commonly recruited during tasks that require deceleration of the center of mass[151]. Having previously asserted that trunk variability will increase during a dual-task[112,113], it would seem appropriate for hip rotational LDS to increase during the dual-task during both jogging and walking to mitigate increased trunk movement. It is expected that decreased gait speed would decrease core stability[113], which would explain why the change in hip LDS was more pronounced between control and dual-task for the walk compared to the jog. A major limitation of this interpretation is that this study did not independently measure trunk variability or gluteus maximus activation, so this analysis should not be overinterpreted. Future studies should investigate the interactions between hip control, trunk deviation, and gait speed during a dual-task to more clearly understand how subjects compensate during cognitive tasks.

4.5 Conclusions

In conclusion, this study found that lower extremity LDS decreases by a larger magnitude during a dual task as the speed of the dual task increases, and that subjects compensate during gait by both increasing and decreasing LDS in different degrees of freedom of the lower extremity. This study did not find evidence of limb dominance effecting the change in LDS during a dual-task while walking or jogging. These findings reveal where healthy adults compensate for simple movement patterns while multitasking. It has been demonstrated that different tasks evoke different, movement-specific compensations, and that the difficulty of these tasks can impact the degree of compensation required by the user to complete both a movement and cognitive task. Future work should further explore the role and relationship between trunk movement and lower extremity compensation, and could help give further context to how the LDS can be interpreted by researchers and clinicians alike.

5 Study 3: Postural Complexity May not be Linked to Lower Extremity Neuromuscular Control[3]

5.1 Abstract

Nonlinear dynamics has been used for many years to perform complex analysis of human dynamical systems. However, the inherent complexity of nonlinear dynamics can make it difficult to interpret findings across multiple nonlinear analyses. Two nonlinear measures in particular that have shown to be especially useful in the field of biomechanics are Local Dynamic Stability (LDS) and Multiscale Entropy (MSE). LDS and MSE have been useful to the field of biomechanics because of their ability to give a deeper and more theoretical understanding of human movement than what can be visually observed. The aim of this study was to establish a relationship between the LDS and MSE during various common movements using nested hierarchical modeling. This study showed that postural complexity does not appear to be directly related to lower extremity neuromuscular control. Additionally, there were significant interaction effects in lower extremity LDS variables, which suggests that lower extremity LDS is prone to significant changes depending on movement task, lower

[3] This chapter presented as submitted for publication: Jacob Larson et al. (2022), "Postural Complexity May not be Related to Lower Extremity Neuromuscular Control," [Manuscript submitted for publication]

extremity joint, and movement plane. Finally, the normality of LDS residuals was improved by the design variables included in this study, although future studies could aim to further improve normality by the inclusion of other explanatory variables such as limb dominance, gender, or injury history. These findings should serve as useful references for future studies meant to explore how nonlinear measures can be used to measure and compare various aspects of human motor control.

5.2 Introduction

Nonlinear dynamics have been used for many years to perform complex analysis of human dynamical systems[152–154]. However, the inherent complexity of nonlinear dynamics can make it difficult to interpret findings across multiple nonlinear analyses[155]. Two nonlinear measures that have shown to be especially useful in the field of biomechanics are Local Dynamic Stability (LDS) and Multiscale Entropy (MSE). LDS and MSE have been useful to the field of biomechanics because of their ability to give a deeper and more theoretical understanding of human movement than what can be visually observed. Although both LDS and MSE have substantial literature validating their applications in biomechanics[91,121] there is a clear need expressed in several studies to investigate how these two metrics may be related[121,155].

The utility of the LDS is its ability to detect changes in cyclic signals to detect how a system can respond to small (local) perturbations. Several examples of this can be seen in studies which measure how elderly subjects respond to disturbances in normal gait cycles[4,5], how runners respond to changes in terrain[156], and how neurological disease effects gait[157]. In these studies, a significantly decreased LDS may indicate that an individual is less able to effectively respond to perturbations or unexpected input than an individual with higher LDS.

While the LDS has been used primarily to detect a system's ability to adapt to small scale perturbations, the utility of the MSE is its ability to detect the complexity of a system over various scales of time[158]. The MSE is typically applied in biomechanics by analyzing the entropy of an individual's center of pressure (COP) during a balance task at different time scales[95], but this robust measure has also been used to measure trunk stability during gait[159] and many other physiological signals[89]. In studies involving the MSE of the COP during balance, larger MSE values show that an individual can produce a greater variety of postural configurations during a balancing task, which is then used to indicate systemic health and adaptability[121].

Although both LDS and MSE have been successfully utilized in the field of biomechanics, there are some challenges when comparing studies that use these metrics. Firstly, there are a variety of user inputs needed to calculate these metrics such as time delay, embedding dimensions, pre-processing data, length of data series, and other metric specific terms[89,138]. Additionally, there are study-specific concerns such as different testing conditions that these metrics can be applied to gait: (overground vs treadmill), different populations (elderly vs adolescent, injury history vs no injury history, neurological condition vs no neurological condition), and even different kinematic features that were used in the calculation (MSE of trunk acceleration vs MSE of COP during single legged balance). As a result, there have been relatively few studies comparing LDS and MSE measures.

The gap in literature for LDS and MSE comparison studies has left many questions about the relationship between these two metrics. While some studies direct future work to understand how LDS and MSE analysis of the same signal (e.g. trunk acceleration) would share information, it could be more beneficial to the broader field of biomechanics to compare how the MSE and LDS are more commonly used in human studies. For example, if the MSE is most commonly used in balance studies to evaluate postural control, it may be more beneficial to understand how the MSE of a balance task compares to lower extremity LDS during a different movement task. In this way, researchers would be able to gain more fundamental understanding of how an individual's postural control would relate to their lower extremity motor control during other movements. Several studies which engage in conceptual frameworks such as complexity theory, human coordinative variability theory, and dynamical systems theory could investigate the underlying mechanics of human movement through different mathematical perspectives. Although these frameworks are distinct, several studies from each field could suggest that a holistic assessment of human movement may yield more broadly useful results to understanding human dynamics[91,96,160,161].

The aim of this study was to establish a relationship between the LDS and MSE during various common movements. This study used multilevel modelling to measure the ability of the MSE of the COP during single legged balance to explain variance in lower extremity LDS during walking, jogging, and single legged hopping. Any relationships found between these two variables would improve the scope of interpretation for future LDS and MSE studies. It was hypothesized that the MSE will not significantly improve the multilevel model of LDS variance. Additionally, it was hypothesized that there would be significant interaction effects between explanatory variables for lower extremity LDS such as lower extremity joint, movement task, and movement plane.

5.3 Methods

Participants:

Study participants included 28 currently enrolled Auburn University students (height = 173.18 ± 9.83 cm, age = 23.64 ± 4.67 yrs, weight = 68.81 ± 11.93 kgs, male = 14, female = 14). Subjects were chosen based on current enrollment status and were taken as a sample of convenience. Activity level (Activity Level 1 (n = 1), Activity Level 2 (n = 9), Activity Level 3 (n = 4), Activity Level 4 (n = 14)) was also recorded for each participant, with Activity Level 1 being least active and Activity Level 4 being most active[143].

Movement Tasks:

This study recorded three separate movement tasks in 30 second intervals for: treadmill walking at a self-selected speed, treadmill jogging at a self-selected speed, and single legged hopping at a self-selected speed. While all movement tasks were completed in the same order, conditions (starting limb, control vs dual-task) were randomized by a MATLAB script before each data collection.

Walking:

Subjects were instructed to find a comfortable walking pace on the treadmill, and notified researchers when they had reached and acclimated to their self-selected speeds. Subjects were then tasked to perform 30 seconds of walking at this speed.

Jogging:

Subjects were instructed to find a comfortable long distance jogging pace on the treadmill, and notified researchers when they had reached and acclimated to their self-selected speeds. Subjects were then tasked to perform 30 seconds of jogging at this speed.

