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Machine Learning Approach to Activity Categorization in Young Adults Using Biomechanical Metrics

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MACHINE LEARNING APPROACH TO ACTIVITY CATEGORIZATION IN YOUNG ADULTS USING BIOMECHANICAL METRICS

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ABSTRACT

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Inactive adults often have decreased musculoskeletal health and increased risk factors for chronic diseases. However, there is limited data linking biomechanical measurements of generally healthy young adults to their physical activity levels assessed through questionnaires. Commonly used data collection methods in biomechanics for assessing musculoskeletal health include but are not limited to muscle quality (measured as echo intensity when using ultrasound), isokinetic (i.e., dynamic) muscle strength, muscle activations, and functional movement assessments using motion capture systems. These assessments can be time consuming for both data collection and processing. Therefore, understanding if all biomechanical assessments are necessary to classify the activity level of an individual is critical. The aims of the study were to determine the relationships between biomechanical measurements used in ascertaining skeletal muscular health using statistical methods, to determine if various machine learning techniques can distinguish between low to moderately active and highly active asymptomatic young adults, and if processing data using machine learning can decrease the number of measurements needed to differentiate between activity levels. The results showed that fundamental statistics alone could not establish connections to all biomechanical variables. Upon employing machine learning, the Support Vector Machine algorithm met minimum performance metrics and was the only method able to differentiate between minimally and highly active adults. Feature reduction was performed, aiming to minimize the number of required biomechanical measurements. The

Support Vector Machine algorithm proved successful performance when applied to the reduced set of necessary biomechanical variables, reducing features from 15 to 11. The feature reduction allowed for the elimination of both muscle activity and strength measurements, eliminating the need for two pieces of equipment in the data collection process yields reduced data collection and processing time. Future work would transition these methods into a clinical setting to inform clinicians and educate patients about the impact of inactivity on their musculoskeletal health.

This dissertation is dedicated to those who dare to believe despite the obstacles.
Be encouraged and press forward.

A special dedication to my children: Benjamin, Jared, Gabrielle, Danielle, and Angela.
Remember, the sky, space, nor the Milky Way are your limits.
Keep rising and spread hope wherever you go

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CHAPTER 1

INTRODUCTION

The World Health Organization underlines that physical activity is still a foremost priority in public health (World Health Organization, 2022a). Physical activity is generally described as movement produced by the musculoskeletal system which necessitates energy expenditure; this indicates that a range of activities and intensity levels could characterize physical activity (Department of Health Human Services, 2018; World Health Organization, 2022c). The World Health Organization recommends regular physical activity as it is identified as a direct contributor to the physical health of an individual. For adults under 60, it is suggested that a minimum of 150 to 300 minutes of moderate-intensity aerobic activity and at least 2 days a week of muscle strengthening activity be achieved weekly (World Health Organization, 2022a). Alternatively, 75-150 minutes of vigorous-intensity aerobic activity or equivalent combination of moderate and vigorous intensities would also meet the recommendation for aerobic activity (World Health Organization, 2022c). 1.4 billion (27.5% of the world's adult population) adults do not meet recommendations, which is equivalent to only one in four adults meeting the suggested amount of physical activity.

Morbidity and mortality are results of noncommunicable diseases associated with inadequate activity level. Chronic conditions including coronary heart disease, hypertension, type-2 diabetes, and the risk for several cancers could be reduced, prevented, or managed by meeting recommended levels of physical activity (World Health Organization, 2022c). Musculoskeletal health (i.e., muscle function, bone quantity, quality, and strength) benefits significantly from physical activity (Fiatarone, 1990; Hawley et al., 2014; World Health Organization, 2022a). A deterioration in musculoskeletal health can give way to wide-spread bodily pain, disease, and conditions that result in impaired mobility and a reduction in quality of life (World Health Organization, 2022b). Inactivity is a risk factor for musculoskeletal conditions such as osteoarthritis (Urquhart et al., 2008), osteoporosis (Carter & Hinton, 2014), muscle atrophy (Evans, 2010). Therefore, it is important to monitor the impact of inactivity on the physiology of the musculoskeletal system.

Muscle Quality, Health, and Strength Exploration Across Diverse Demographics

A thorough assessment is crucial for understanding the impact of inactivity, particularly on the muscles of the lower extremities in the musculoskeletal system. Examining lower extremity muscle condition has been used as an important assessment tool in literature. An example of assessing lower limb muscle ability is illustrated in a study involving firefighters, as firefighters require leg strength and the ability to move at fast velocities to meet the demands of their work. Firefighters are categorized in some literature as not meeting the recommended fitness levels that their occupation necessitates (Clark et al., 2002; Li et al., 2017; Poston et al., 2011). Gerstner et al. (2018) reports on lower body strength and performance by evaluating the relationship between ultrasound derived muscle quality and percent decrease in peak torque (i.e., strength) between slow and fast velocities. The results of this study were that muscle quality and strength had a significant positive relationship when adjusting for age or age and body mass index in this demographic. It was suggested from this result that strength of muscle at different velocities may be related to the composition of the muscle tissue of the firefighter, which is consistent with findings from studies conducted beyond the firefighter population (Choi et al., 2016; Evans & Lexell, 1995; Gerstner et al., 2017; Rahemi et al., 2015).

Older populations are often prioritized in lower extremity research. The elderly are prone to falls, which could be the result of musculoskeletal system maladaptation (Iwamoto et al., 2017; Lo et al., 2017). To reduce the risk of falls and maintain stability, older individuals tend to increase lower limb muscle co-contraction (Iwamoto et al., 2017; Lo et al., 2017). Thus, increased muscle co-contractions and possibly muscular fatigue are thought to be possible predictors to falls (Helbostad et al., 2010; Lo et al., 2017). In other research, kinematics, kinetics, and electromyography are utilized to understand the lower extremities of the elderly in comparison to young populations during gait for varying surface conditions (Holcomb et al., 2022). Lower extremity strategies that young adults employ to navigate challenging surfaces could better inform clinicians on suitable interventions for seniors (Holcomb et al., 2022).

A valuable addition to research would involve exploring methods to enhance task performance in young adults. This demographic engages in a wide array of activities, some that may require strenuous physical exertion or high physical demand (Naimo et al., 2021). Like older populations, understand their abilities to maintain balance to support an upright position is important. One study explored ankle range of motion and lower-extremity muscle strength on balance control for young adults for example (Kim & Kim, 2018). This study used a dynamometer and goniometer to access muscle strength and range of motion of the ankle and determined that lower extremity muscle strength and ankle plantarflexion range of motion affected static balance control in young adults. It was concluded that that both contractile and non-contractile structures were important to static balance control. The study examined previous research on ankle range of motion and sway and found that there was a majority focus on the elderly as opposed to young adults. Such studies concluded that weakened balance control was due to a limitation in dorsiflexion range of motion limitation for the elderly, although opposing results could be found in literature.

Obesity and its effects on lower extremity walking mechanics and center of mass control have often been explored in biomechanics. A study (Kim et al., 2023) highlighted how force generation in the lower extremity contributes to center of mass control for the overweight and non-overweight. The experimental protocol involved the collection of ground reaction force from force plates in combination with three-dimensional motion capture. The research concluded that different demands were required of lower extremity muscles of the overweight group when replicating similar whole-body center of mass trajectories of the non-overweight group. Gait patterns are affected and risk of degenerative diseases of the joint like osteoarthritis are increased for the overweight when attempting to correct for center of mass sway (Kim et al., 2023).

Literature has provided support for the utilization of certain biomechanical measurements across diverse demographics. For example, ultrasound derived muscle quality and percent decrease in peak torque between slow and fast velocities for male firefighters (Gerstner et al., 2018). Determining and understanding relationships that exist between lower limb muscular biomechanical measures could be useful for clinics and laboratories with limited assets. Resources of time and cost can be minimized if one biomechanical variable could inform on another without requiring more specialized equipment. Musculoskeletal biomechanical research of the lower extremity has proven to be a useful tool for a myriad of applications and demographics, so this study prioritizes the research of lower extremity muscular health for an asymptomatic, non-athletic, young adult cohort with varying activity level effects.

International Physical Activity Questionnaire

Physical activity level is typically evaluated with accelerometers and pedometers, or questionnaires. Although subjective, questionnaires are practical because they are low-cost and simple to use. The International Physical Activity Questionnaire was developed to standardize population level surveillance of adherence to World Health Organization recommendations for physical activity (Craig et al., 2023; Healey et al., 2020). It is not recommended for small-scale intervention studies but is used regularly in neuromuscular disease research. The free questionnaire is intended for adults aged 15 to 69 and can be conducted by self-administration or by interview. The International Physical Activity Questionnaire has a long and short form version. The International Physical Activity Questionnaire short form has seven items where the participant indicates the number of days in the past week along with hours and minutes per day, they were engaged in vigorous intensity physical activity, moderate intensity physical activity, walking, and sitting (sedentary behavior). The Ainsworth Compendium (Ainsworth et al., 2000) is used to convert walking, moderate, and vigorous scores to metabolic equivalents in minutes per week, which is then categorized into low, moderate, and high-level activity. Automatic scoring templates are available to determine results (Healey et al., 2020).

International Physical Activity Questionnaire was first reported to be reliable and valid (Craig et al., 2003). However, recent literature questions its validity (Hagströmer et al., 2006; Kurtze et al., 2008; Lee et al., 2011; Roberts-Lewis et al., 2022). One systematic review showed an overestimation of physical activity and low to moderate validity due to inaccuracies in recall and social desirability (Healey et al., 2020). It was suggested that real-time response guidance for the administration of International Physical Activity Questionnaire could reduce self-reporting errors. Combing approaches where objective monitoring is included is another approach that leans towards acceptability of the questionnaire (Healey et al., 2020; Roberts-Lewis et al., 2022). The questionnaire is widely used despite competing ideals.

Muscle Quality

Muscle quality is an umbrella term for indexing muscle function (Fragala et al., 2015; Naimo et al., 2021). It includes force production, contraction and relaxation, metabolism, and electrical conduction amongst other physiological functions (Naimo et al., 2021). Muscle quality is defined as the amount of non-contractile tissue relative to total muscle size (Radaelli et al., 2021) or the measure of strength normalized to muscle mass (Fragala et al., 2015). For the purposes of this dissertation, muscle quality will be used to describe the amount of non-contractile tissue relative to total muscle size.

Muscle imaging can be used to find muscle quality. Muscle quality is assessed using radiological density for magnetic resonance imaging and computed tomography imaging. For ultrasonography imaging it is determined with echo intensity. Although the muscle quality measures will be dependent on the method used, results are reported as being reliable across different populations (Naimo et al., 2021). Muscle quality is thought to improve with aerobic and anaerobic exercise (Naimo et al., 2021; Watanabe et al., 2013).

Ultrasound is considered noninvasive, low-cost, portable, accessible, and safe (since it does not emit radiation) for evaluating muscle quality. Ultrasonography has been acknowledged as a valid and reliable tool for obtaining echo intensity (Fragala et al., 2015). The importance of ultrasonography standardization of rest position prior to employment is emphasized as it can result in measurement discrepancies due to hydrostatic blood pressure and distribution and morphological changes in the muscle (Varanoske et al., 2019). Compression of body tissue is also a concern with this method as it can influence the ability of fluid to filtrate from the capillaries, ultimately changing the size of the muscle (Varanoske et al., 2019).

Echo intensity is typically found through use of image-processing software. The pixel intensity of an ultrasound image is found by selecting a region of interest while not including subcutaneous fat or bone. The region is typically evaluated on a scale of 0 (black) to 255 or 256 (white) with an intensity closer to 0 representing better muscle quality as there is less fibrous and adipose tissue. Echo intensity is based on the idea that intramuscular content effects muscle performance (Wong et al., 2020).

Several concerns center around the use of ultrasound to evaluate echo intensity. One study mentions that investigators should consider the subtleties in orientation when probing over structures of the body as a slight tilting of the probe at all angles is said to result in significant changes in echo intensity results which in turn impacts test-retest reliability (Dankel et al., 2020; Stock & Thompson, 2021). However, ultrasound has been determined to be valid and reliable for establishing echo intensity (Fragala et al., 2015). Single assessors for a study are therefore recommended in addition to standardization of acquisition protocols. There is a debate on whether to correct for subcutaneous adipose tissue thickness (Stock & Thompson, 2021). Corrections are used as women typically have more adipose tissue compared to men. Racial/ethnic differences in results need to be evaluated as well, which is evidenced when evaluating black and white college football players (Stock & Thompson, 2021). This article discusses how for research involving these football players (Melvin, Smith-Ryan, Wingfield, Ryan, et al., 2014) there was a non-significant difference with black players having a lower echo intensity than white players. When looking outside of football, at overweight subjects, there was significance demonstrated for the black cohort having lower echo intensity than the white cohort (Melvin, Smith-Ryan, Wingfield, Fultz, et al., 2014).

Muscle Activation

Surface electromyography is used to detect activation patterns from skeletal muscles and so aids in the understanding of human movement. Impaired muscular activation is associated with poor movement performance and incapacity (Disselhorst-Klug & Williams, 2020). By placing electrodes over the skin, electrical activity of the muscle is detected. Many fields benefit from its use including biomechanics, rehabilitation, sports medicine, and kinesiology as it provides a pain-free and ready-to-use way to take measurements (Disselhorst-Klug & Williams, 2020; Merletti et al., 2008).

Surface electromyography is commonly used in research environments and limited in use for clinical applications (Felici & Del Vecchio, 2020). This problem may be influenced by the need to be able to correctly interpret signals which are a summation of motor unit action potentials that reach the muscle over time (Felici & Del Vecchio, 2020). This issue in interpretation of the signal is worsened by having many interwoven influences that affect signal output. Extrapolations of muscle force is clouded by including non-isometric contractions. Specifically, muscle length, contraction velocity of the muscle, lever arm of the muscle, contraction type, and the redundancy of the musculoskeletal system influence force and torque output (Disselhorst-Klug & Williams, 2020). Electromyography is found to be more readily interpreted when information about movement (movement cycle intervals, joint positions, movement velocities, and external forces) execution is supplied for non-isometric conditions as typically applied in gait analysis.

Many musculoskeletal disorders that can be treated with rehabilitation are known to result in modification of soft tissues and develop abnormalities in the joint which cause biomechanical changes in the body (Disselhorst-Klug & Williams, 2020). An advantage of surface electromyography is its ability to distinguish pathologically altered muscle activations (e.g., stroke, paraplegia, cerebral palsy) and physiological control of muscles through application of primitive muscle synergies (Disselhorst-Klug & Williams, 2020).

Isokinetic Dynamometry and Motion Capture

Muscle strength can be expressed in terms of its ability to produce joint torque. Joint stability, assistance, posture, and human mobility can be attributed in part to joint torque. Muscle strength measures are vital to determining the influence of aging and/or illness on its condition or to evaluating the success or failure of training or rehabilitation (de Araujo Ribeiro Alvares et al., 2015). Isokinetic dynamometry is the benchmark used in training, rehabilitation, and evaluation of the musculoskeletal system by computing torque of a muscle contraction moving through a circular motion. The desired angular velocity is specified by the operator and regulated through resistance, while the user undergoes a range of motion. Studies involving dynamometry have spanned both biological sexes and all age groups and has included varying disorders including musculoskeletal ailments (de Araujo Ribeiro Alvares et al., 2015).