Hopping:

Subjects were told to hop as many times as they could in 30 seconds on one leg at a consistent speed. Subjects were then tasked to perform 30 seconds of hopping on the left and right leg.

Local Dynamic Stability Analysis:

The main variables of interest in this study were LDS values for each rotational DOF (e.g. flexion, rotation, abduction) for the ankle, knee, and hip. The analysis in this paper follows Rosenstein's method for calculating the maximum Lyapunov exponent[138]. The embedding dimensions used in this study were calculated using the false nearest neighbors method, and the time delay was calculated using the autocorrelation function[139]. Embedding dimensions were calculated individually for each trial and participant. This study used standard LDS measures which can be further referenced at the previous publication[80].

Multiscale Entropy Analysis:

This study calculated multiscale entropy by analyzing deviation of center of pressure in the mediolateral (ML) and anteroposterior (AP) directions. Here, sample entropy was calculated with m = 2, r = 0.15, and tau = 20, as shown in Gow et al.[95]. Multiscale entropy was calculated by integrating the sample entropy over all measured timescales.

Data Processing:

All data was normalized from foot strike to foot strike, as determined by the minimum vertical position of heel markers[146].Data before the first full movement cycle and after the last full movement cycle was removed from analysis. LDS data were corrected by taking the natural logarithm of LDS in order to correct for a right skew distribution of residual data.

Statistical Analysis:

Statistical analysis was performed using R software (R Core Team (2020)). A multi-level nested model was created in the following order. Step 1: no input factors, Step 2: Step 1 + limb dominance, semantic dual-task, joint, movement plane, movement task, Step 3: Step 2 + interaction effects, Step 4: Step 3 + MSE, MSE AP/ML. Using this technique, the AIC and BIC were recorded to measure effectiveness of the model at explaining LDS variance, which were tracked in the model. After an optimal model was selected, predicted means of each movement task separated by limb dominance and semantic dual-task effect. Finally, LDS residuals were plotted for both the null and optimal model to visualize how the model had affected data normality.

5.4 Results

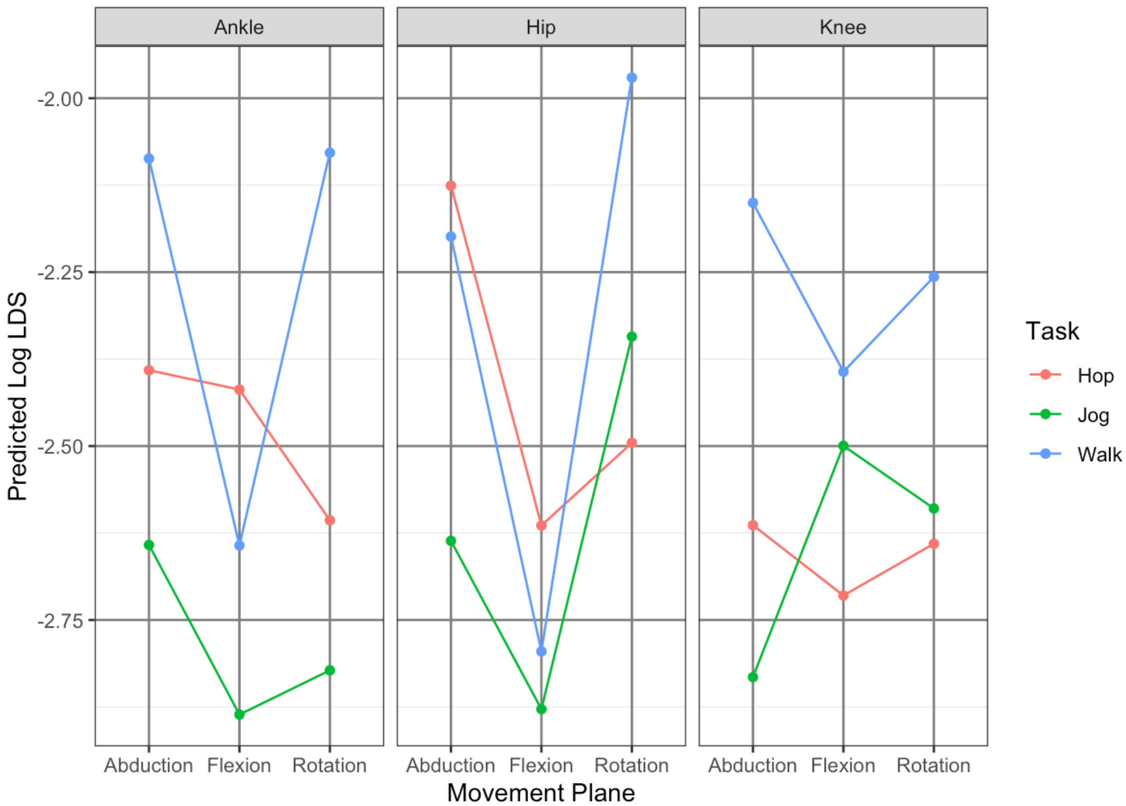

Figure 16: Predicted Log LDS separated by movement plane and joint.

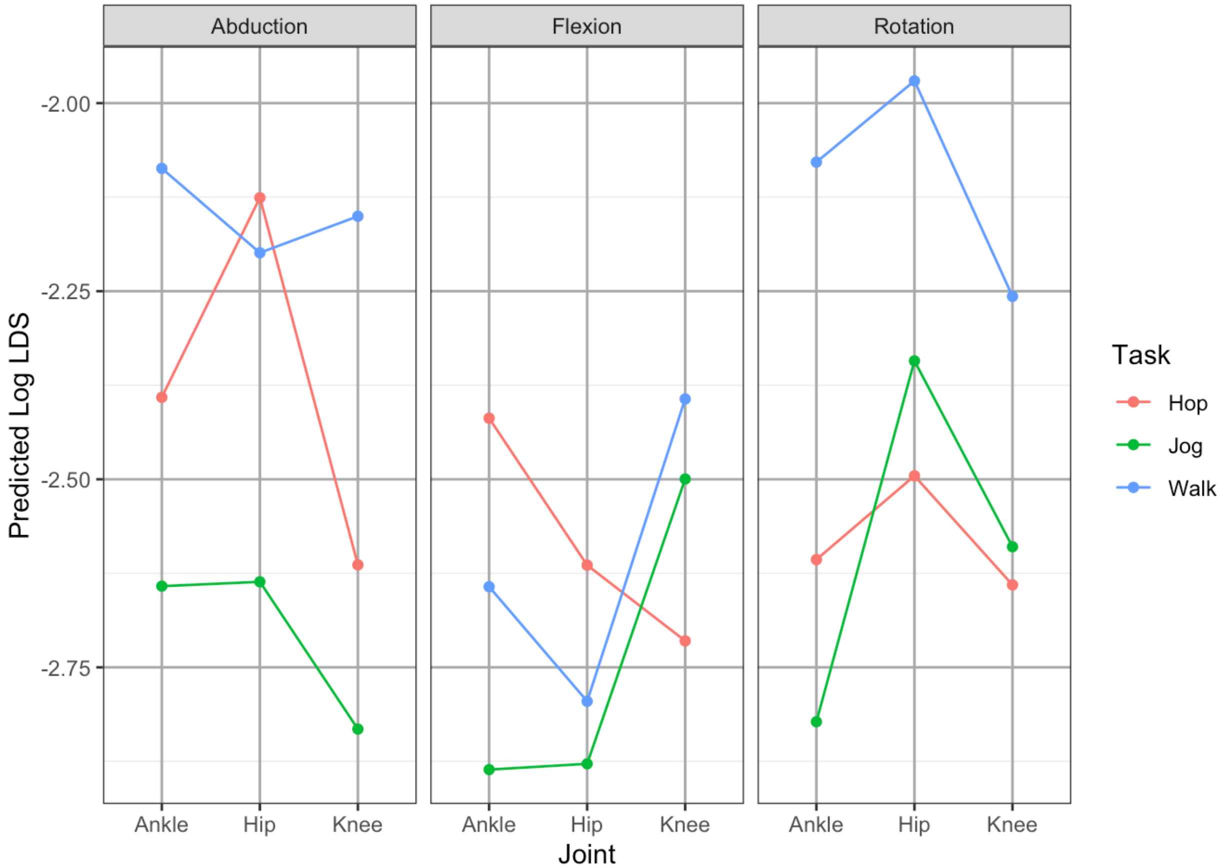

Figure 17: Predicted Log LDS separated by lower extremity joint and movement plane.