One concern of isokinetic dynamometer use is that the equipment can contribute to performance changes due to seat and lever arm padding deformity, equipment comfort, or the straps used to restrain the subject (de Araujo Ribeiro Alvares et al., 2015). These are the possible concerns but does not appear to have restricted its widespread acceptance in assessing strength.

Information gathered from motion analysis could be helpful in diagnosis of musculoskeletal conditions and the design of treatment and prevention strategies (Roggio et al., 2021). When assessing functional activity, it creates pathways to for personalized diagnostics and treatment as the data is related to the inherent traits of the individual. Motion can be captured with a two-dimensional or three-dimensional system (Roggio et al., 2021).

Three-dimensional motion systems specialize in analyzing movement on multiple planes. Roggio et al. (2021) notes that optoelectronic stereophotogrammetric multi-camera motion capture with reflective markers on the body is the gold standard for motion capture. Kinetic, kinematic, as well as spatiotemporal movement data with high accuracy and precision can be produced with its use due to the tracking of joint movement in time and space. Markers placed on anatomical landmarks aid in the approximation of joint centers (Roggio et al., 2021).

Challenges with motion capture include the ability to properly find anatomical landmarks. Issues are amplified if the same researcher is not recruited for marker placement throughout a study or if a study has multiple sessions; this especially affects transverse plane (horizontal plane through the body, separating upper and lower portions) markers (Roggio et al., 2021). Protocol also varies across literature, which creates variability, notably for sagittal plane (vertical plane through the body from head to toe, dividing left and right halves) placements. Dependability of results can be reduced as an outcome of these challenges (Roggio et al., 2021). However, serval studies underscore the reliability and validity of motion capture for inter-laboratory studies (Bates et al., 2017; Dao et al., 2023; Paul et al., 2016).

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Countermovement Jump

Countermovement jump is an effective physical movement that has three phases. In the first phase, called the eccentric phase, the hip and knee are bending. The hip moves down towards the feet. The next phase, the concentric phase, involves the hip and knee in extension. The hip moves away from the foot in preparation for takeoff. There is an option whether to include arm swing in this phase (Bosco & Komi, 1979; de Villarreal et al., 2009; Lees et al., 2004b). In the last phase, one is in flight. The hip and knee move together in a coordinated direction (Raffalt et al., 2016) and if using arms, the arms are extended. It should be noted that terms and methods for countermovement jump phases have been defined in many different ways across literature (McMahon et al., 2018). Countermovement jump is used by clinicians to assess movement performance and execution. Countermovement jump is a tool that can help clinicians understand injury risk and rehabilitation status (Teufl et al., 2019).

Advantages of accessing countermovement jump is that it is a discrete task with a distinct start and end that requires bilateral coordination of the limbs in conjunction with precise positioning of the upper body for balance. Including arm swing is noted to increase takeoff velocity and the overall height of the jump (Feltner et al., 2004; Harman et al., 1990; Lees et al., 2004a, b). Outside of athletics that involve countermovement jump, adults do not train for its execution. Testing the countermovement jump on persons that do not oft use this task could give better insight into developed whole-body coordination. Opportunities are then presented to evaluate biomechanical features such as knee-hip joint coordination and flexion range of the knee during the task (Raffalt et al., 2016). Force-time curves can also be analyzed from performing countermovement jump to give comprehensive insight into neuromuscular function (McMahon et al., 2018).

Machine Learning

Machine learning can be descried as a tool that incorporates computer science, mathematics, and statistics to convert raw data into valuable insights (Sabharwal & Miah, 2022). It has also been defined as a technique enabling the exploration of multi-dimensional parameter spaces (Nichols et al., 2018). Regardless of the accepted definition, it is said to be the central focus of modern biomedical research because it continuously adapts to challenging datasets, has exponential processing power, and can handle large datasets irrespective to complexity or pattern abnormality (Sabharwal & Miah, 2022).

The framework for machine learning involves three key components: feature engineering, model selection and training, and then model testing (Halilaj et al., 2018). Feature engineering is the conversion of the raw high-dimensional data in to a lower-dimensional representation which can be accomplished through several techniques: manual extraction, automated, principal component analysis, etc. Data is then split into a training and testing set, where the testing will be used for performance evaluation during model testing (Halilaj et al., 2018). Model selection and training then occurs alongside feature selection and hyperparameter tuning, if decided. The first allowing for only key features or measures to be included in the model and the latter for determination of parameters to be included in the model. Each is stated to possible improve model performance and reduce the possibility of overfitting (i.e., analysis which corresponds too closely or exactly to a particular set of data (Oxford University Press, 2023)). Testing data is then incorporated to determine preferred performance metrics (e.g., accuracy, etc.) (Halilaj et al., 2018).

According to Edwards et al. (2021)when determining the appropriate model to employ one should determine if the data is labeled or not. If the data is labeled, then a supervised learning experience should be employed; if not labeled, an unsupervised (explanatory variables are labeled but not the response variables) learning should be used. A supervised approach is said to have the advantage of having data that is labeled before analysis; The implementer understands the aims and properties of the data. Results are easily interpreted as well. An advantage of note is the ability for the implementer to understand how a chosen algorithm learns relationships between the input and response variable. An additional advantage of is being able to determine the number of classes due to the data being labeled (Edwards et al., 2021). Disadvantages include a chance for misclassification of new inputs, seeing that algorithms are trained on given data. A lot of computational time may be needed for large datasets. Classification of features cannot be done by the algorithm since features are predefined. Overall, having predefined domains and structures for the data can limit information and insight (Edwards et al., 2021).

In a supervised approach, it should be determined if the response (i.e., target) variable is numerical or not (Edwards et al., 2021). Response variables that are numerical should employ a regression type algorithm. Regression involves the determination of a relationship between input and output variables and using input variables to predict numerical target variables. Non-numerical response variables should employ a classification type algorithm. Classification involves the determination of a relationship between input and out variables, where input variables predict response variables (Edwards et al., 2021). There are several classification type algorithms, but a few of note are Random Forest, K-nearest neighbors, and Support Vector Machine. Edwards et al, describes Random Forest as a technique that employs many randomly, uncorrelated decision trees in which the prediction is decided from the average vote from the trees of the forest. K-Nearest Neighbors searches through a dataset for similar instances (i.e., neighbors) and summarizes the response variable using the neighbors (Edwards et al., 2021). Finally, Support Vector Machine creates a boundary in a transformed space to separate different classes. The goal is to maximize this space or margin as much as possible between the classes and the boundary. The desire is to move the closest points in each group as far away from the boundary as possible (Shmilovici, 2005).

Machine learning has a number of strengths and limitations (Edwards et al., 2021). One strength is the ability to easily find patterns and trends that would otherwise not be apparent to humans or through traditional statistical methods. Machine learning can handle multidimensional data and variety of data types. Algorithms continue to increase in accuracy and efficiency with experience, which results in faster and more correct predictions as data volume increases. Limitations can include interpretation of results due to patterns not having biological context or reasonableness. Determined patterns can also be overinterpreted and have no practical context or application. Models require substantial amounts of data for training to ensure accuracy and reduce overfitting. Results also may not be reproducible without robust validation (Edwards et al., 2021).

Machine learning has been implemented in several biomechanical studies. One example includes research that employed machine learning to estimate lower extremity muscle and joint loading during daily activities. The researchers report success in the ability to predict the mechanics of their patients (Burton et al., 2021). Another study employed machine learning to determine the accuracy of predicting lower limb joint kinematics, kinetics, and muscle forces derived from wearable sensors (Moghadam et al., 2023). The results of this study demonstrated that Random Forest and a Convolutional Neural Network outperformed Support Vector

Machine, which results in lower prediction errors and lower computational cost (Moghadam et al., 2023).

When examining running biomechanics, a systematic review including twenty-four articles determined that using machine learning models to extract running measures from wearable sensors as a growing trend, but noted that not all studies validated their models and that attention to this shortcoming should be prioritized for future research (Xiang et al., 2022). For instance machine learning is increasingly used in biomechanics for classification of pathological movements (Halilaj et al., 2018), in diagnosis of cardiovascular disease and prediction (Madani, 2019), in assessment of running strategies (Xiang et al., 2022), approximate musculoskeletal dynamic changes (Smirnov et al., 2021), and identification of relationships between wearable sensors and biomechanical variables (Nurse et al., 2023). Machine learning implementation illuminates relationships that cannot typically be gleaned from traditional statistical measures.

Specific Aims

The principal goal of this research is to employ machine learning to categorize activity levels using a reduced set of common lower extremity biomechanical measurements (i.e., features). This objective is divided into three aims.

Specific Aim 1: Determine relationships between biomechanical measurements used in ascertaining musculoskeletal health using traditional statistical methods (e.g., scatterplots, linear regression, Pearson's correlations).

Hypothesis 1: Traditional statistical methods will not be able to determine correlations for all biomechanical measurements of interest. Literature acknowledges that human movement is intricate, dynamic, multidimensional, and highly non-linear (Phinyomark et al., 2018).

Specific Aim 2: Determine if various machine learning techniques can distinguish between low to moderately active and highly active asymptomatic young adults aged 18 to 30.

Hypothesis 2: An ability to differentiate between low to moderately active and highly active asymptomatic young adults will be achievable based upon applicable machine learning performance metrics. Machine learning has been successfully employed in biomechanics to categorize complex relationships (Halilaj et al., 2018).

Specific Aim 3: Determine if a reduced number of biomechanical measurements will be able to differentiate between activity levels using machine learning.

Hypothesis 3: A reduced number ($n < 15$) of biomechanical measures will be found and able to distinguish active and inactive groups. A successfully minimized combination of biomechanical metrics will be able to demonstrate for clinics and laboratories with limited resources, the ability to approximate a category of activity without the associated burden of cost or time from specialized equipment.

CHAPTER 2

EVALUATION OF BIOMECHANICAL RELATIONSHIPS IN YOUNG ADULTS: A SEX-STRATIFIED FUNDAMENTAL STATISTICAL APPROACH

To gain insights into the status of lower extremity skeletal muscular health, certain metrics, specifically, echo intensity, subcutaneous fat thickness, and countermovement jump height, have proven to be invaluable indicators (Bartolomei et al., 2021; Kitagawa et al., 2023; Stock et al., 2018). The assessment of skeletal muscular health is significant, as it plays a central role in human locomotion, overall functionality, balance and stability, promoting joint health, injury prevention, and the enhancement of the quality of life (Argiles et al., 2016; McCuller et al., 2023; McLeod et al., 2016). Several studies underscored the significance of skeletal muscular health by establishing a link between declining lower limb muscle strength and an increased risk of falls among older individuals (Rubenstein, 2006). Another study emphasized the importance of skeletal muscular health by correlating insufficient lower limb muscle strength to the inability to perform routine daily activities (Muehlbauer et al., 2015). However, studies have not given much attention to young adult populations.

The link between echo intensity and physical performance among older adults (Mateos-Angulo et al., 2021) and muscle strength in middle-aged and elderly individuals (Fukumoto et al., 2023) have been well-established. When combined with measurements of muscle thickness and strength, echo intensity has shown a strong correlation with physical performance (Wu et al., 2022). Numerous studies have used brightness mode (b-mode) ultrasound to determine the echo intensity value, utilizing the mean gray-scale within a specified image region as an indicator of muscle quality (Fukumoto et al., 2023; Mateos-Angulo et al., 2021; Naimo et al., 2021; Song et al., 2021; Wu et al., 2022).

B-mode ultrasound has also proven valuable for assessing subcutaneous fat, serving as an indirect tool to gauge skeletal muscular health (Störchle et al., 2018). Subcutaneous fat, which represents the adipose tissue between the skin layer and underlying muscles (Pausova, 2014), offers insights into both echo intensity correction, mitigating the effects of ultrasound wave attenuation (Canever et al., 2022), and changes in skeletal muscular health resulting from shifts in overall body composition and well-being (Ryan et al., 2016).

While countermovement jump is a simple assessment tool for evaluating lower limb skeletal muscle condition and does not necessitate ultrasound, it is often assessed alongside other methods such as ultrasonography, electromyography, or dynamometry for a comprehensive muscle evaluation. Countermovement jump involves multiple joints and requires precise motor coordination throughout its various phases of standing position, push-off, toe-off, flight, and landing. It is useful for determining strength and power of lower extremity muscles (Petrigna et al., 2019). Researchers frequently utilize countermovement jump height as a performance metric, as it closely correlates with explosive muscle strength and the generation of mechanical power (Linthorne, 2021; Petrigna et al., 2019).

There is still limited information on how the metrics of echo intensity, subcutaneous fat thickness, and countermovement jump height are used to evaluate lower limb skeletal muscular health in young adult female populations. Examples are the previously mentioned studies that discussed the relationship of echo intensity to lower extremity health; they focused on middle-aged and elderly individuals (Fukumoto et al., 2023; Mateos-Angulo et al., 2021). In another investigation, echo intensity and its relationship to force production differences of a quadricep muscle for career male firefighters was examined, which is a very specialized population and renders no information on female performance (Gerstner et al., 2018). Another looks at bilateral landings from a jump and encompasses males and females, though with an average age close to 30 years old (Pappas et al., 2007). Addressing the lack of young female populations in biomechanical research is essential to comprehensive and inclusive understanding of human biomechanics, even as it pertains to lower limb skeletal muscular health. Neglecting female populations in research could lead to incomplete understanding of human biomechanics, a lack of tailored interventions for musculoskeletal disorders or injury prevention strategies, and contribution to biased findings. Consequently, studies should consider inclusion of both biological sexes and incorporate younger populations to promote equitable and insightful biomechanical research.

Fundamental statistics provides essential insight into the data. Key information can be obtained such as the dispersion of data and its variability through descriptive statistics. It offers the utility of graphical representation which when combined with statistical summaries can enhance the comprehension of patterns and differences within the data. Direct comparisons and the ability to establish the strength and direction of relationships is easily determined with this methodology. Lastly, fundamental statistics utilizes tools that are often the groundwork for more advanced techniques allowing for the understanding of data distribution and detection of outliers which is often preliminary steps required for preparing the data for more complex modeling.

The purpose of this study is to examine both female and male populations, to access lower extremity muscular health through the indicators of echo intensity, subcutaneous fat thickness, and countermovement jump height with fundamental statistics. It is hypothesized that there might be some discernible relationships between some of the metrics.

For subcutaneous fat thickness and countermovement jump height, prior studies have shown promising evidence of a connection. For instance, Kerns (2013) focused on NCAA D1 female soccer players and found that as percent body fat increased, countermovement jump height decreased, indicating a possible association. Additionally, Lisón (2022) explored subcutaneous fat thickness above the rectus femoris in adolescent basketball club players and its correlation with countermovement jump height. However, it is worth noting that factors such as body size and countermovement jump technique may potentially confound such relationships, as suggested by Markovic et al. (2014).

Similarly, in the case of echo intensity and countermovement jump height, the researcher anticipates a potential relationship. While one systematic review didn't reveal a strong influence of skeletal muscle architecture on vertical jumping performance across a wide age range and limited female participants (Ruiz-Cárdenas et al., 2018), another study on middle school boys found a significant correlation between echo intensity and countermovement jump height (Mota et al., 2016), hinting at the possible influence of age on muscle architecture and performance.

Lastly, regarding echo intensity and subcutaneous fat thickness, there are varying viewpoints in the literature. One study suggested that subcutaneous fat thickness might play a role in ultrasound attenuation but found no association between subcutaneous fat thickness and muscle echo intensity for a mixed-gender population across a wide age range (Paris et al., 2022), and another suggested a potential impact of glucose impairment on results in older males (Paris et al., 2021).

This study intends to test these hypotheses through the employment of fundamental statistical methods to confirm or refute associations between the metrics of echo intensity, subcutaneous fat thickness, and countermovement jump height.

Methods

Forty-one asymptomatic individuals aged 18-30 years participated in this study. The average age, height, mass, and body mass index (BMI) of the nineteen females was 24.8 ± 3.2 years, 1.67 ± 0.06 m, 70.3 ± 17.8 kg, and 25.3 ± 5.7 kg/m^2, respectively. The twenty-two males recruited averaged 23.8 ± 3.6 years, 1.81 ± 0.08 m, 84.9 ± 18.4 kg, and 25.9 ± 5.02 kg/m^2, correspondingly. The Institutional Review Board at Old Dominion University (ODU) gave their approval to conduct this study. Informed written consent was obtained from each participant. A questionnaire was administered to each subject as well to determine biological sex and establish medical history. Exclusion criteria for the study was having undergone surgery in the past 12 months or having had a recent injury in the past three months to the lower extremity that caused immobility or limited function for two or more days. Additional exclusion criteria were a “yes” indication to any question of the medical history section of the questionnaire or to the statement of having an implanted electronic device (e.g., cardiac pacemaker, electronic infusion pump, implanted stimulator). More than a minimal risk of injury was posed for individuals who met any of the exclusion criterion. Subject testing was performed during a single session in the Biomechanics Laboratory at ODU. For the session, participants were asked to wear fitted spandex shorts and given standardized laboratory shoes (UA Charged Gemini Running Shoes, Under Armour, Baltimore, MD, USA).

Participants lay supine on an examination table with knee joints in full extension and hip and ankle joints in the neutral position for 10 minutes, which allowed for fluid redistribution and minimized ultrasound imaging error (Cerniglia et al., 2007). ultrasound imaging of the rectus femoris midbelly was done on the dominant limb, which was established as the ipsilateral side corresponding to the participant's dominant hand. The rectus femoris was located at half the distance between the greater trochanter and the femoral condyle (Kleinberg et al., 2016). This location was marked on the leg.

Ultrasound

A portable brightness mode (B-mode) ultrasound imaging device, GE Logiq e BT12 (GE Healthcare, Milwaukee, WI, USA), was put into logic view (i.e., panoramic mode). The ultrasound imaging device utilized a multi-frequency linear-array probe (12 L-RS, 5–13 MHz frequency, 39-degree field of view; General Electric Company) to capture images. The ultrasound settings were 68 dB for gain, 6.0 cm for depth, and 10 MHz for frequency; the depth being adjusted from literature references to accommodate seeing the whole rectus femoris (Kleinberg et al., 2016). Aquasonic 100 Ultrasound Transmission Gel (Bio-medical Instruments, Inc., Clinton Township, MI, USA) was applied to the skin and probe to enhance acoustic coupling and reduce near-field artifacts (Rosenberg et al., 2014). The probe was moved slowly and continuously while perpendicular to the skin and in the transverse plane (lateral to medial panoramic) with minimal pressure applied to the skin (i.e., no muscle compression) at the marked location (Kleinberg et al., 2016).

Echo intensity of the rectus femoris ultrasound image was found using FIJI (Fiji is Just) ImageJ (2.3.0/1.53q version, National Institutes of Health, Bethesda, MD, USA). The straight-line function in combination with the set scale feature was used to convert image measurements from pixels to centimeters. The polygon function was used to select the rectus femoris. When selecting the muscle, selection of the surrounding fascia was minimized. The measure function was used to determine a mean grayscale value between 0 and 255 arbitrary units (black = 0; white = 255) for the image (Rosenberg et al., 2014). It has been determined that ultrasound visualization for deeper tissue is more difficult to measure due to reduced attenuation of sound waves because of reflection(s) or absorption. To accommodate for attenuation reduction due to subcutaneous fat thickness a correction factor was applied to the echo intensity (Young et al., 2015).

$$\boldsymbol{corrected\ EI = uncorrected\ EI + (SCF \times 40.5278)} \quad \text{(Equation 2-1)}$$

where EI stands for echo intensity and SCF for subcutaneous fat. Subcutaneous fat thickness was determined by using the straight-line function to draw a line from the skin to the superficial aponeurosis; this was done at approximately half the distance between the medial and lateral borders of the rectus femoris muscle. The measure tool was then used to find the length of the line. The logged measurement was then taken from the results window which was then used as the subcutaneous fat value in the corrected echo intensity equation.

The plug-in gait lower body model based on the Newington-Helen Hayes gait model (Kadaba et al., 1990) was implemented in this study. Reflective markers were placed bilaterally at the following anatomical landmarks: anterior and posterior superior iliac spines, femur lateral epicondyles, fibula apex of lateral malleolus, calcaneus, and second metatarsal heads. Additional markers were positioned bilaterally on the lateral side of the thigh and tibia.

The 12-camera motion capture system was calibrated, and force plates zeroed. A static trial was collected for post-hoc processing tasks of the motion capture. Five trials of the subject performing a maximum effort countermovement jump was recorded after a demonstration and practice jump(s) to ensure proper form. The subject used arm-swing while dropping to a countermovement depth of choice before takeoff. The participant jumped as high as possible with their hip, knee, and ankle joints and arms fully extended.

Jump height was determined using the participant's time in air. Force plate data was reviewed for locations where the force plate read zero during the participants countermovement jump. The difference of these frame values was taken and divided by the sample frequency, which provided the participant's time in flight (t). Jump height was then calculated by using a reduced version of the projectile (vertical) motion, $y = y_0 + v_0 yt - \frac{1}{2}gt^2$, in a gravitation field (g), where g was taken to be constant on Earth, 9.81 m/s^2.

$$\boldsymbol{h = \frac{1}{2} g \left(\frac{t}{2}\right)^2 = \frac{gt^2}{8}} \text{ (Equation 2-2)}$$

Statistical Analysis

A statistical analysis was carried out using SPSS (IBM SPSS Statistics for Windows, Version 28.0, IBM Corp, Armonk, NY). Descriptive statistics were computed for the overall sample population and separately for each sex across all variables. Scatterplots were generated with regression lines for the combined female and male samples, as well as for each sex individually. Additionally, the scatterplots included box plots for both independent and dependent variables for the combined female and male sample population. Pearson correlation (R) and significance (p) were also determined. R was categorized as follows: strong if it was above 0.8, moderate between 0.6 and 0.8, fair between 0.3 and 0.5, and poor if less than 0.3 (Akoglu, 2018; Chan, 2003). The variables investigated were echo intensity and uncorrected echo intensity versus subcutaneous fat, countermovement jump versus echo intensity and uncorrected echo intensity, and countermovement jump versus subcutaneous fat. A minimum two-tailed confidence level of 95% ($\alpha = 0.05$) was required.

Results

Descriptive statistics are provided for the combined and stratified cohorts (Table 1). Utilizing descriptive statistics in conjunction with boxplots, the analysis of scatterplots for the combined female and male cohort indicates a positive skew in subcutaneous fat, characterized by a prolonged right tail. The mean of the subcutaneous fat values is approximately greater than the median. subcutaneous fat has two outliers in the female cohort. echo intensity and corrected echo intensity both approach a normal distribution. Jump height also tends to approximate a normal distribution, although it exhibits a longer right tail.

The results indicate a significant ($p < 0.001$, $\alpha = 0.01$) strong negative linear correlation ($R = -0.837$) between echo intensity (EI) and subcutaneous fat (SCF) for the female cohort (Figure 1a). With the outliers removed this relationship remained ($R = -0.807$, $p < 0.001$, $\alpha = 0.01$). A significant ($p < 0.006$, $\alpha = 0.01$) fair negative linear relationship ($R = -0.426$) is observed for the cohorts combined; the relationship is poor and no longer significant with the removal of the outliers ($R = -0.277$, $p = 0.088$, $\alpha = 0.01$).

For corrected echo intensity versus subcutaneous fat, the male cohort exhibits a significant ($p = 0.014$, $\alpha = 0.05$) fair positive linear relationship ($R = 0.517$; Figure 1b). For the cohorts combined, a significant ($p = 0.014$, $\alpha = 0.05$) moderate positive linear relationship ($R = 0.603$) is found; this relationship exists even when outliers are removed ($R = 0.550$, $p < 0.001$, $\alpha = 0.01$) with fair to moderate strength.

No significant relationship was found for the female, male, or cohorts combined for jump height and echo intensity (Figure 1c). A significant fair to moderate ($R = -0.535$) negative linear relationship ($p = 0.010$, $\alpha = 0.05$) is found for the male cohort when analyzing the relationship between jump height and corrected echo intensity (Figure 1d). A significant moderately strong negative linear correlation ($R = -0.750$) is found for the sexes combined ($p < 0.001$, $\alpha = 0.01$). With removal of the outliers, this relationship remains moderately strong ($R = -0.728$, $p < 0.001$, $\alpha = 0.01$).

A significant moderate ($R = -0.743$) negative linear relationship ($p < 0.001$, $\alpha = 0.01$) found for the male cohort when analyzing the relationship between jump height and subcutaneous fat (Figure 1e). The sexes combined also showed a significant moderate ($R = -0.717$) negative linear relationship ($p < 0.001$, $\alpha = 0.01$). This remains when eliminating outliers ($R = -0.741$, $p < 0.001$, $\alpha = 0.01$).

No other significant correlations were found among the variables (Figure 1a-e).

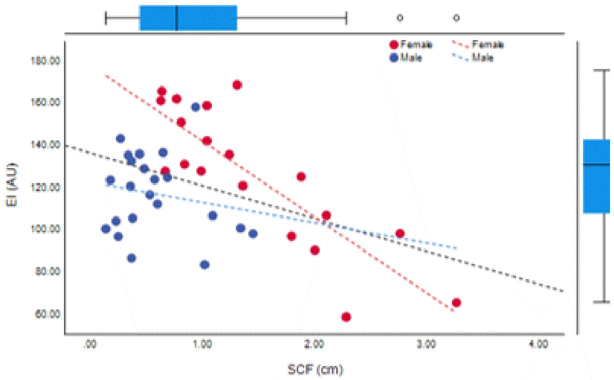
Table 1

Descriptive statistics for uncorrected Echo Intensity (EI), corrected EI, jump height, and Subcutaneous Fat (SCF) thickness for the cohorts combined and for the cohort stratified by biological sex

	N	Range	Minimum	Maximum	Mean		Std. Deviation	Variance
					Statistic	Std. Error		
Female + Male								
EI	41	109.99	58.35	168.34	120.88	4.14	26.51	702.75
Corrected EI	41	120.03	101.40	221.43	160.51	4.69	30.05	902.78
Jump Height	41	0.36	0.15	0.51	0.29	0.02	0.11	0.01
SCF	41	3.12	0.14	3.26	0.98	0.11	0.73	0.53
Female								
EI	19	109.99	58.35	168.34	125.69	7.55	32.92	1083.70
Corrected EI	19	70.52	150.91	221.43	184.15	4.21	18.36	337.17
Jump Height	19	0.17	0.15	0.32	0.21	0.01	0.04	0.00
SCF	19	2.63	0.63	3.26	1.44	0.18	0.76	0.58
Male								
EI	22	74.69	83.13	157.82	116.72	4.10	19.25	370.62
Corrected EI	22	94.67	101.40	196.07	140.09	4.71	22.10	488.49
Jump Height	22	0.31	0.20	0.51	0.36	0.02	0.09	0.01
SCF	22	1.31	0.14	1.45	0.58	0.08	0.37	0.14

Figure 1

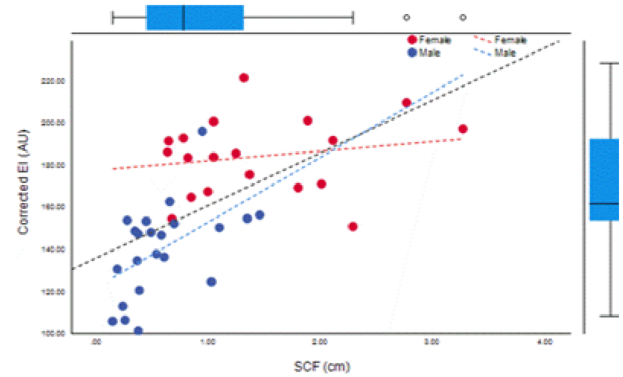
Model summaries and scatterplots with linear regressions for the whole cohorts and cohorts stratified with boxplots on the axes representing whole cohort distributions. Relationships examined were (a) EI and SCF thickness, (b) corrected EI and SCF thickness, (c) jump height and EI, (d) jump height and corrected EI, (e) jump height and SCF thickness



Model Summary: EI versus SCF		
Model	**Pearson Correlation (R)**	**Significance (p)**
Female + Male *(no outliers)*	-0.426** *(-0.277)*	0.006 *(0.088)*
Female *(no outliers)*	-0.837** *(-0.807**)*	<0.001 *(<0.001)*
Male	-0.185	0.409

***Correlation is significant at the 0.01 level (2-tailed).*

(a)



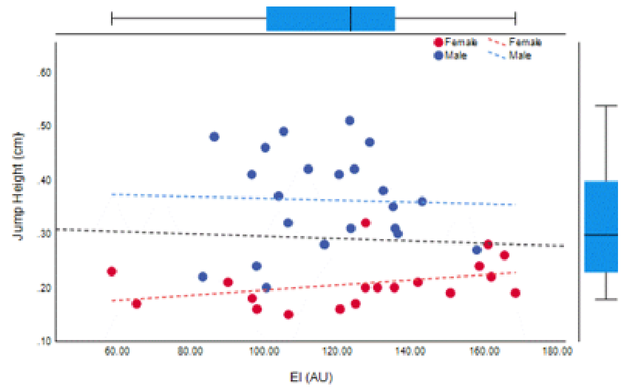
Model Summary: Corrected EI versus SCF		
Model	**Pearson Correlation (R)**	**Significance (p)**
Female + Male *(no outliers)*	0.603** *(0.550**)*	<0.001 *(<0.001)*
Female *(no outliers)*	0.188 *(-0.107)*	0.44 *(0.684)*
Male	0.517*	0.014

***Correlation is significant at the 0.01 level (2-tailed).*

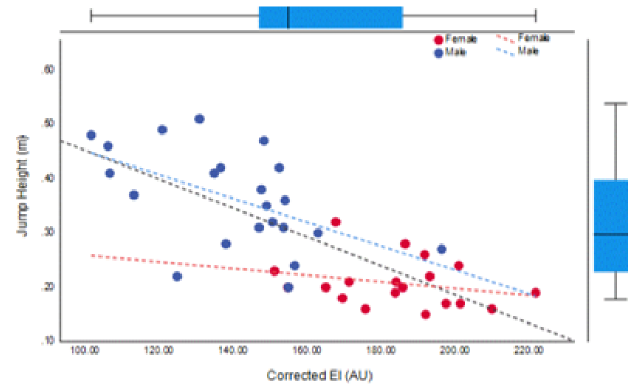
**Correlation is significant at the 0.05 level (2-tailed).*

(b)

Figure 1 (continued)