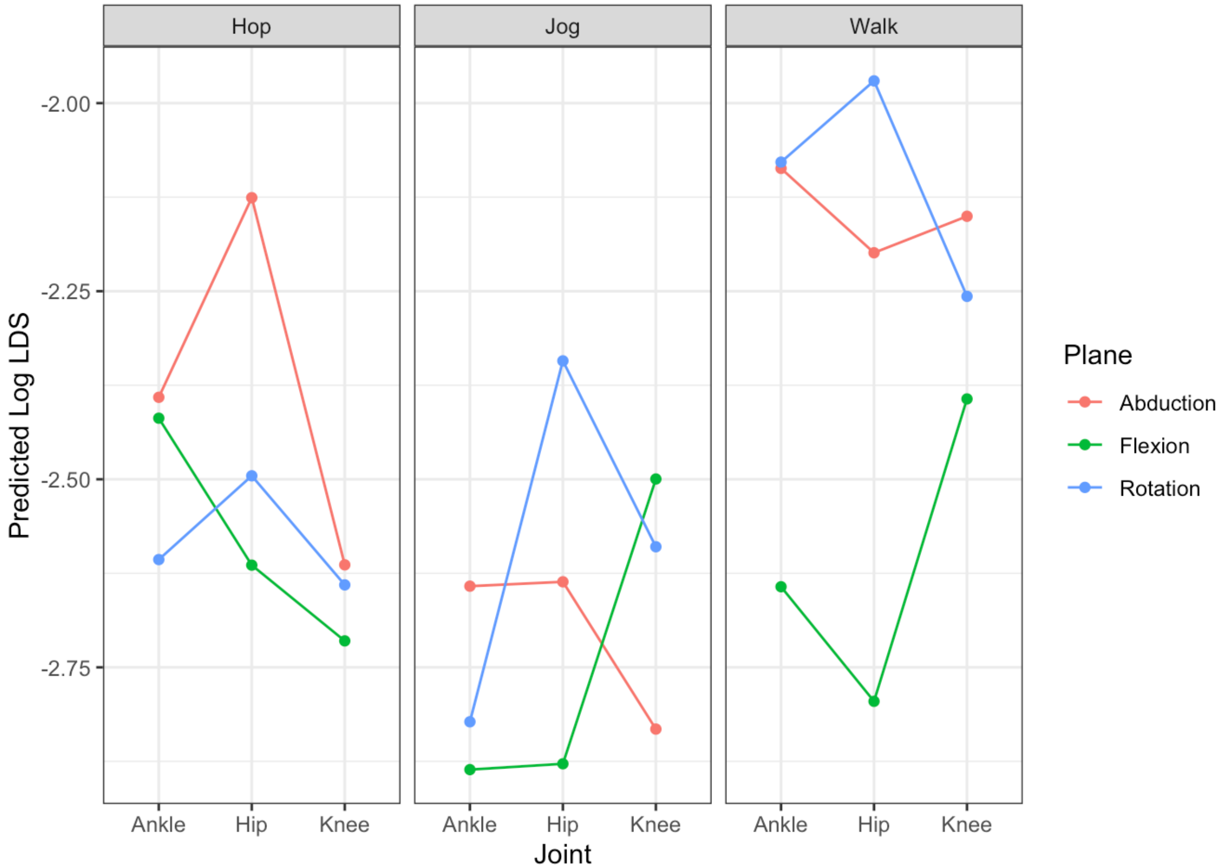

Figure 18: Predicted Log LDS separated by lower extremity joint and movement task.

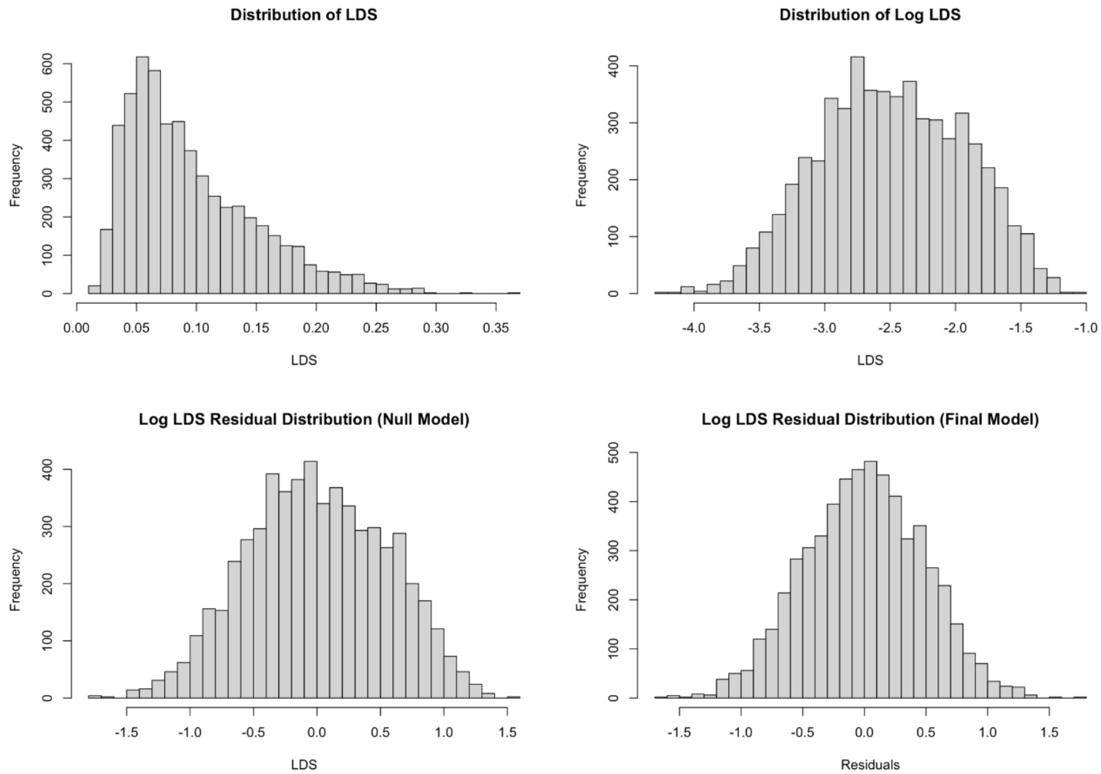

Figure 19: Distributions of LDS. Top-Left) Raw distribution of LDS before application of mixed effects model. Top-Right) Distribution of LDS residuals after Log correction applied. Bottom-Left) Distribution of Log LDS after application of Null model. Bottom-Right) Distribution of Log LDS residuals after applying design + interaction effect model.