Model Summary: Jump Height versus EI		
Model	**Pearson Correlation (R)**	**Significance (p)**
Female + Male *(no outliers)*	-0.055 *(-0.163)*	0.730 *(0.320)*
Female *(no outliers)*	0.357 *(0.248)*	0.134 *(0.337)*
Male	-0.036	0.874



Model Summary: Jump Height versus Corrected EI		
Model	**Pearson Correlation (R)**	**Significance (p)**
Female + Male *(no outliers)*	-0.750** *(-0.728**)*	<0.001 *(<0.001)*
Female *(no outliers)*	-0.257 *(-0.146)*	0.289 *(0.577)*
Male	-0.535*	0.010

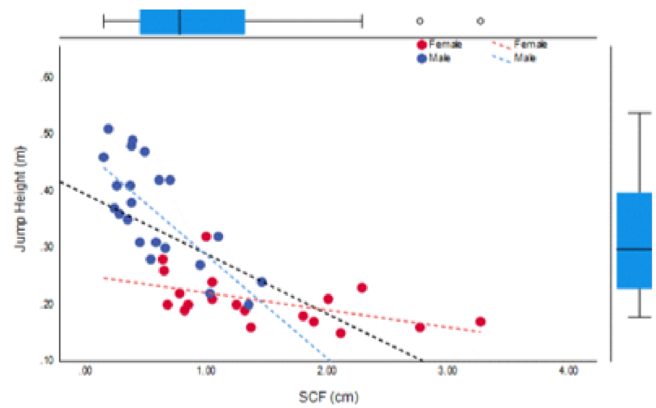
***Correlation is significant at the 0.01 level (2-tailed).*

**Correlation is significant at the 0.05 level (2-tailed).*

(c)

(d)

Figure 1 (continued)



Model Summary: Jump Height versus SCF		
Model	**Pearson Correlation (R)**	**Significance (p)**
Female + Male *(no outliers)*	-0.717** *(-0.741**)*	<0.001 *(<0.001)*
Female *(no outliers)*	-0.257 *(-.0450)*	0.289 *(0.070)*
Male	-0.743**	<0.001

***Correlation is significant at the 0.01 level (2-tailed).*

(e)

Discussion

It was hypothesized that discernible connections between the metrics of echo intensity, subcutaneous fat thickness, and countermovement jump height could possibly be established using fundamental statistical methods. This was determined by limited available research; all that which did not specifically target the same populations or variables used in this study. Such research typically focused on males and elderly, athletic, and adolescent populations.

The combined cohort demonstrated normal distributions for all the variables except subcutaneous fat thickness. Note that the combined cohort was comprised of forty-one individuals, which eliminated the concern for violating normality assumption and confirmed the ability to use parametric testing, given that the sample size exceeded thirty (Ghasemi & Zahediasl, 2012). When reviewing the stratified cohorts of female and male, there were nineteen and twenty-two persons, respectively. A violation of the normality assumption is apparent if considering the variables when stratified by biological sex. It should be noted, that Pearson's correlation does not have specific assumptions, although this has been the subject of significant debate (Schober et al., 2018).

The female cohort demonstrated a negative relationship between subcutaneous fat and echo intensity. A decline in echo intensity with increasing thickness might be attributed to greater attenuation of soundwaves (Young et al., 2015). Thus, a correction factor could be advantageous when applied to female populations; as in one study (Young et al., 2015) group-, gender-, and muscle-specific equations were derived for echo intensity measurements. It is also widely reported and accepted that females typically have larger subcutaneous fat thickness than males (Chang et al., 2018; Gavin & Bessesen, 2020). Seeing that subcutaneous fat thickness is typically larger in females than males, the correlation of subcutaneous fat thickness to a decrease in echo intensity is likely the reason it is pronounced in this cohort. Not to say it is not necessary for the cohort overall, but it only has a fair association in this case.

Examination of the male cohort showed a positive relationship between subcutaneous fat and corrected echo intensity index. When considering this correlation, an increase in subcutaneous fat would normally demonstrate an increase in corrected echo intensity value, which would be attributed to increase attenuation. Because the behavior of this relationship contrasts with what would be logically expected, it could be assumed that a correction factor is not necessary in the case of males. It should be reiterated that this relationship was only of fair strength. No immediate conclusion could be drawn from the moderate positive relationship being evidenced for the cohort overall; it could imply the need for no correction needed when considering young adult female and male cohorts together but seems unlikely.

When examining countermovement jump height and corrected echo intensity, the male cohort showed that for increases in corrected echo intensity, a decrease in countermovement jump height. This was observed for the cohort overall as well. This association would seem to be due to first correcting for attenuation to be able to observe the relationship and secondly to possible poorer muscle morphology or health attributing to the inability for increased jump height. An example is one study (Mangine et al., 2014) demonstrating that vertical jump performance was related to vastus lateralis architecture in young adults. When looking at athletic adolescent boys with an average age of 12 years, a significant correlation was found between vastus lateralis echo intensity and countermovement jump height (Stock et al., 2017). These studies help substantiate the results for the males and combined cohort. It should be reiterated that the male cohort only had fair strength while overall had a strong association.

Countermovement jump height and subcutaneous fat thickness showed that for increasing subcutaneous fat thickness that there was a decrease in jump height for the male and combined cohorts, with moderate strength. The observation seems appropriate when considering that increased subcutaneous fat thickness could be indicative of overall health in the body to include body fat percentage, which could possibly attribute to jumping ability. There is limited research on this topic, but it was determined in one study, (Lisón, 2022) that subcutaneous fat thickness was predictive of physical performance (e.g., countermovement jump height) for adolescent basketball club players.

It is not always clear why some correlations are established in some cases amongst a stratified cohort but found within the groups combined; the phenomenon is thought to be the product of complex relationships between the variables that are not immediately apparent when using fundamental statistical methods alone; some relationships are non-linear (van Emmerik et al., 2016) . It should not be omitted that possibly more intrinsic relationships could exist for one biological sex when compared to another when examining the influences of variables amongst one another. Outliers in the female cohort require additional investigation as well. It could be representative of a special sub cohort or the effect of random error during data collection.

There are several limitations to the study. First, as with nearly all human subjects research, recruitment was from a population of convenience; in this study, many were students or locals associated with the university. Having many subjects from this demographic may have restricted generalizations determined in the results. Increasing the sample size could have enhanced the strength of the study and confirm the results more. Data collection presented a few concerns of note. Additionally, during post-hoc analysis of the ultrasound images, it was not always clear where to differentiate the selection of the RF from the surrounding fascia or where the subcutaneous fat layer began or ended above the RF. Accuracy could have been impacted as a result. Due to operator error, dynamic range was altered for one subject, but the discrepancy was deemed negligible with further analysis. Not all subjects were able to perform the countermovement jump in the manner demonstrated and requested, even after multiple attempts. It is worth noting that some countermovement jump protocols involve arm swing, while others do not; this study opted for arm swing. Some participants also had difficulty with controlling their mechanics to land precisely on the force plate. Lastly, when examining subcutaneous fat in the female cohort, there were outliers which could have influenced the analysis. Further inspection would be required to determine if the outliers were associated with a specific subgroup in that cohort. It should also be highlighted that the study did not explore distributions among the individual cohorts. Researchers recommend that samples come from random or representative grouping and that both variables exhibit continuous and bivariate normal distribution (Schober et al., 2018). Upon visually inspection of the scatterplots for each biological sex, the data points do not seem to closely fit a curve, suggesting compliance with the bivariate normal distribution recommendation (Schober et al., 2018).

There are a few suggestions for future work. Adding other biomechanical variables to determine additional relationships to support results obtained in this study may prove advantageous. For instance, a qualitative component could allow for a better connection to the statistical relationships that were observed. One example would be to survey physical activity and the effect on measures for echo intensity and subcutaneous fat thickness. Incorporating other muscle groups for echo intensity analysis or for determine subcutaneous fat thickness above would allow for expanded comparisons. Although the rectus femoris is commonly imaged, it is markedly weaker than the vastus lateralis and is biarticular, contributing to hip flexion, which is antagonistic to the hip extension required for jumping tasks. More diversification of the sample or cohorts with consideration to factors such as age, ethnicity, or having a pathology could be insightful.

In conclusion, the findings therefore confirm the hypothesis. There were some limitations to this study such as recruitment and subject jump mechanics, and a scope of future work suggested such as increasing the sample size, this study establishes discernable correlations between echo intensity, subcutaneous fat thickness, and countermovement jump height for evaluating lower limb skeletal muscular health. Generally, this research topic is limited, so the associations presented offer more insight into lower extremity skeletal muscle health, especially as it pertains to young adult female populations. The continued vitality of fundamentals statistical methods was demonstrated through this study although there is a chance for increased understanding by examining all of correlations with more complex methodologies.

CHAPTER 3

MACHINE LEARNING BASED CLASSIFICATION OF PHYSCAL ACTIVITY IN YOUNG ADULTS FROM BIOMECHANICAL METRICS

Physical activity is widely acknowledged and accepted as a major influence to shaping the overall well-being and quality of human life (American Health Association, 2023; Mahindru et al., 2023). Specifically, some of the documented benefits of physical activity include weight management, improved cognitive function, reduced risk of depression and anxiety, improved sleep, and increased muscle and bone strength. Additionally, physical activity reduces the risk of chronic diseases such heart disease, diabetes, and some cancers (Centers for Disease Control, 2023a, 2023b; Mayo Clinic, 2023). It is recommended that an individual engage in at least 150 minutes of moderate-intensity aerobic activity each week and at minimum two days per week of muscle-strengthening activities to realize these advantages (Bull et al., 2020). Although the importance of physical activity is widely reported, many adults fail to meet such requirements. This trend was outlined in 2020 where it was reported that only approximately 1 in 4 adults worldwide met aerobic guidelines; preventative measures were advised as there seemed to be no improvements forecasted for coming years (Bull et al., 2020). More preventatives are needed to educate adults and to encourage physical activity.

There are some uncertainties and challenges with accurately differentiating between active and inactive individuals when using survey tools such as the International Physical Activity Questionnaire. The International Physical Activity Questionnaire was developed nearly twenty-five years ago by the International Consensus Group. It has long form and short form versions and is intended to be administered through interviewing or self-administration. Respondents are intended to reference their last 7 days or a typical week when reporting their physical activity (Craig et al., 2003). Specifically, in the International Physical Activity Questionnaire short form version, the amount of vigorous, moderate, walking, and sitting activity is expected to be detailed correspondingly. The International Physical Activity Questionnaire short form was originally validated on a 12-country sample and in additional studies established as suitable assessment tool (Craig et al., 2003). Later studies demonstrated a significant underestimation of sedentary behavior and over estimation of physical activity (Grimm et al., 2012; Lee et al., 2011). A systematic review found that when the International Physical Activity Questionnaire is compared to objective measures of activity or fitness (e.g., anthropometric measurements, device body motion monitoring, etc.) that there were low correlations in many studies (Lee et al., 2011). Some studies demonstrated high variability in correlations when comparing vigorous or moderate activity sections of the International Physical Activity Questionnaire to such an objective standard, while the questionnaire still met minimal acceptable standards (Lee et al., 2011). Despite some of the limitations, International Physical Activity Questionnaire is widely used, and the short form version has been tested in various populations with varying results. For example, a study involving older adults (Lenz et al., 2012) and another examining adolescent boys (Rääsk et al., 2017), International Physical Activity Questionnaire was deemed unsuitable while another that involved individuals with chronic obstructive pulmonary disease, the questionnaire appeared to be valid (Flora et al., 2023).

In the field of biomechanics, various metrics have been utilized to investigate the physical well-being and capability of a given demographic. Anthropometrics like weight, height, and body mass index are often utilized in support of ascertaining the physical ability of humans and in the design of spaces and tools for analyzing human biomechanics. Echo intensity, a mean gray scale measure for a given region in an ultrasound image, has been employed in several biomechanical studies to determine muscle quality (Fukumoto et al., 2023; Mateos-Angulo et al., 2021; Naimo et al., 2021; Song et al., 2021; Wu et al., 2022). One study demonstrated that echo intensity could be linked to physical performance in the elderly (Fukumoto et al., 2023). In combination with muscle attributes like architecture and strength, countermovement jumping was found to be a strong indicator of physical ability (Wu et al., 2022). Countermovement jump has been proven to be a great assessment tool for evaluating the physical condition of the lower extremity and has been found to be even more informative when evaluated alongside tools such as electromyography (Padulo et al., 2013) or dynamometry (O'Malley et al., 2018). Investigating the impact of physical activity on biomechanical measures may offer insight into the link between physical fitness level and the ability for one to perform in everyday tasks and activities.

Machine learning can be described as a technique used for exploring multi-dimensional parameter spaces (Nichols et al., 2018). Biomechanics and human mobility have inherent complexities, which often possess many parameters. Machine learning serves as a useful tool for using these parameters to predict clinical outcomes or to facilitate biomechanical analysis. Machine learning can be understood and does not have to be an incomprehensible entity, its operation can be transparent and explained (Nichols et al., 2018). In supervised machine learning, data is split into training and testing sets, where machine learning algorithms are employed to determine classifications from the given data. Specifically, the collected training data is used to generate features in which decision boundaries are formed. The machine “learns” from this data and takes the collected testing data with generated features and creates boundaries for which the data is classified. The use of machine learning in biomechanical research may prove to be useful in unraveling correlations and meaningful connections between physical activity and overall physical health and ability.

A detailed investigation into the various machine learning algorithms could improve understanding of their effectiveness in analyzing biomechanical measures toward determining the physical condition of an individual. In addition to algorithm capabilities, potential limitations could be highlighted as well. In supervised classification techniques, methods such as k-nearest neighbors, random forest, and support vector machines might be useful. Each has a goal of creating boundaries for data to be classified, but the approaches are unique (Nichols et al., 2018). K-nearest neighbors essentially classifies data based on its k (a specified number, usually 3, 5, or 7) closest neighboring trained examples (Taunk et al., 2019). Random Forest utilizes an arbitrary set of features and divides the features using decision trees. Essentially, features are found in a root node and various conditional statements create a threshold for how to classify features. Many trees are formed and through majority vote a final classification is determined (Nichols et al., 2018). Support Vector Machines utilizes a max margin classifier. Boundaries are formed for the features through the use of lines or curves with the intent to ensure the maximum separation between different classifications of features (Nichols et al., 2018). Each algorithm has been employed in various biomedical studies to detect or identify pathologies or diseases (Hasan et al., 2018; Jagadev & Virani, 2017; Shimpi et al., 2017; Wu et al., 2017).

The aim of this study is to determine the effectiveness of a specific combination of biomechanical measurements in differentiating low to moderate from highly physically active asymptomatic young adults. Classification is attempted through three machine learning algorithms: K-nearest neighbors, Random Forest, and Support Vector Machine. The accuracy of these algorithms using the supplied biomechanical metrics is reviewed to identify which is the most effective, while also ensuring that minimum performance criteria is met. Ultimately, this work intends to either confirm or disprove the validity of the International Physical Activity Questionnaire short form as an effective assessment tool as well.

Methods

Forty-one asymptomatic adults (22 males) between the ages of 18 and 30 inclusive were recruited to participate in this study. Correspondingly, the mean age, height, mass, and body mass index of these individuals was 24.7 ± 3.4 years, 1.74 ± 0.1 m, and 78.2 ± 19.4 kg, and 25.7 ± 5. 3 kg/m^2. The Institutional Review Board at Old Dominion University authorized this investigation. Informed written consent was obtained from each person prior to data collection. An individual was permitted to participate in the study if they had not undergone surgery in the past 12 months or had an injury in the past 3 months to the lower extremities that rendered them immobile or reduced their mobility for 2 or more days. If an individual responded “yes” to any of the medical history questions or had an implanted electronic device such as a cardiac pacemaker, electronic infusion pump, or implanted stimulator, they were excused from participating. Having irritated skin or an open wound where an electromyography electrode would have been applied or a known allergy to silver, as the electrode contacts were made of silver, were also criterion for prohibiting involvement.

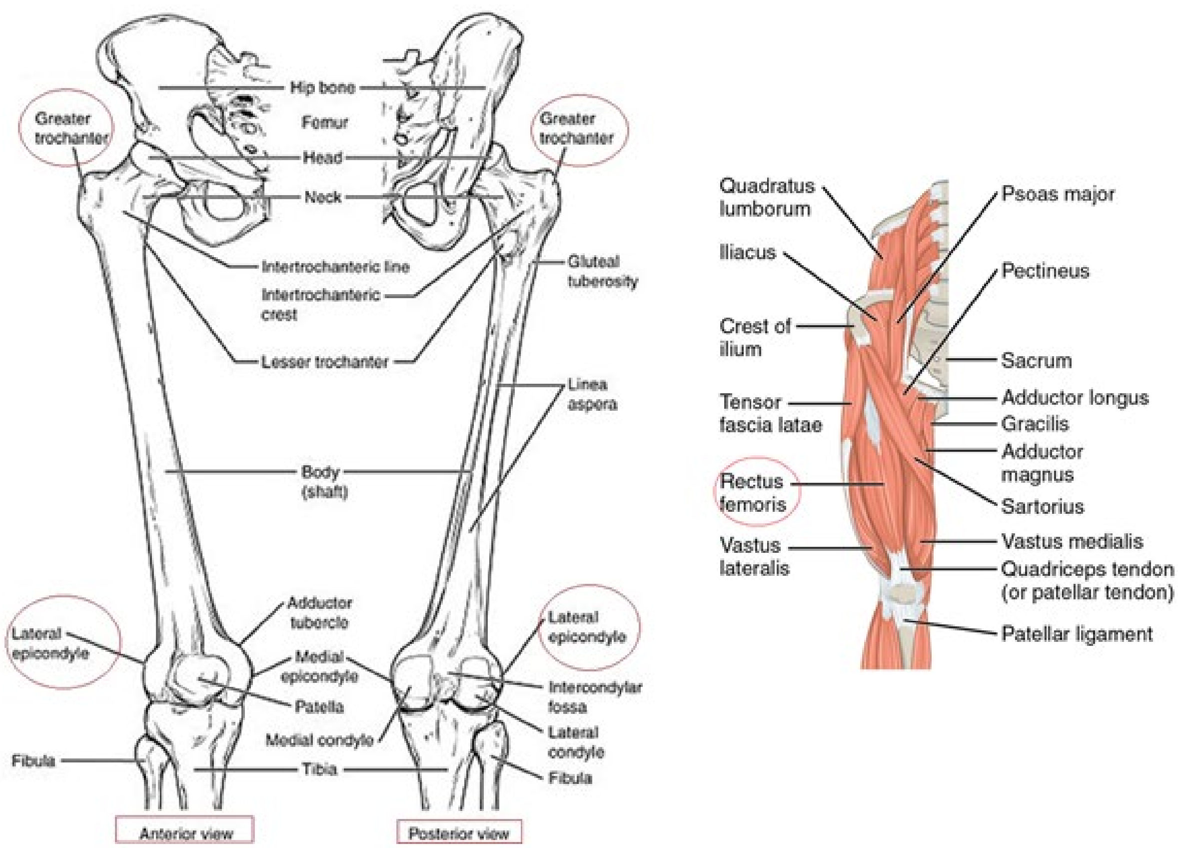
Subjects were tested in a single session and requested to wear fitted spandex shorts and standardized laboratory shoes (Under Armour Charged Gemini Running Shoes, Under Armour, Baltimore, MD, USA). A questionnaire was completed by each participant to determine their biological sex, race/ethnicity, medical history, and level of physical activity as determined by the International Physical Activity Questionnaire – short form (Craig et al., 2003). Weight and height for each subject was also measured and recorded.

To ascertain echo intensity, the participant was requested to lie quietly and supine on the examination table for 10 minutes, which allowed for fluid redistribution and minimized ultrasound imagining error (Cerniglia et al., 2007). The mid-belly of the rectus femoris was determined by marking half the length of the femur, from the greater trochanter to the articular cleft (femoral condyle) of the knee (Kleinberg et al., 2016; Figure 2**)**. A portable brightness mode US imaging device, GE Logiq e BT12 (GE Healthcare, Milwaukee, WI, USA) is put into logic view (panoramic mode) and is used in combination with a multi-frequency linear-array probe (12 L-RS, 5–13 MHz frequency, 39-degree field of view (General Electric Company)) to capture images. The ultrasound was set to 68 dB for gain, 6.0 cm for depth, and 10 MHz for frequency (Kleinberg et al., 2016). Aquasonic 100 Ultrasound Transmission Gel (Bio-medical Instruments, Inc., Clinton Township, MI, USA) was applied to the skin and probe, enhancing acoustic coupling, and reducing near-field artifacts (Rosenberg et al., 2014). The probe was moved gradually, perpendicular to the skin while in the transverse plain, medial to lateral. Consideration was taken to minimize muscle compression (Kleinberg et al., 2016).

Echo Intensity was determined using FIJI (Fiji is Just ImageJ;.3.0/1.53q version, National Institutes of Health, Bethesda, MD, USA) which is an open-source image processing software that is an extended distribution of ImageJ. The scale was set to convert image measurements from pixels to centimeters. The polygon function was employed to select the rectus femoris and caution exercised to minimize including the surrounding fascia. The area of the rectus femoris was recorded. A mean echo intensity value with a range between 0 (black) to 255 (white) arbitrary units was determined using the measure function (Rosenberg et al., 2014). This uncorrected echo intensity value was recorded but a corrected value was ascertained to adjust for subcutaneous fat thickness, which was noted to have an independent influence on echo

Figure 2

Images demonstrating bone landmarks: Greater trochanter and lateral epicondyle in anterior and posterior view and the rectus femoris of the quadriceps (OpenStax College, 2013, 2017).



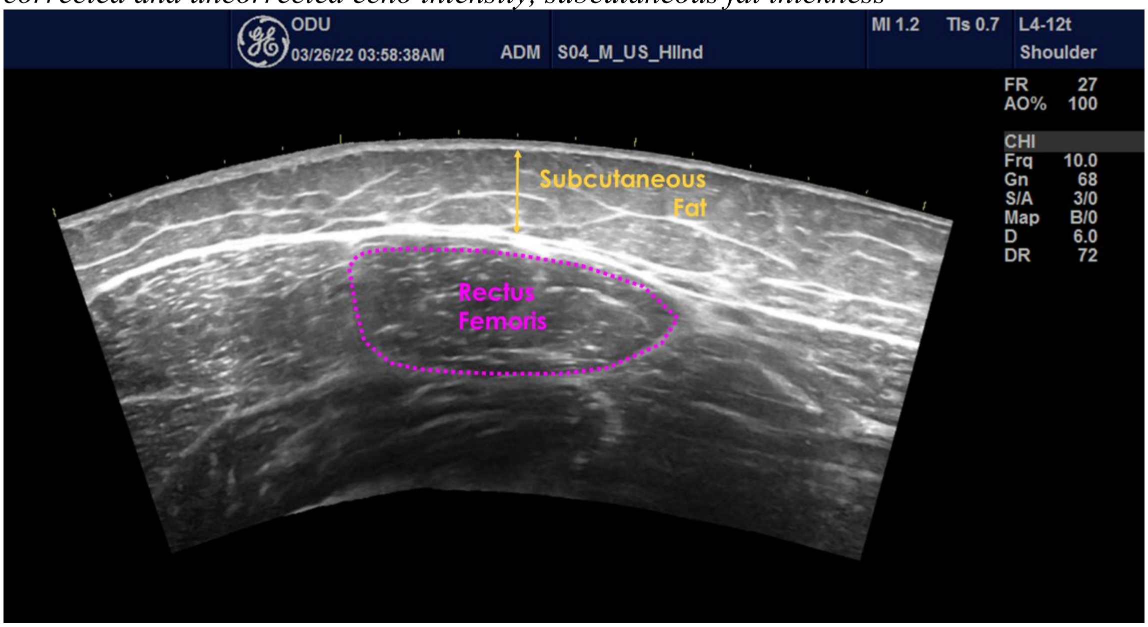
intensity estimates due to reduced sound wave attenuation (Young et al., 2015). The corrected echo intensity equation used was

$$\boldsymbol{corrected\ EI = uncorrected\ EI + (SCF\ x\ 40.5278)} \quad \text{(Equation 3-1)}$$

where EI was echo intensity and SCF was subcutaneous fat thickness. Subcutaneous fat thickness was measured as the straight-line expanse between the superficial aponeurosis at approximately half the distance between the medial and lateral borders of the muscle. This distance was logged and used as the SCF value for the corrected echo intensity equation. See Figure 3.

Figure 3

Ultrasound image, where rectus femoris is identified and the approximate location where subcutaneous fat thickness is determined above the rectus femoris. Results are used to determine corrected and uncorrected echo intensity, subcutaneous fat thickness



A 16-channel EMG system (2000 Hz, Delsys Trigno, Delsys Inc., Natick, MA, USA) was used to collect muscle activations from the rectus femoris during strength assessment. Placement of wireless surface electrodes followed prescribed guidelines (Cram et al., 1998), which included shaving hair as needed, abrading, and cleaning of the skin above the palpated muscle belly prior to electrode placement. The electrode was secured with sports wrap (Mueller Sports Medicine, Prairie du sac, WI) and then with athletic tape (Collins Sports Medicine, Raynham, MA).

An isokinetic strength assessment was performed on a calibrated HUMAC Norm dynamometer (Computer Sports Medicine, Inc., Stoughton, MA, USA). The subject was seated with their dominant leg secured to the dynamometer lever arm using a padded strap (90 mm width) placed proximal to the lateral malleolus of the ankle. The dynamometer axis of rotation was aligned with the lateral epicondyle of the dominant leg's femur. Restraining straps were placed over the chest, pelvis, and thigh; participants utilized the left and right handlebars of the chair during testing. The range of motion for the muscle actions were set to allow for full extension; a minimum of one hundred degrees of flexion was required.

Before strength testing, participants performed a warm-up(s) of submaximal isokinetic voluntary contractions at 50–75% of their perceived maximal effort. Each participant then completed five maximal voluntary isokinetic muscle actions of the leg extensors at 1.05 and at 2.09 rad/s with a 1-minute rest between reps for each testing velocity. Strength testing and EMG signals from the rectus femoris were recorded simultaneously. Over the duration of each muscle action, participants received verbal encouragement during extension and flexion (Gerstner et al., 2018). HUMAC reported all torque values in foot-pounds. Isokinetic peak torque percent decrease was calculated using the equation:

$$\% \boldsymbol{decrease\ in\ PT} = \frac{\boldsymbol{PT\ at\ slow\ velocity - PT\ at\ fast\ velocity}}{\boldsymbol{PT\ at\ slow\ velocity}}\ \boldsymbol{x\ 100} \quad \text{(Equation 3-2)}$$

where PT is an abbreviation for peak torque. Peak torque for each speed was the maximum of two trials where in each trial 5 repetitions of peak torque during extension were averaged together.

Reflective markers were placed in accordance with Vicon Nexus 2.15.0x64 (Vicon Industries, Inc., Hauppauge, NY) plug-in gait for the lower body (Vicon Motion Systems, 2023) which is based on the Newington-Helen Hayes gait model (Kadaba et al., 1990). Specifically, markers were placed bilaterally at the anterior and posterior superior iliac spines, fibula apex of lateral malleolus, femur lateral epicondyles, calcaneus, second metatarsal heads and lateral sides of the thigh and tibia. See Figure 4.

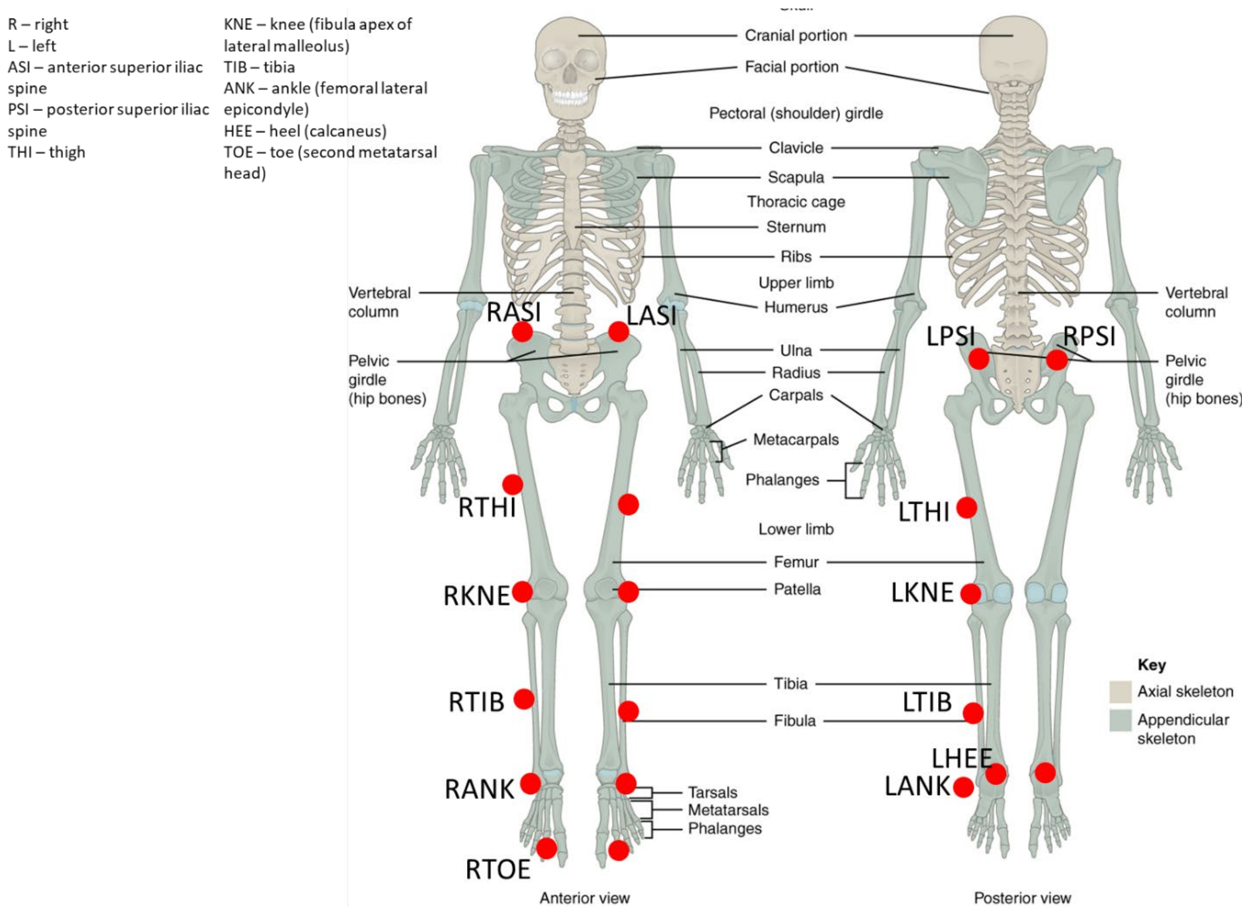
A 12-camera motion capture system was calibrated (Vicon Vantage cameras), and the force plates (FP-4060, Bertec Corporation, Columbus, OH, 2000 Hz) were zeroed. A static trial was collected, ensuring marker visibility by all cameras. The subject performed five trials of countermovement jumping at maximum effort after a demonstration and practice jump(s). Subjects used arm-swing while dropping to a countermovement depth of choice. The subject jumped as high as possible and fully extended the hip, knee, and ankle joints and arms. Jump height was determined using the participant's flight time. Force plate data was used for confirming time in flight; this corresponded with the force plate reading zero force. The difference of the ending and beginning frames where the fore plates read zero were taken and divided by the sample frequency, which provided the participant's time in flight (t). Jump height was then calculated by using a reduced version of the projectile (vertical) motion,

$$\boldsymbol{h = \frac{1}{2} g \left(\frac{t}{2}\right)^2 = \frac{gt^2}{8}} \quad \text{(Equation 3-3)}$$

where h was the jump height in meters, g was taken to be gravitational field on Earth, 9.81 m/s^2, and t time in air in seconds.