Table 3: Comparing estimated log LDS mixed effects models

	Null	Design	Design Interaction	Add MSE
(Intercept)	-2.49***	-2.45***	-2.69***	-2.38***
	(-0.02)	(-0.02)	(-0.04)	(-0.06)
JointHip		0.06***	0.27***	0.27***
		(-0.02)	(-0.05)	(-0.05)
JointKnee		-0.01	-0.22***	-0.22***
		(-0.02)	(-0.05)	(-0.05)
TaskJog		-0.17***	-0.25***	-0.25***
		(-0.02)	(-0.05)	(-0.05)
TaskWalk		0.23***	0.30***	0.30***
		(-0.02)	(-0.05)	(-0.05)
PlaneFlexion		-0.24***	-0.03	-0.03
		(-0.02)	(-0.05)	(-0.05)
PlaneRotation		-0.01	-0.22***	-0.22***
		(-0.02)	(-0.05)	(-0.05)
JointHip:TaskJog			-0.26***	-0.26***
			(-0.07)	(-0.07)
JointKnee:TaskJog			0.03	0.03
			(-0.07)	(-0.07)
JointHip:TaskWalk			-0.38***	-0.38***
			(-0.07)	(-0.07)
JointKnee:TaskWalk			0.16*	0.16*
			(-0.07)	(-0.07)
JointHip:PlaneFlexion			-0.46***	-0.46***
			(-0.07)	(-0.07)
JointKnee:PlaneFlexion			-0.07	-0.07
			(-0.07)	(-0.07)
JointHip:PlaneRotation			-0.15*	-0.15*
			(-0.07)	(-0.07)
JointKnee:PlaneRotation			0.19**	0.19**
			(-0.07)	(-0.07)
TaskJog:PlaneFlexion			-0.22**	-0.22**
			(-0.07)	(-0.07)
TaskWalk:PlaneFlexion			-0.53***	-0.53***
			(-0.07)	(-0.07)
TaskJog:PlaneRotation			0.04	0.04
			(-0.07)	(-0.07)
TaskWalk:PlaneRotation			0.22***	0.22***
			(-0.07)	(-0.07)

Table 4 (cont.): Comparing estimated log LDS mixed effects models

JointHip:TaskJog:PlaneFlexion			0.46***	0.46***
			(-0.09)	(-0.09)
JointKnee:TaskJog:PlaneFlexion			0.65***	0.65***
			(-0.1)	(-0.1)
JointHip:TaskWalk:PlaneFlexion			0.42***	0.42***
			(-0.09)	(-0.09)
JointKnee:TaskWalk:PlaneFlexion			0.39***	0.39***
			(-0.1)	(-0.1)
JointHip:TaskJog:PlaneRotation			0.63***	0.63***
			(-0.09)	(-0.09)
JointKnee:TaskJog:PlaneRotation			0.23*	0.23*
			(-0.09)	(-0.09)
JointHip:TaskWalk:PlaneRotation			0.37***	0.37***
			(-0.09)	(-0.09)
JointKnee:TaskWalk:PlaneRotation			-0.30**	-0.30**
			(-0.09)	(-0.09)
MSE				0.00
				0.00
MSEAP				0.00
				(-0.02)
AIC	9560.14	8752.21	8093.57	8097.51
BIC	9580.13	8812.18	8286.8	8304.06
Log Likelihood	-4777.07	-4367.11	-4017.79	-4017.76
Num. obs.	5784	5784	5784	5784.00
Nim. Groups: SubjectID	28	28	28	28.00
Var:SubjectID (Intercept)	0.01	0.01	0.01	0.01
Var:Residual	0.3	0.26	0.23	0.23

***p < 0.001; **p < 0.001; *p < 0.05

Table 5: Comparing the Null Model to the design model

	npar	AIC	BIC	logLik	deviance	Chisq	Df	Pr(>Chisq)
Null	3	9560.14	9580.13	-4777.07	9554.14			
Design	9	8752.21	8812.18	-4367.11	8734.21	819.93	6	0

Table 6: Comparing design model with and without interaction effects

	npar	AIC	BIC	logLik	deviance	Chisq	Df	Pr(>Chisq)
Design	9	8752.21	8812.18	-4367.11	8734.21			
Design + Interaction	29	8093.57	8286.8	-4017.79	8035.57	698.64	20	0

Table 7: Comparing design model with and without MSE

	npar	AIC	BIC	logLik	deviance	Chisq	Df	Pr(>Chisq)
Design + Interaction	29	8093.57	8286.8	-4017.79	8035.57			
MSE	31	8097.51	8304.06	-4017.76	8035.51	0.06	2	0.97

Table 3 shows the steps used in creating the nested hierarchical model to explain variance in LDS. The model with the design factors was a better fit to the data than the null model $\chi 2$ (3,9) = 454.14, p<.001), suggesting that joint, movement task, and movement plane are important to include in the model when predicting LDS (Table 4). The model that included interactions between joint, movement task, and movement plane, was a better fit than the model without these interaction terms (Table 5), suggesting that the relation between any two of these factors depends on the context of the movement (e.g. the relationship between the ankle and adduction will change based on whether the task is a walk or a jog). Finally, there was no evidence that including MSE and directional effects of MSE (AP/ML) improved the fit of the model (Table 6). Therefore, the authors did not find support for a relation between these variables and log LDS.

Figures 16-18 show the mean normative values found from the model created in Table 3. These values were logarithmically transformed to improve normality of distribution. These values show some of the important interactions seen in Table 3, and further illustrate how lower extremity LDS can change based on movement task, joint, and movement plane.

Finally, Figure 19 shows how the distribution of LDS residuals became more normal after applying multilevel modeling techniques. This visual confirmation technique shows that applying design and interaction terms to the multilevel model does significantly explain some sources of variance in lower extremity LDS.

5.5 Discussion

The aim of this study was to establish a relationship between the LDS and MSE during various common movements using nested hierarchical modeling. This study had two main findings. First, the MSE of COP deviation from a single legged balance did not significantly improve the model of LDS variance. Second, there were significant interactions between design effects in the lower extremity LDS. This hypothesis was further supported by the increased normality of the lower extremity LDS after applying the nested hierarchical model. This study showed that postural complexity does not appear to be directly related to lower extremity neuromuscular control, that lower extremity LDS is prone to significant changes depending on movement task, joint, and movement plane.

The first main finding in this study was that postural complexity did not appear to be directly related to lower extremity neuromuscular control. This finding is supported by the results presented in Table 3, which demonstrate that the MSE of COP deviation from a single legged balance did not significantly improve the model of lower extremity LDS variance. This finding is supported by both theoretical studies[121] and empirical studies[155] which express caution when trying to find linear relationships between nonlinear measures. However, one important distinction between the aforementioned studies and this study is that the aforementioned studies compared the LDS and MSE of identical signals, whereas this study compared MSE and LDS from different movements. Therefore, while the above studies are correct to be cautious about linear interpretations of multiple nonlinear signals, this study used appropriate tools to model nonlinear relationships and was still unable to find any significance between MSE and LDS. This finding is beneficial to the field of biomechanics because it suggests that systemic complexity in the human body (as measured by MSE of COP deviation) has no relation to how effectively an individual can respond to unexpected stimuli in the lower extremity (LDS).

The second main finding in this study was that there are significant interactions between design effects in the lower extremity LDS. Although there are not many studies to the authors' knowledge regarding lower extremity LDS, this finding does indicate that the LDS of the lower extremity is not constant for any joint, movement plane, or task. This suggests that individuals can adapt the LDS of these constraints as needed to complete any necessary motor tasks. This finding provides useful context for previous studies which suggest that certain lower extremity LDS values may be injury risk factors[80]. For example, previous work by the authors[80] indicated that the LDS of ankle rotation during a vertical jumping task was a significant predictor of previous ACL injury in a post-hoc analysis. This finding could suggest that future injury screenings based on the lower extremity LDS would be highly task specific. For example, an individual with high ankle rotation LDS during a vertical jump task may not necessarily have poor ankle control during a jog or walk.

Further validating the interaction effects of this model was the improved normality of lower extremity LDS was after applying the nested hierarchical model. This finding can be seen in Figure 19, and provides a simple visualization to demonstrate that the residuals of lower extremity LDS do become more normally distributed after using nested hierarchical modeling techniques. This finding indicates that the explanatory variables included in the design model (Table 3) were sufficient to describe the variance in LDS, although future studies could also aim to improve normality by including other explanatory variables.