Figure 1

A diagram of landmarks for maker placement as outlined Vicon lower body plug-in gait (OpenStax College, 2016)



MATLAB (MathWorks, R2021a. Natick, MA; 2023) was used to filter and process raw electromyography signals. All signals were detrended then band-passed at 5-450 Hz, high-pass filtered at 20 Hz with a recursive second order Butterworth filter. Full-wave rectification of the signal was applied, then a low-pass filter at 5 Hz using a recursive 2nd order Butterworth filter to create a linear envelope (Medved, 2000). The maximum recorded amplitude for the rectus femoris muscle activation for each speed during strength assessments on the dynamometer was recorded.

All collected parameters were recorded in an Excel (Microsoft Excel for Microsoft 365, Microsoft Corporation, Redmond, Washington) worksheet for machine learning implementation.

A Python script was written to build and evaluate three machine learning classification methods. The techniques evaluated were Random Forest, K-Nearest Neighbors, and Support Vector Machine. The script was executed in Google Colaboratory, where the Google Drive was mounted to access the required data. Several Python libraries were imported to facilitate data analysis, visualization, and machine learning implementation. A comma-separated values file containing tabular data of anthropometric measures: sex, age, height, weight, BMI, and limb dominance, and biomechanical measures: rectus femoris muscle area, subcutaneous fat thickness above the muscle, uncorrected and corrected echo intensity, % peak torque difference, countermovement jump height, max amplitude of electromyography isometric 60 degrees/second and 120 degrees/second, and physical activity score was used.

To prepare the data, the target variable, Physical Activity Score, was removed from the feature set. Categorical variables of the feature set (i.e., sex, race, and dominance) were converted into numerical features through ordinal encoding. Preliminary data analysis was conducted by displaying statistics and histograms for the numerical features. A correlation matrix heatmap was also created to visualize feature correlations. The initial analysis allowed for the assessment of the quality of the data and for deciding if any further preprocessing was needed.

The three algorithms were created and hyperparameter grids created for each model. For K-Nearest Neighbors, parameters such as n_neighbors (3, 5, and 7) and weight ('uniform' or 'distance') were tested. In the case of Random Forest, estimators (100, 200, and 300) and max depth ('None', 10, and 20) were explored and for the Support Vector Machine 'C' values (0.1, 1, and 10) and kernels ('linear' and 'rbf'). 'C' is a regularization parameter which prevents overfitting by controlling trade-off of obtaining a low training error and low testing error, and the kernel takes the shape of decision boundary. For Random Forest, having a depth limit of 'none' implied that a node of a tree could be expanded until all the leaves were pure or all leaves contained less than the minimum number of splits at an internal node, which had a default of 2 (scikit-learn developers, 2023a).

70% of the subjects were reserved for training and the remaining 30% for testing. In the' GridSearchCV,' cross-validation focused on hyperparameter tuning,

The data was normalized using 'OrdinalEncoder' function for K-Nearest Neighbors and Support Vector Machine models. The data was split into 70% (n= 28) training and 30% (n=13) testing sets. A loop was created to go through each technique and perform hyperparameter tuning with the 'GridSearchCV' function and evaluate how each model performed in terms of accuracy. 'GridSearchCV' systematically works through all combinations of the hyperparameters and uses cross-validation in determining the best hyperparameter combination that yields the highest performing model. Twenty-three subjects were trained on, five were held out for testing. This split was repeated 5 times, each time changing the testing points. Figure 7 visually demonstrates what is occurring in the code. An evaluation of cross-validation accuracy with standard deviation, test accuracy, precision, recall, and F1 score are evaluated for each model. Accuracy was defined as the proportion of observations that were classified correctly, precision , recall, and F1 score being a harmonic mean between precision and recall which uses the equation TP/(TP+FP), where T, F, P, N stand for True, False, Positives, and Negatives respectively (Bailly et al., 2022). The mean performance metrics for each model are found and plots of performance across folds and models created. Visualization of metrics is created in the code for easy comparisons.

Results

The variables of interest (units) included Sex, Age (years), Height (m), Weight (kg), body mass index (BMI, m/kg^2), Uncorrected echo intensity (EI, AU), area of the rectus femoris Area (Area, cm^2), central subcutaneous fat thickness above the rectus femoris (C, cm), Corrected EI (AU), % Peak Torque (%PT) difference, Jump Height (m), Isometric (Iso) 60 rectus femoris (RF, V), electromyography (EMG) Iso 120 RF (V), and Physical Activity Score.

Descriptive statistics are provided in Table 2. Values significantly below Q1 or above Q3 were considered possible outliers. Specifically, a lower outlier threshold is Q1 - 1.5 * (Q3 - Q1), and the upper outlier is Q3 + 1.5 * (Q3 - Q1). Area, C, % PT, Weight, BMI, Jump Height, EMG ISO 60 RF, and EMG ISO 120 RF had outliers.

To complement the descriptive statistics, bar graphs demonstrating the data distribution are found in Figure 5. Sex, Age, and Dominance follow binomial distributions. The remaining variables appear to be non-symmetric, skewed, having long tails, except for Uncorrected and Corrected EI, which tend more toward normal distributions. From visual inspection, outliers are confirmed for Area, BMI, EMG Iso 60 RF, and EMG Iso 120 RF.

Correlations were determined for the 16 features. They can be visually determined in the correlation heatmap. Strong to moderate correlations were determined to be the magnitude of values approximately 0.6 and higher. Variables determined to have this relationship were Sex and Height (R = -0.72), Sex and C (R = 0.6), Sex and Corrected EI (R = 0.74), Sex and Jump Height (R= -0.74), Weight and Area (R = 0.6), Weight and BMI (R = 0.88), BMI and Uncorrected EI (R = -0.59), C and Jump Height (R = -0.72), C and Corrected EI (R = 0.6), Corrected EI and Jump Height (R = -0.75), and EMG Iso 60 RF and EMG Iso 120 RF (R = 0.89)

The best hyperparameters for K-Nearest Neighbors was having 7 neighbors and a uniform weight. For Random Forest, hyperparameters of a max depth of none and having 100 decision tree estimators rendered the best performance. For Support Vector Machine it was a C of 10 and a linear kernel.

Results demonstrated that across folds, K-Nearest Neighbors had a cross validation accuracy of 0.65 ± 0.16, accuracy of 0.69, precision of 0.7, recall of 0.675, and F1 of 0.675. Random Forest respectively had 0.68 ± 0.16, 0.54, and 0.29, 0.44, and 0.35 for these performance metrics. Support Vector Machine scored 0.72 ± 0.16, 0.69, 0.58, and 0.51, respectively. Between .70 - .90 are desired scores. The Support Vector Machine performed the best in cross-validation accuracy for the final model. The Support Vector Machine and K-Nearest Neighbor algorithms performed equally as well in the remaining metrics and better than Random Forest. Reference Table 3 for model performance and Figure 8 for visual demonstration of the performance of each model.

Table 2 *Descriptive statistics of features*

	N	Mean	Std. Deviation	Minimum	Q1 (0.25)	Q2 (0.5)	Q3 (0.75)	Maximum
Age (years)	41	24.27	3.40	18.00	22.00	23.00	28.00	30.00
Height (m)	41	1.74	0.10	1.59	1.65	1.75	1.80	1.96
Weight (kg)	41	78.18	19.35	50.90	65.83	76.55	85.66	138.37
BMI (m/kg^2)	41	25.66	5.30	16.93	22.08	24.68	27.76	38.36
Uncorrected EI (AU)	41	120.88	26.51	58.35	100.47	123.51	135.57	168.34
Area (cm^2)	41	8.29	3.21	3.41	5.90	7.69	10.25	19.77
C (cm)	41	0.98	0.73	0.14	0.44	0.77	1.31	3.26
Corrected EI (AU)	41	160.51	30.05	101.40	146.77	154.66	185.53	221.43
% PT difference	41	28.64	19.20	2.75	13.27	24.21	40.00	82.61
Jump Height (m)	41	0.29	0.11	0.15	0.20	0.27	0.37	0.51
EMG Iso 60 RF (V)	41	1.64 x 10^-04	1.01 x 10^-04	4.30 x 10^-05	9.86 x 10^-05	1.36 x 10^-04	1.90 x 10^-04	5.49 x 10^-04
EMG Iso 120 RF (V)	41	1.61 x 10^-04	1.23 x 10^-04	2.96 x 10^-05	8.06 x 10^-05	1.40 x 10^-04	1.84 x 10^-04	5.94 x 10^-04

Figure 5

Bar graphs demonstrating distributions of the features.

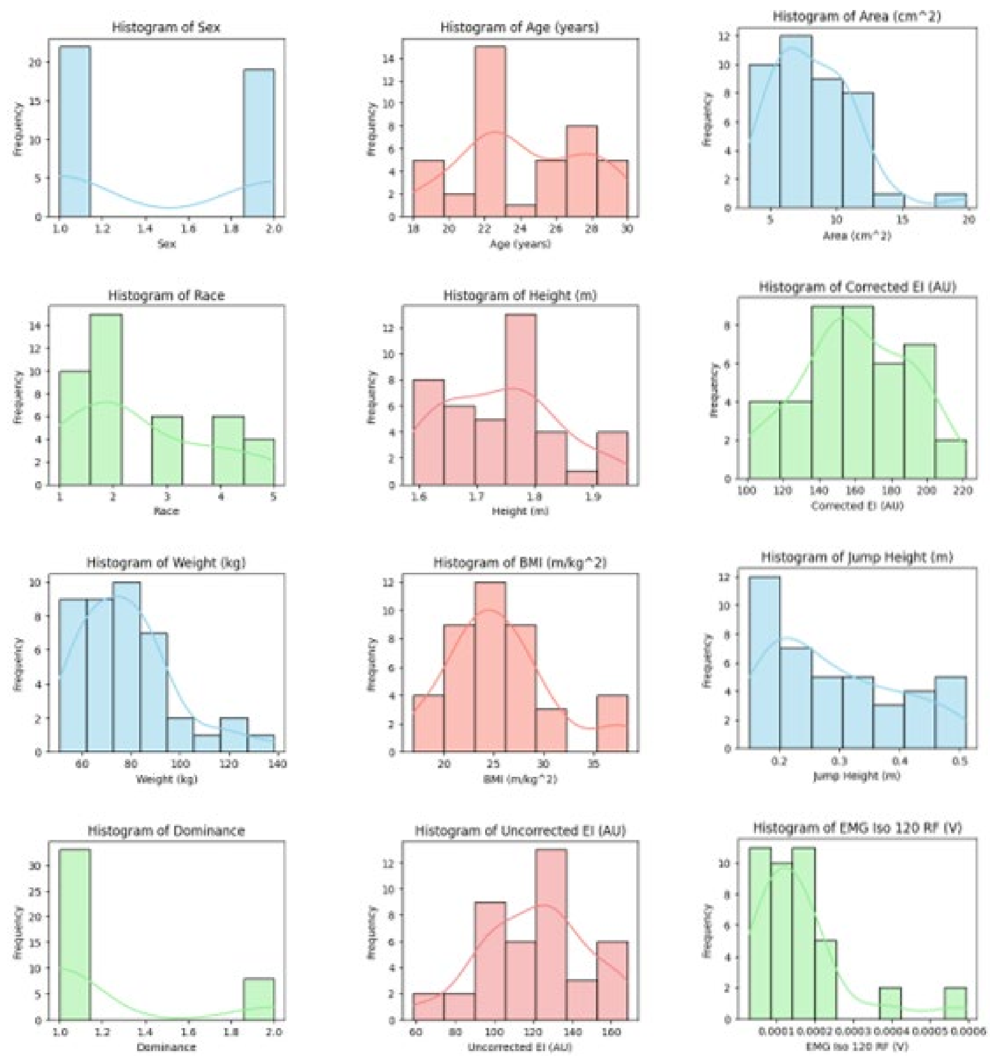


Figure 6

Correlation heatmap of the features

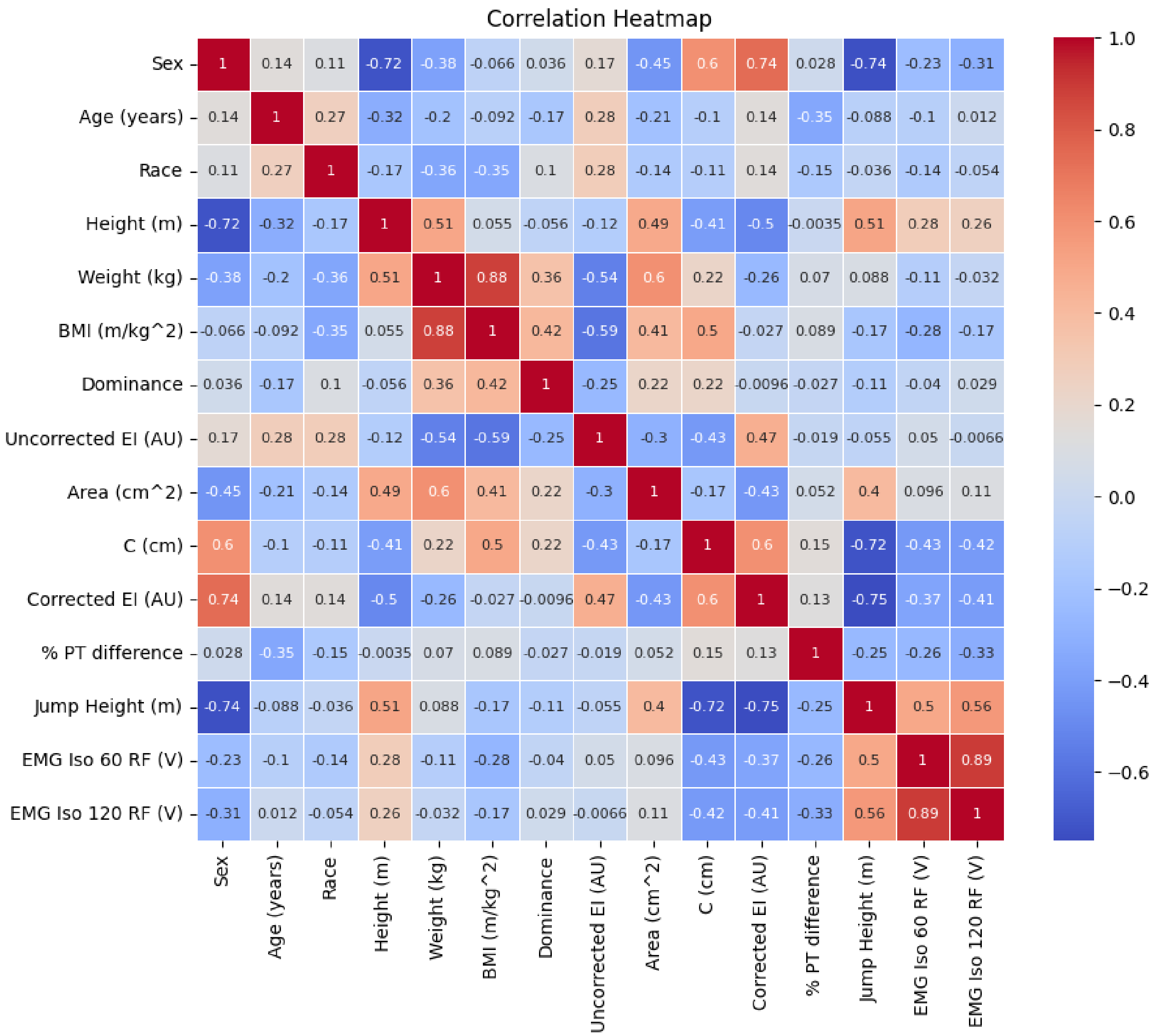


Figure 7

Cross-validation demonstrated

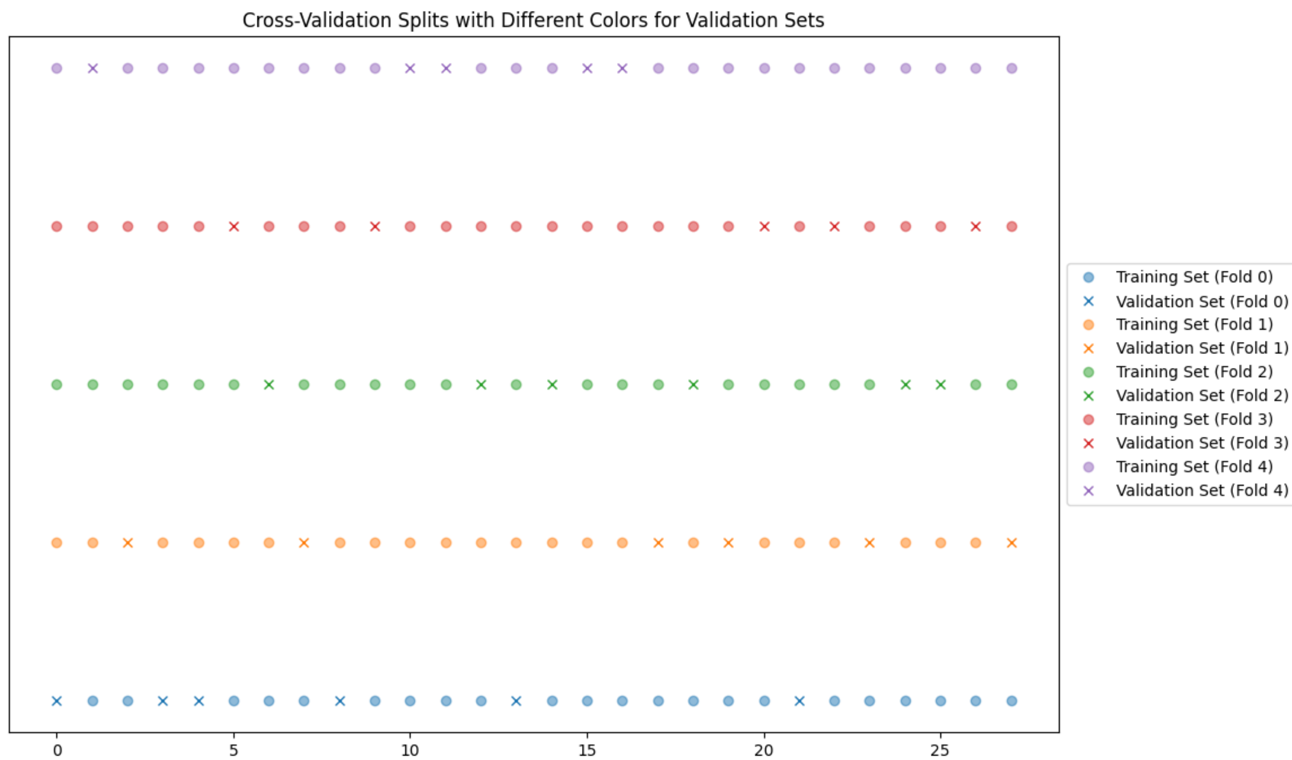


Figure 8

Scatterplots for a) cross validation accuracy, b) test set accuracy, c) precision, d) recall and e) F1 bar graphs of performance for each machine learning model

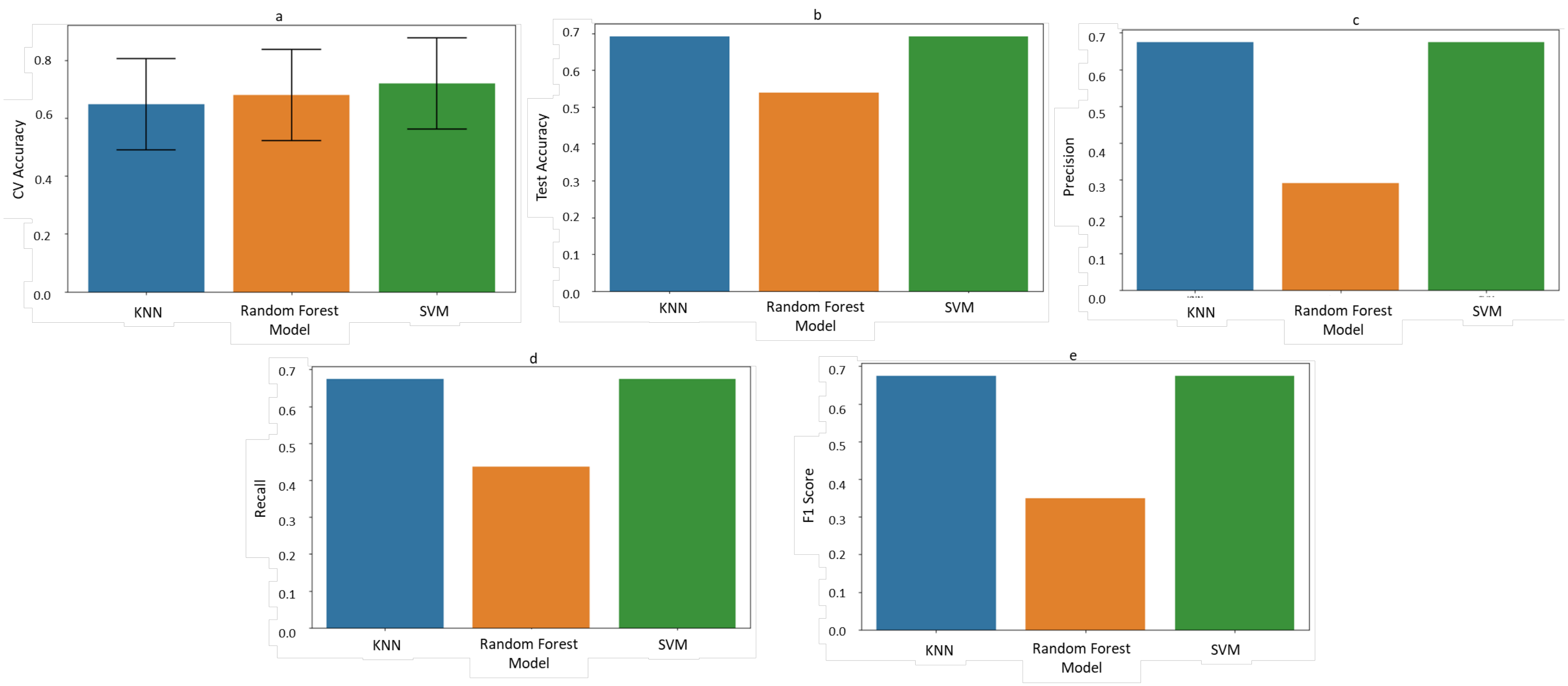


Table 3

Results from running Machine Learning Models

	Cross-Validation Accuracy	Test Set Accuracy	Precision	Recall	F1
KNN	0.65 ± 0.16	0.69	0.675	0.675	0.675
Random Forest	0.68 ± 0.16	0.54	0.29	0.44	0.35
SVM	0.72 ± 0.16	0.69	0.675	0.675	0.675

Discussion

Data quality is viewed as important for machine learning, yet literature typically fails to address how to identify and improve it; more specifically, statistical analysis is usually not employed for investigating distributions and possible outliers. Outliers in the data has been viewed as having a significant risk to skewing models. This is especially important for medical diagnosis (Dai et al., 2018). One study employed statistics to determine control limits, but also incorporated the central limit theorem, which assumes a normal distribution for a sample size of 30 or more (Dai et al., 2018). Descriptive statistics and distributions were reported as a point of inspection should none of the algorithms perform well. The sample size was greater than 30 for this study which implies that an assumption of normal distribution can be used despite outliers and skewed distributions.

The Support Vector Machine model outperformed Random Forest outperformed and K-Nearest Neighbors. This supports one study that determined that the Support Vector Machine algorithm was more robust than random forest for limited medical data, but included the caveat that the most robust model does not mean the best performing (Althnian et al., 2021). Additional work would be needed to see if the Support Vector Machine technique could be more robust than the other models in this study. In other words, a determination would be needed to see if Support Vector Machine would perform well on training data that includes some noise or imprecise data (Pang et al., 2022). Properties of the models may have had an influence on their performance for instance Support vector machines have demonstrated an ability to detect disease, but are said to be disadvantaged by having no optimization or enhancement and in cases limitation on the number of hyperplanes that can be utilized for predicting classes (Ruchi et al., 2020). K-Nearest Neighbors has been praised for its accuracy, particularly when optimized, and in its effectiveness in detection of disease, even scenarios involving large datasets. It is also commended for its lack of complexity, accuracy, and ability to be quickly executed when used in combination with feature selection. It has been reported in some studies as impossible with large datasets or having significantly reduced accuracy with such data and generally having a poor convergence rate (Ruchi et al., 2020). Random Forest has been reported in literature aimed at medical diagnosis as being a highly efficient model, with high reliability, precision, and/or accuracy for disease detection, though it has been criticized for lacking the ability to be optimized or enhanced, which would be helpful for achieving improved results. Random forest has been reported as not having good performance for large datasets too (Ruchi et al., 2020).

The International Physical Activity Questionnaire-short was validated as the machine learning was able to accurately categorize to self-reported physical fitness levels. This finding is notable as systematic reviews found issues such as underestimations of sedentary behavior and overestimations of physical activity and low correlations to measures found with body motion monitoring (Grimm et al., 2012; Lee et al., 2011).It is possible that subjects for this study reported their physical fitness levels within a minimal margin of error that allowed for patterns amongst features to be identified. Future work could incorporate accelerometer data as an additional feature or in place of International Physical Activity Questionnaire-short categorizations. Further investigation may be required to determine the International Physical Activity Questionnaire-short validity in the young adult population while it was found invalid for certain studies that had involved older adults (Lenz et al., 2012) and adolescent boys (Rääsk et al., 2017), respectively. One perspective is that older adults and adolescent boys may have found it more difficult to recall their typical physical activity with an appropriate accuracy.

A limitation of this study was that there was a small number of data points (or subjects). One study suggested that although there has been an attempt to establish measures for the minimum number of samples that there is no recognized definition for what represents a small dataset (Althnian et al., 2021) . The study instead compared related works to determine what constitutes a small versus large dataset. When comparing to the categorization used in that study, it is confirmed that the dataset used for this study is small. It should be noted that there are few concerns surrounding small datasets (Althnian et al., 2021). There is possibility for decreased performance from the classification algorithm because fewer details could restrict the algorithm from generalizing patterns in the training set. There is also the possibility of over-fitting, which affects both the training data and the validation set (Althnian et al., 2021). This does not appear to have been an issue as possibly the performance was based on the distribution of the dataset as opposed to its size. Another issue was that there was an imbalance of classification types in the dataset. Using a ‘balanced’ class weight model parameter allowed for maintain of the same class distribution as the original dataset. Future work could include targeted recruiting to improve the balance the classifications. An additional limitation of this study was that only three machine learning classification algorithms were attempted in this study. Other supervised classification algorithms include Naïve Bayes classifier and Logistic Regression (Edwards et al., 2021). Future work could include these models for additional comparisons on training performance.

The most immediate feature future work for this study includes optimizing the Support Vector Machine algorithm by determining the minimum number of features needed for an acceptable outcome. This is desired as computation time and storage space can be reduced and "essential characteristics" of the data can be ascertained. Accuracy is also thought to be influenced by dimensionality (Jia et al., 2022). In successfully being able to distinguish between active and inactive individuals, for real-world scenarios, this should be achieved with minimal data collection equipment. This would conserve financial resources and time. The work presented appears to be novel and underscores the potential for improved interventions for inactive persons for suggestions for sustaining.

CHAPTER 4

STREAMLINING BIOMECHANIAL METRICS FOR YOUNG ADULT PHYSICAL ACTIVITY CLASSIFICATION

INTRODUCTION

Acquiring a deeper understanding of human biomechanics could be crucial in developing preventative measures and personalized care. Biomechanics of human locomotion is complex (Lu & Chang, 2012) and the integration of machine learning models could help in interpretability (Bisele et al., 2017; Phinyomark et al., 2018). Specifically, the use of the Support Vector Machine algorithm may prove helpful in the implementation of machine learning and in understanding results. The Support Vector Machine algorithm is lauded for several characteristics including the ability to render reliable results even when there is not enough information that can be gathered from the data. It is also known for its ability to work well with unstructured data (Akkaya & Çolakoğlu, 2019). It is known for its ability to solve complex problems with kernel implementation. Also it noted to be perform relatively well at scaling high dimensional data (Akkaya & Çolakoğlu, 2019). Akkaya et al, notes that the algorithm also has several disadvantages. One such example is difficulty in selecting the appropriate kernel. For large datasets, training time can be prolonged. Interpretability of results can be difficult due to variable weighting. Each variable's contribution to the decision boundary is variant, also compounding issues with understanding results (Akkaya & Çolakoğlu, 2019).

Innovation can be achieved with feature reduction, contingent upon the method by which features are reduced, because key information is more easily understood due to having a simplified model (Jia et al., 2022). With feature reduction, redundant information is eliminated, and models run more efficiently due to a decrease in training time or computational burden. Concerns with overfitting are addressed because the measures used for training are more streamlined (and independent/orthogonal). Overall, the curse of dimensionality, the phenomenon that as dimensionality increases, the volume of data becomes sparse, is thwarted (Jia et al., 2022). Increases in dimensionality of data requires an increase in data to maintain performance in tasks (Venkat, 2018). The result of high dimensionality is increased computational effort and decreased visualization of results (Venkat, 2018).