This study has some notable limitations. First, treadmill gait was used instead of overground gait. Therefore, the gait patterns seen in this study were not identical to gait that our participants may experience in everyday ambulation. However, treadmill studies are most commonly used by researchers due to space constraints, and the findings from this study will be most consistent with other literature in this field. Secondly, this group studied healthy college students which may not have findings which reflect the general adult or elderly populations. However, the specific scope of this study allows us to add new LDS information into the field of biomechanics, as most LDS studies target elderly or neurologically impaired individuals.

5.6 Conclusions

In conclusion, this study showed that postural complexity does not appear to be directly related to lower extremity neuromuscular control. Additionally, there were significant interaction effects in lower extremity LDS variables, which suggests that lower extremity LDS is prone to significant changes depending on movement task, lower extremity joint, and movement plane. Finally, the normality of LDS residuals was improved by the design variables included in this study, although future studies could aim to further improve normality by the inclusion of other explanatory variables such as limb dominance, gender, or injury history. These findings should serve as useful references for future studies meant to explore how nonlinear measures can be used to measure and compare various aspects of human motor control.

6 Future Studies

This section is comprised of three future studies which could be addressed through similar methods. Therefore, these methods have been compiled in this section and can be referenced for all future studies.

6.1 Proposed Methods

6.1.1 Participants

Study participants should include 650 collegiate D1 soccer players tracked for three years. Participants should be disqualified from the study if they had sustained a previous ACL injury or other lower limb injury requiring surgical intervention.

6.1.2 Instrumentation

Subjects should be fitted with 79 reflective markers following the same format as seen in previous studies[80] using the point cluster technique[117] and perform a walking task on a single belt treadmill (Urevo, Strol Lite). Kinematic data should be captured with a multi-camera motion capture system. Kinematic data should then be filtered, as suggested by Visual 3D, using a 6Hz Butterworth filter[120]. The lower kinematic model should be assigned three degrees of freedom for the hip, knee, and ankle by restraining translational movement, as done by Charlton et al. (2004)[118]. The International Society for Biomechanics recommendations for coordinate systems should be applied to each segment[162].

6.1.3 Movement Tasks

Because this study will be testing subjects after ACL injury, low-impact and simple movements should be chosen to allow for easier data collection during recovery. Walking data should be recorded in 60-second intervals at a self-selected speed. Subjects should be given 60 seconds to become acquainted with the treadmill at their self-selected speed before data is collected.

6.1.4 Data Collection Timeline

Participants should be tested initially and then asked to inform researchers if they sustained an ACL injury during the next year. If participants do sustain an ACL injury, they should be asked to return for follow-up studies at 3-month intervals after they are cleared to return to sport following ACL reconstructive surgery[155].

6.1.5 Local Dynamic Stability Analysis

LDS values should be recorded for each rotational DOF (e.g. flexion, rotation, abduction) for the ankle, knee, and hip. The analysis in this study should follow Rosenstein's method for calculating the maximum Lyapunov exponent[138]. The embedding dimensions in this study should use the false nearest neighbors method, and the time delay should be calculated using the autocorrelation function[139]. Embedding dimensions should be calculated individually for each trial and participant.

6.1.6 Data Processing

All data should be normalized from foot strike to foot strike, as determined by the minimum vertical position of heel markers[146]. Data before the first full movement cycle and after the last full movement cycle should be removed from the analysis.

6.1.7 Power Analysis

A power analysis was performed using effect size d = 0.8, $\alpha = 0.05$, and ß = 0.05, and determined that a minimum of 35 subjects per group would be a sufficient sample size to compare injured and uninjured groups. Previous studies have shown that an average collegiate season generates an average of 88 athletic exposures per individual per season[163]. At an average injury rate of 0.2 ACL injuries per 1000 athletic exposures[164], an estimated 650 subjects would be a sufficient sample size to generate 35 ACL injuries for three years to give significant results.

6.2 Future study 1: Monitoring LDS of ACL reconstructed subjects before and after reconstruction

6.2.1 Background

Local Dynamic Stability (LDS) is an increasingly utilized measure for assessing motor proficiency in healthy populations, but relatively little is known about how LDS measures change before and after musculoskeletal injury. While there are several screening metrics to identify risky movement patterns, elite athletes create highly variable movement patterns[165] which could circumvent injury screening protocols. The LDS is especially useful in these circumstances, as it can characterize patterns of movement that may still detect individuals at risk of injury despite their compensatory mechanisms. Therefore, a longitudinal study of athletes gathering baseline LDS data will inform researchers of any potential risk factors which may indicate that a particular movement pattern is too repetitive and may indicate an increased risk of injury.

Using the LDS to measure the variance of a kinematic movement pattern is an increasingly popular method for quantifying movements in biomechanics. Many studies have used the LDS to measure fall risk in elderly subjects[4,5,7] as well as the complexity and adaptability of mechanical systems[1,2]. These studies have shown that a decreased LDS indicates a decreased ability for a system to adapt to new perturbations (mechanical) or movement scenarios (biomechanics). A mechanical system with a low LDS may become heavily damaged, whereas a mechanical system with a high LDS would easily respond to perturbations and return to a state of normal operation. Biomechanically, this means that elderly subjects with a decreased LDS can successfully walk in a straight line when a perturbation is introduced, but may fall when turning sharply or walking on an uneven surface. A decreased LDS indicates that a movement will be more “robotically” rigid and repeated, with a poor ability to respond to unexpected changes. Therefore, a decreased LDS is generally seen as a risk factor in elderly populations.

However, this LDS measure which has been extensively studied in elderly populations has not been given nearly as much attention in a young and healthy population. While elderly falls are a large source of financial burden on the USA healthcare system (~$1,000 - $42,000 per fall)[166], ACL injuries in young athletes are also a large financial burden which justifies further investigation using this method[10,12]. Due to the relative difficulty of measuring LDS, many researchers undertaking longitudinal studies have avoided using the LDS to streamline and simplify the volume of data processing. To make any meaningful observations about lower extremity LDS, a large dataset of baseline measures must be taken before sustaining an ACL injury to understand how the motor skills of an athlete might place them at an increased risk for injury.

The purpose of this study will be to gather longitudinal data of elite collegiate athletes to more closely investigate the role that LDS may have in predicting risk of injury. The authors hypothesize that baseline lower extremity LDS values for participants who go on to sustain ACL injuries would be significantly lower than the lower extremity LDS of participants who do not go on to sustain ACL injuries for the walking task.

6.2.2 Statistical Analysis

The LDS of lower extremity walking tasks should be compared between control and injured groups using a two-sided t-test.

6.2.3 Expected Results

It is expected that there will be a significant difference between the LDS of the lower extremity during the walk and the knee and hip during a jog using a two-sided t-test, and a hypothetical figure of these results is shown in Figure 20.

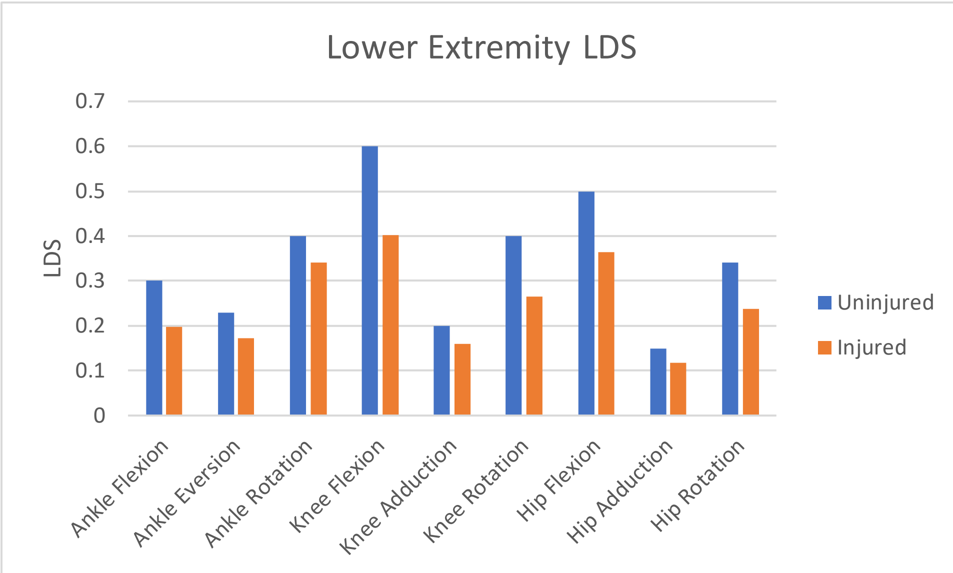

Figure 20: This figure shows a hypothetical representation of the lower extremity LDS for the walking task in both injured and uninjured groups. It is expected that the injured population will have decreased baseline LDS values in the lower extremity.

6.2.4 Discussion

The purpose of this study is to gather longitudinal data of elite collegiate athletes to more closely investigate the role that LDS may have in predicting risk of injury. It is expected that this study will have one main finding. Baseline lower extremity LDS values should be significantly lower in the group of participants that sustained ACL injuries compared to the group that did not sustain ACL injuries. This study could suggest that lower extremity LDS should be used as a screening measure to reduce risk of ACL injuries in elite-level athletes.

It is expected that baseline lower extremity LDS values will be significantly lower in the group of participants that sustained ACL injuries compared to the group that did not sustain ACL injuries. To the author's knowledge, no previous longitudinal studies of lower extremity LDS and ACL injury risk exist. However, this finding would be supported by existing literature[4,5,7] which shows that the risk of elderly falls is greatly increased with decreased LDS. This existing research for elderly falls should apply to high-level athletes, as the decreased LDS for elderly subjects shows fall risk due to a lack of ability to adapt to new stimuli. Similarly, elite-level athletes with a greater capacity to respond to new stimuli may be able to avoid getting into injurious positions, therefore supporting the idea that subjects with increased lower extremity LDS may avoid ACL injuries longer than their peers. This study suggests that the lower extremity LDS can serve as an effective screening mechanism, and should be implemented by clinicians and researchers alike.

The main anticipated finding of Chapter 6.2 is that baseline lower extremity LDS values will be significantly lower in the group of participants that sustained ACL injuries compared to the group that did not sustain ACL injuries. This would suggest that clinicians could implement this metric as a way to potentially detect risk for ACL injury and subsequently give at-risk athletes rehabilitative exercises to reduce their risk of injury. This finding would also suggest that nonlinear metrics may provide more reliable measures of movement patterns on an individual level, and the application of the LDS in injury screening scenarios should be further explored in the field of biomechanics

6.3 Future study 2: Local Dynamic Stability as an Effective Means of Monitoring Return to Sport after ACL Injury

6.3.1 Introduction

Measuring an athlete's return to sport after sustaining an ACL injury has been a challenge to the sports medicine community for many years[167,168]. This is problematic as there are an estimated 250,000 ACL reconstructions each year in the United States[167], and the risk of sustaining a second ACL injury is almost 15x greater in the year following ACL reconstructive surgery[169]. Although there are several contributing factors to this increased injury risk, a major aspect of the increased risk of ACL reinjury is the lack of effective screening tools to evaluate readiness to return to sport[170]. Athletes returning to sport prematurely have been shown to have an increased risk for ACL reinjury[167,168], and ensuring that athletes are returning to competition at the appropriate time could significantly reduce the number of ACL reinjuries.

Existing methods of measuring return to sport track certain metrics like quadriceps strength, range of motion, functional task performance, and neuromuscular control[171–176]. Although some of these studies may have found evidence at a small scale, they have been unable to effectively reduce the risk of ACL reinjury at the clinical level or in large-scale studies[172]. While the specific metrics included in these studies do indeed measure relevant aspects of an athlete's rehabilitation, it is not yet clear how to best utilize the existing metrics to measure safe return to sport, or even if these metrics are appropriate to measure return to sport at all.

Conversely, several studies have shown that athletes that have been cleared to return to sport after ACL injury have shown large neuromuscular deficits in common movement patterns despite having appropriate strength and range of motion[172]. However, there are no existing metrics to assess neuromuscular performance in the lower extremity. If there were a robust measure of lower extremity neuromuscular control, it could be applied to more effectively understand an individual's movement patterns at the joint level, which could allow researchers and clinicians alike to make more informed decisions about an athlete's readiness to return to sport.

The LDS is a popular and robust measure of neuromuscular control which can assess gait patterns in the lower extremity[80]. LDS has been used to effectively determine elderly fall risk[4,177], and has gained popularity in the field of biomechanics due to its ability to characterize subtle variations in repeated movement patterns instead of analyzing individual points in time[81].

The purpose of this proposed study is to track ACL injured athletes before their injury, after their surgical reconstruction, and throughout rehabilitation to understand if lower extremity LDS can be used to determine a more effective guideline for return to sport. The authors hypothesize that the LDS for individuals that go on to compete at their previous level of competition would not be significantly different than their baseline LDS levels, while individuals that failed to compete at their original levels of competition or that suffered a reinjury would have lower extremity LDS levels that were significantly lower than their preinjury levels.

6.3.2 Statistical Analysis

The LDS of lower extremity walking tasks should be compared between control and injured groups using a two-sided t-test.

6.3.3 Expected Results

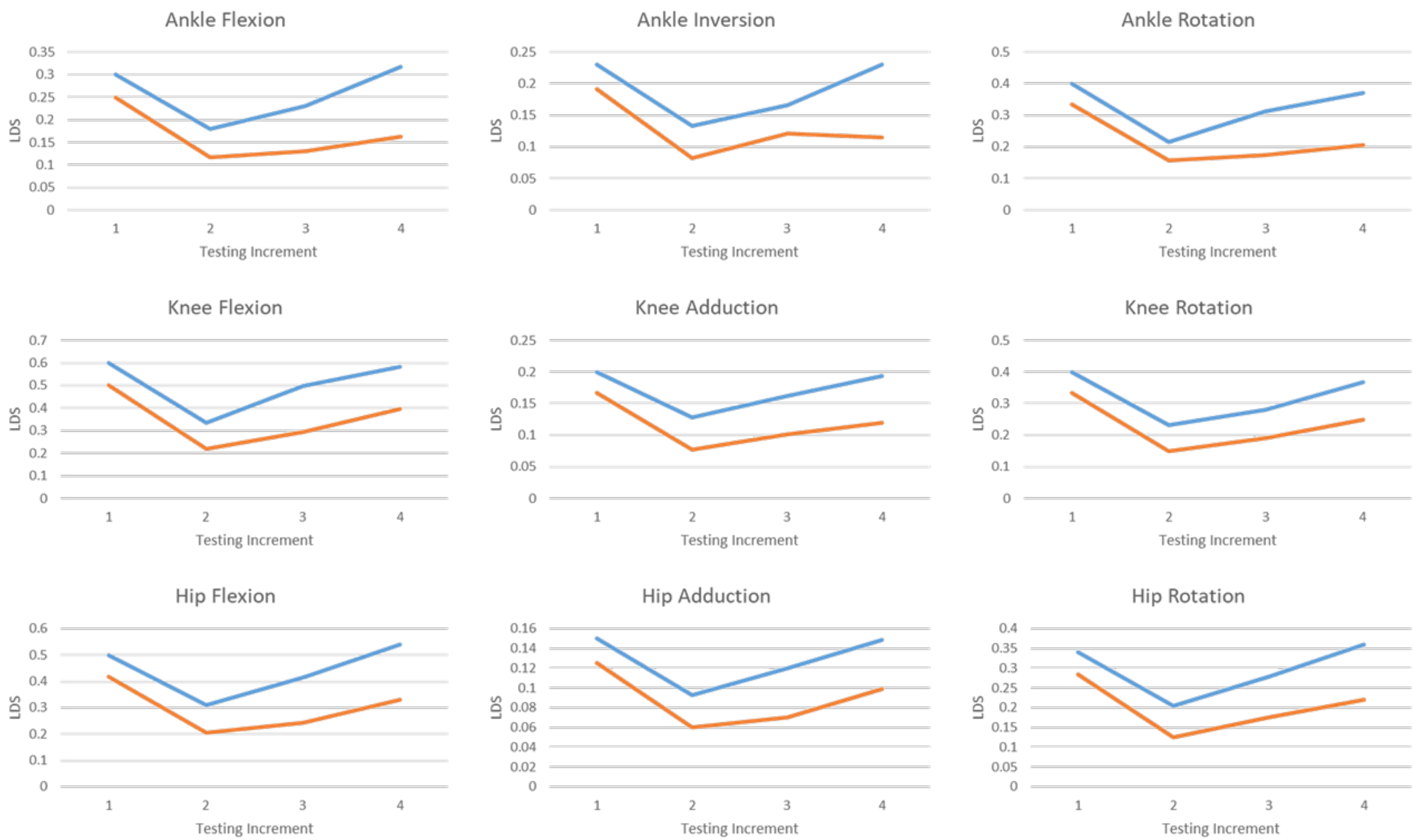

Figure 21 : This figure shows a hypothetical representation of the LDS of the lower extremity during a walk at four data points: 1) pre-injury, 2) 6 months post surgery, 3) 9 months post surgery, and 4) at return to competitive sport. In this figure, the blue line represents the long-term success group, while the orange line represents the long-term reinjury group.

It is expected that this study should find a significant difference between the lower extremity LDS at the time of return to sport for the ACL reinjury group and the healthy control group as visualized in Figure 21. It is also expected that the long-term success group post-ACL injury will return to or exceed their original baseline LDS values, while the long-term reinjury group will not return to their original baseline LDS values.

6.3.4 Discussion

The purpose of this study was to track ACL injured athletes before their injury, after their surgical reconstruction, and throughout rehabilitation to understand if the LDS can be used to determine a more effective return to sport. It is expected that this study will have two main findings: 1.) that the long-term success group did not show any significant differences in lower extremity LDS between baseline and return to sport after rehabilitation, and 2.) that the long-term failure group will show a significant difference in lower extremity LDS between baseline and return to sport after rehabilitation.

These findings would suggest that participants who successfully return to sport can return their lower extremity motor control to pre-injury levels. Similarly, participants who are not able to return their lower extremity motor control to pre-injury levels may be more likely to become reinjured or fail to return to their sport at pre-injury levels of competition. These findings could show that lower extremity LDS is a sufficient measure of readiness to return to sport, and should be used in the future to reduce the risk of re-injury and improve athletes' quality of life in the long term.

The long-term failure group is expected to show a significant decrease in lower extremity LDS. This finding is supported by existing literature[155], as this study will further expand the Oliveira study by recording lower extremity LDS at the individual level pre and post-injury instead of only recording post-injury. This study is expected to show that an individual decreases their lower extremity LDS from baseline levels after an ACL injury, and then fails to raise the lower extremity LDS back to baseline levels after rehabilitation. This is an important distinction because previous studies do not capture the pre-injury LDS. In summary, this finding would indicate that if lower extremity motor control does not return to its original pre-injury level, an individual is not likely to compete at their original level or play without an increased risk of injury.

This study is not expected to show any significant differences in lower extremity LDS between baseline and return to sport after rehabilitation in the long-term success group. There are no previous studies investigating lower extremity LDS before and after ACL injury to the author's knowledge, although the general information from the Oliveira study seems to suggest that control/healthy subjects have a greater lower extremity LDS than injured subjects. The key difference that will not allow for direct comparisons in data is that the Oliveira study did not test athletes, whereas the studies in Section 6.3 will be focused on athletes and their rehabilitative efforts in returning to sport. It is therefore likely that the subjects in the Oliveira paper would not need the same level of motor skills and/or strength training to return to a non-athletic life, which could explain why the LDS in the study after 90, 180, and 360 days remained so low compared to the control group. This expected lack of evidence should be interpreted with caution until future studies can replicate this finding, but could serve to show a general benchmark of performance for an individual to aim for.

This study is expected to show that ACL injuries significantly reduce lower extremity LDS and that failing to return to pre-injury lower extremity LDS increases the risk of ACL reinjury and failure to return to sport at original levels of competition. This study should show that the lower extremity LDS during gait can be used as an effective measure of readiness to return to sport. This finding could be utilized by clinicians and researchers alike to safely monitor an athlete's return to sport and consider limiting an athlete from competing until their lower extremity LDS have returned to preinjury levels.

6.4 Future Study 3: Methods for Increasing Local Dynamic Stability after ACL injury

6.4.1 Introduction

ACL injuries alter the biomechanical profile of many movements, and common existing measures to return athletes to sport may not accurately measure and track biomechanical patterns before assessing safe return to sport[173]. Previous studies have shown that the lower extremity LDS decreases after ACL injury[155], but do not provide insight into how rehabilitation could be altered to more effectively return athletes to sport. Existing literature shows that neuromuscular control is a modifiable biomechanical trait[178,179] which suggests that lower extremity LDS could be trained to reduce the risk of ACL reinjury.

The purpose of this study is to compare the lower extremity LDS recovery during rehabilitation after ACL injury in collegiate athletes both with and without a neuromuscular training intervention. The authors hypothesize that the cohort that receives the neuromuscular training intervention will return more quickly to baseline lower extremity LDS values than the control group. Additionally, the authors hypothesize that the cohort that received the neuromuscular training intervention would have significantly more of the individuals return to baseline LDS values at the time when they were cleared to sport than the cohort that did not receive the neuromuscular training intervention.

6.4.2 Statistical Analysis

The LDS of lower extremity walking tasks should be compared between control and injured groups using a two-sided t-test. Additionally, this study should use paired t-tests to measure differences between a participant's baseline and rehabilitative lower extremity LDS as they progress through the recovery.

6.4.3 Expected Results

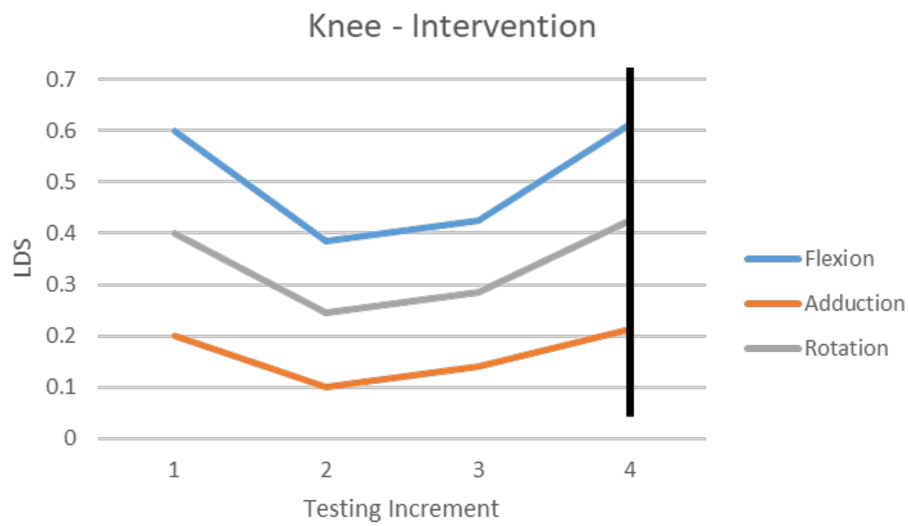

Figure 21: This figure shows a representation of the lower extremity LDS values for the knee during a walking task for the intervention group. The vertical black bar shows the time when athletes were cleared to return to sport by traditional metrics. In this figure, knee LDS has returned to original, pre-injury values for flexion, rotation, and adduction. Knee LDS data was collected at 4 points: 1) pre-injury, 2) 6 months post-surgery, 3) 9 months post-surgery, and 4) at return to competitive sport.

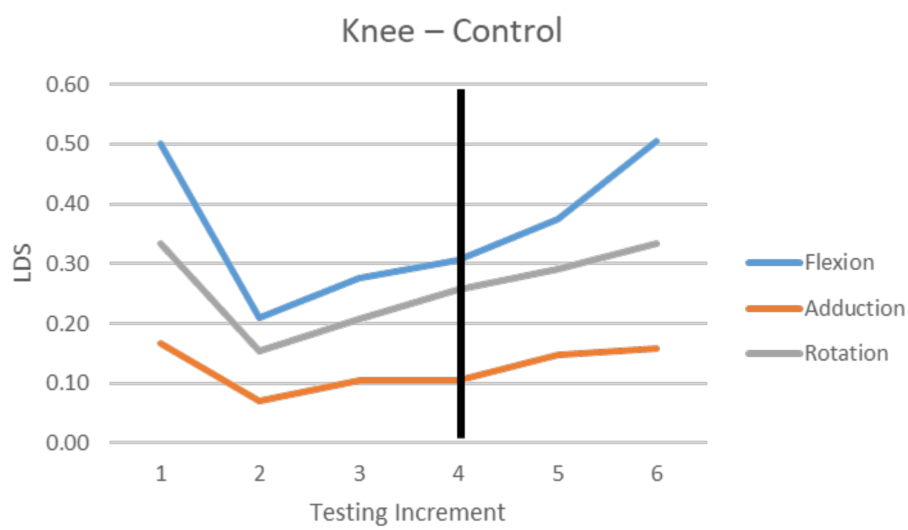

Figure 22: This figure shows a representation of the lower extremity LDS values for the knee during a walking task for the control group. The vertical black bar shows the time when athletes were cleared to return to sport by traditional metrics. In this figure, knee LDS at the time when athletes were cleared to return to sport had not returned to original levels for knee flexion, rotation, or adduction. Knee LDS data was collected at 4 points: 1) pre-injury, 2) 6 months post-surgery, 3) 9 months post-surgery, and 4) at return to competitive sport.

This study is expected to show that the intervention group that received neuromuscular training intervention returned to baseline lower extremity LDS values more quickly than the control group (Figure 23 and Figure 24). This study is also expected to show that the cohort that received the neuromuscular training intervention had significantly more individuals return to baseline LDS values at the time when they were cleared to sport than the cohort that did not receive the neuromuscular training intervention.

6.4.4 Discussion

The purpose of this study is to compare the lower extremity LDS recovery during rehabilitation after ACL injury in collegiate athletes both with and without a neuromuscular training intervention. This study is expected to have two main findings. First, participants receiving the neuromuscular training intervention should recover from their ACL injuries more quickly than participants that did not receive the training intervention. The second main finding of this study is that participants receiving the neuromuscular training intervention should return to sport safely at a higher rate than the participants that did not receive the training intervention. These findings should show that neuromuscular intervention during ACL rehabilitation can play a large role in ensuring a fast and safe return to sport.

The first main finding of this study should be that participants receiving the neuromuscular training intervention recovered from their ACL injuries more quickly than participants that did not receive the intervention. This finding is supported by previous studies which show that the lower extremity LDS is a modifiable factor that can be safely affected by neuromuscular training[179]. However, previous studies did not analyze various rehabilitation intervention techniques or the speed of recovery of their individuals. This finding could suggest that subjects that return to sport without neuromuscular training interventions may either have a stronger muscular foundation or may ambulate in a way throughout their recovery that more actively stimulates and trains their lower extremity motor control. These inherent features may passively contribute to lower extremity LDS values increasing to baseline preinjury LDS levels. This finding should show that while some athletes may be able to return to sport without neuromuscular interventions, most participants would benefit from additional neuromuscular training during rehabilitation to return to sport more quickly.

The second expected finding of this study is that participants receiving the neuromuscular training intervention safely returned to sport at a higher rate than the participants that did not receive the intervention. Although understanding the importance and modifiability of lower extremity LDS during rehabilitation is important, future studies should further explore the most effective neuromuscular exercises for an individual to perform during rehabilitation to understand the most effective ways to get an individual to safely return from an ACL injury.

This study should show that individuals rehabilitating from ACL injuries return to sport more quickly and safely when given a neuromuscular intervention to return their lower extremity LDS values to preinjury baseline levels. This study could be immediately implemented by clinicians to help improve individual outcomes when recovering from ACL injuries with little to no additional cost of equipment and only needing to implement new exercises to augment existing rehabilitation protocols.

7 Conclusions

The purpose of this dissertation was to explore the relationships between the lower extremity LDS and MSE as they relate to previous injury and neuromuscular control. This was achieved by studying the kinematic patterns of collegiate athletes in various conditions using an optical-passive reflective marker-based system to gather precise movement data. Participants were studied under various conditions including during multi-tasking, and during varied movement tasks. The hypotheses from three studies are listed below to reiterate the findings discussed in this dissertation.

Study 1: This study showed that LDS categorized previously injured subjects at a high rate of success using a multivariate logistic regression during a fatigue jump task. Ankle instability appeared to play a large role in this categorization, although interpreting the cause for ankle instability in the previously injured group is out of the scope of this study. Findings showed no statistical difference in kinematic position at maximum knee flexion during all jumps between previously injured and uninjured subjects, including ankle kinematics. Additionally, kinematic position at maximum knee flexion was not correlated to LDS values, which would indicate LDS cannot be effectively inferred from kinematics. These results suggest that the LDS provides unique movement information that should be critically analyzed in future studies, which may provide new information that could allow for more effective injury screening tests in the future.

Regarding the findings of this study, it is important to note that the data collected from the 7 previously injured subjects was gathered after the injury was sustained. Because of this, it is unclear if the findings indicate that increased LDS put subjects at a higher risk of sustaining future ACL injuries or if the decreased LDS is a result of surgery and/or rehabilitation.

Any interpretations from this dataset should be tempered when concerning populations other than women's collegiate soccer players and a repetitive vertical jump. Because there is a limited body of work in this area, the findings presented in this paper are intended to serve as a foundation for the possibility of using the LDS as a screening metric.

Study 2: This study found that lower extremity LDS decreases by a larger magnitude during a dual-task as the speed of the dual-task increases, and that subjects compensate during gait by both increasing and decreasing LDS in different degrees of freedom of the lower extremity. This study did not find evidence of limb dominance affecting the change in LDS during a dual-task while walking or jogging. These findings reveal where healthy adults compensate for simple movement patterns while multitasking. It has been demonstrated that different tasks evoke different, movement-specific compensations and that the difficulty of these tasks can impact the degree of compensation required by the user to complete both a movement and cognitive task. Future work should further explore the role and relationship between trunk movement and lower extremity compensation and could help give further context to how the LDS can be interpreted by researchers and clinicians alike.

Study 3: This study showed that postural complexity does not appear to be directly related to lower extremity neuromuscular control. Additionally, there were significant interaction effects in lower extremity LDS variables, which suggests that lower extremity LDS is prone to significant changes depending on movement task, lower extremity joint, and movement plane. Finally, the normality of LDS residuals was improved by the design variables included in this study, although future studies could aim to further improve normality by the inclusion of other explanatory variables such as limb dominance, gender, or injury history. These findings should serve as useful references for future studies meant to explore how nonlinear measures can be used to measure and compare various aspects of human motor control.

In conclusion, this dissertation furthers the understanding of how nonlinear dynamics can be applied to study movement patterns during various movement tasks and with varied amounts of cognitive load. Additionally, this dissertation established the use of LDS in lower extremity kinematics as opposed to trunk dynamics, and suggested that assessment of non-gait movements could be viable to analyze in future studies. Future studies should gather longitudinal data for the lower extremity LDS and track lower extremity LDS during rehabilitation to better understand the role of LDS in injury risk.

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