Methods

In the previous chapter, K-Nearest Neighbors, Random Forest, and Support Vector Machine learning models were used to categorize self-reported physical activity from the International Physical Activity Questionnaire short form among forty-one asymptomatic adults aged 18 to 30. Their mean age, height, mass, and body mass index were determined to be 24.7 ± 3.4 years, 1.74 ± 0.1 meters, 78.2 ± 19.4 kilograms, and 25.7 ± 5.3 kg/m^2, respectively.

In addition to these basic metrics, anthropometric and biomechanical data were gathered including sex, race, limb dominance, echo intensity (both uncorrected and corrected), rectus femoris area, subcutaneous fat thickness, percent peak torque difference, jump height, and peak amplitudes of electromyography signals during isokinetic leg extension at speeds of 60 and 120 degrees per second. These measurements were acquired using surveys, ultrasound, a dynamometer, electromyography, and motion capture combined with a force plate. Many of these measures required additional effort after data collection.

With the employment of machine learning the best model and hyperparameters were determined. This process identified the Support Vector Machine with C: 10 and a linear kernel as the top performer meeting minimum standards.

In this chapter, continued work is done on the Support Vector Machine model. Specifically, a univariate (one-variable) feature selection technique is used. The 'SelectKBest' function is used to determine the relationship of each individual feature to the target variable and scores the feature using the 'f_classif' function. The 'f_classif' function computes the ANOVA F-value, an analysis of variance, for the feature in respect to the target variable and the p-value associated with each F-value. Large F-values indicate that a feature is more informative in distinguishing classes. The specified top features are then selected (scikit-learn developers, 2023b, 2023c). Once the training data is fitted, a transform method is used convert the original feature set into a reduced set of only the selected features for the test and train set. The Support Vector Machine model is defined with a C:10 and linear kernel and class weights are balanced. Cross-validation is done with the hyperparameters. The Support Vector Machine model is trained with the selected features and the hyperparameters. Accuracy, precision, recall, and F1 score are then reported.

Results

The performance metrics of the original Support Vector Machine model from Chapter 1 are shown in Table 4-1. The resulting cross-validation accuracy, test set accuracy, precision, recall, and F1 scores are respectively 0.72 ± 0.16, 0.69, 0.675, 0.675, and 0.675. Feature reduction was not implemented for this model.

In the process of feature reduction, optimal performance with the least number of features is achieved at 11 features. These features are sex, age, race, height, body mass index (BMI), dominance, uncorrected echo intensity (EI), area, subcutaneous fat thickness (C), corrected echo intensity (EI), and countermovement jump height. The performance metrics were determined to be 0.79 ± 0.21, 0.69, 0.675, 0.675, and 0.675. Table 4 summarizes the scores.

Figure 9

Scatterplots of accuracy, precision, recall, and F1 Support Vector Machine learning model. The Support Vector Machine model performance with feature reduction, where 11 features was optimal

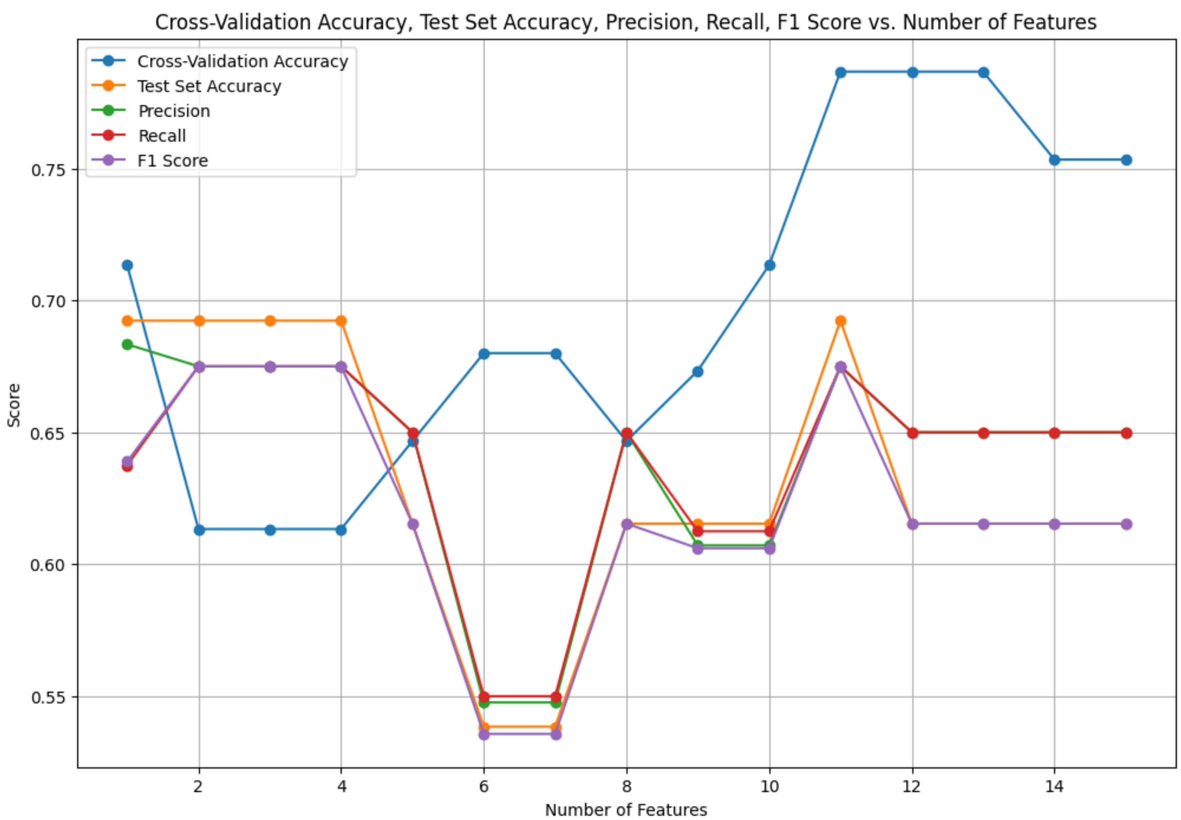


Table 4

Support Vector Machine performance metrics

	Cross-Validation Accuracy	**Test Set Accuracy**	**Precision**	**Recall**	**F1**
Support Vector Machine, original model	0.72 ± 0.16	0.69	0.675	0.675	0.675
Support Vector Machine, (feature selection = 11)	0.79 ± 0.21	0.69	0.675	0.675	0.675

Discussion

Results from the previous chapter did not incorporate feature reduction, necessitating the use of all 15 biomechanical measures (features) to execute the final Support Vector Machine algorithm. Using feature reduction with the Support Vector Machine algorithm for this study not only reduced computational time but made ultrasound and motion capture with force plates the only equipment necessary for determining the final features Electromyography and dynamometry were ultimately eliminated. A significant reduction in data collection and processing time would occur in a clinical setting as, on average, the laboratory testing required 2 hours to collect all biomechanical measures.

As mentioned in the previous chapter, a small dataset was utilized for this study and concerns arise with such. A possible decrease in classification performance and the possibility of over-fitting (Althnian et al., 2021) should be considered.

Future work includes using Naïve Bayes classifier and Logistic Regression, which are other supervised classification algorithms (Edwards et al., 2021) that were not attempted.

Attempting to improve Random Forest and K-Nearest Neighbor results beyond the scope of the previous chapter. Substantial benefits may be realized with additional refinement and advancement of these algorithms, as K-Nearest Neighbors performed nearly as well as the Support Vector Machine model. This should be highlighted as K-Nearest Neighbors is noted to be easier to implement and understand, can be applied to multi-class classification problems with ease, and is said to have a quick response to changes in input when used in real-time (Akkaya & Çolakoğlu, 2019).

Additional research could include simplifying the data collection procedure. Obtaining jump height without the use of motion capture and a force plate would further reduce data collection efforts. Seeing how the algorithm performs when this metric is not collected as precisely would be advantageous and more reflective of what would be desired in a clinical setting. Automatizing the segmenting of the ultrasonography image to determine corrected and uncorrected echo intensity, muscle area, and subcutaneous fat could also beneficial toward time saving. The main objective of this work would be prompt physical activity assessment and to allow clinicians to offer patients personalized recommendations. Future aim would include exploring the potential for predicting acceptability to chronic disease and conditions based on the current assessed level of physical activity.

CHAPTER 5

SUMMARY AND CONCLUSION

The objective of this research was to employ machine learning to categorize activity levels of young adults using a reduced set of biomechanical measurements that would commonly be used for lower extremity assessment. To accomplish this, an analysis of some key biomechanical measurements was conducted using traditional statistical methods. It involved the incorporation of scatterplots, boxplots, linear regression, and Pearson's correlation to ascertain relationships. Human movement is often described as multi-dimensional and non-linear, so it was thought that fundamental statistical methods would not be able to fully describe existing relationships amongst the biomechanical variables of interest. Next, K-Nearest Neighbors, Random Forest, and Support Vector Machine were employed to investigate if low to moderately active and highly active asymptomatic young adults could be categorized correctly with the biomechanical features investigated. Seeing that machine learning has been successfully employed to categorize complex relationships in other studies, it was hypothesized that this could be done with success. The next goal was to take the best performing algorithm and to reduce the number of biomechanical measures (or features) needed for categorization. It was believed that this could be accomplished. All hypotheses were confirmed for each aim. To the knowledge of the author, there is limited existing research that explores the range of lower-limb biomechanical features presented and their impact in categorizing physical activity levels of young adults.

The statistical method approach revealed that there was not a relationship for every biomechanical variable combination; this statement was demonstrated whether assessed across the entire cohort or stratified based on biological sex. Echo intensity and subcutaneous fat thickness showed a strong negative correlation for females and fair negative correlation for the cohorts combined. In the case of corrected echo intensity and subcutaneous fat thickness, the male cohort demonstrated a fair positive relationship and the combined cohort a moderate positive one. Corrected echo intensity and countermovement jump demonstrated a fair negative relationship for males and moderate negative correlation for the combined cohort. Major take aways if discussing gender-specific observations was that the female cohort had a decrease in echo intensity with increase subcutaneous fat thickness, which was an implication for using corrected echo intensity. The male cohort saw an increase in corrected echo intensity with subcutaneous fat thickness, which was an implication for not using corrected echo intensity. The male cohort demonstrated decreased countermovement jump height with increasing echo intensity, which seems appropriate that decreased muscle quality would result in decreased jump height. It was noted that the study was not without its limitations which included recruitment and demographic limitations, concerns with data collection and its possible impacts on results, inconsistencies with how countermovement jumps were performed, and outliers in the female cohort which was determined through review of the data distribution. Ideas for study improvement involved adding additional biomechanical variables, incorporating qualitative components, and diversifying the sample and demographic, and including interventions or longitudinal studies. The study enriches understanding on the lower limb skeletal muscular system; however, it underscores the need for additional analysis using advanced statistical methods or intricate methods to unravel the complexities of human locomotion and the interplay between various biomechanical variables.

Machine learning was employed to categorize physical activity for young adults, but the study first began with a review of the data quality as it could have an impact on the success or failure of the machine learning. It was noted that literature has generally failed to address how to identify and to improve imperfect data. This is especially important since outliers can affect medical diagnosis. K-Nearest Neighbors, Random Forest, and Support Vector Machine are compared in the study. Literature review discussed properties and limitations of each model, but a point of note was Support Vector Machine being identified as robust especially when compared to other models. The study validated the International Physical Activity Questionnaire short form for young adult populations despite mixed reviews of its legitimacy. Limitations were acknowledged for the study, such as having a small dataset and the fact that its size can result in reduced algorithm performance and increase risk for overfitting. There was an imbalance among the classes; however, a solution was implemented to address this concern. Future work involves optimizing the Support Vector Machine algorithm by determining the minimum number of features needed for an acceptable outcome. By doing so, the goal of reducing computational time and storage by utilizing a streamlined featured set is met. Additionally, the possibility of improved accuracy through decreased dimensionality may be experienced. There has been limited exploration of machine learning classification using the proposed feature set to classify activity levels. The Support Vector Machine algorithm was successfully employed and met the objective of this study. It appears that work demonstrated here is novel for the area of biomechanical focus. The research highlights the potential for improved interventions for inactive individuals and provides avenues for sustainable future research.

The last study addressed the absence of feature reduction as the original Support Vector Machine algorithm utilized 15 biomechanical measures. The implementation of feature reduction not only had an impact on computational time but equipment requirements. Having a significant reduction in data collection and processing time in a clinical setting offers a distinct advantage.

Feature reduction in this application allowed for sole reliance on ultrasound, motion capture, and force plate equipment for final features. Electromyography and dynamometry dependencies were eliminated. This increases efficiency for data collection and processing time. As with each study, the dataset was small which has its own potential concerns of decreased classification performance and risk for overfitting. There were unexplored algorithms like, Naïve Bayes classifier and Logistic Regression. This could be included for future work. Potential benefits could be found in refining the comparable K-Nearest Neighbors algorithm as it is noted for its ease in implementation and responsiveness. Future work would involve simplifying data collection procedures, including obtaining jump height without the use of motion capture and a force plate. Automatizing segmentation of ultrasonography images for various measures could also reduce post-hoc analysis. The realization of prompt physical activity assessment and personalized recommendations becomes more achievable with this work. Exploring pathways to predict susceptibility to chronic diseases through evaluated physical activity could be a potential next step.

This work has successfully differentiated low to moderately active and highly active asymptomatic young adults aged 18 to 30 beginning with 15 biomechanical metrics. These 15 biomechanical metrics were further reduced to 11 features allowing for a reduction in computational time. It should be emphasized how the success of this study contributes to work in a clinical setting, as all the features are collected through a brief surveying of the individual, collection of weight and height, employment of ultrasound, and use of motion capture with force plates. This reduces manpower for equipment operation and use which is essential for clinical work.

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APPENDICES

APPENDIX A - INTERNATIONAL PHYSICAL ACTIVITY QUESTIONNAIRE DIRECTIONS

(August 2002)

SHORT LAST 7 DAYS SELF-ADMINISTERED FORMAT

FOR USE WITH YOUNG AND MIDDLE-AGED ADULTS (15-69 years)

The International Physical Activity Questionnaires (International Physical Activity Questionnaire) comprises a set of 4 questionnaires. Long (5 activity domains asked independently) and short (4 generic items) versions for use by either telephone or self-administered methods are available. The purpose of the questionnaires is to provide common instruments that can be used to obtain internationally comparable data on health–related physical activity.

1. Background on International Physical Activity Questionnaire

The development of an international measure for physical activity commenced in Geneva in 1998 and was followed by extensive reliability and validity testing undertaken across 12 countries (14 sites) during 2000. The final results suggest that these measures have acceptable measurement properties for use in many settings and in different languages and are suitable for national population-based prevalence studies of participation in physical activity.

2. Using International Physical Activity Questionnaire

Use of the International Physical Activity Questionnaire instruments for monitoring and research purposes is encouraged. It is recommended that no changes be made to the order or wording of the questions as this will affect the psychometric properties of the instruments.

3. Translation from English and Cultural Adaptation

Translation from English is supported to facilitate worldwide use of International Physical Activity Questionnaire. Information on the availability of International Physical Activity Questionnaire in different languages can be obtained at www.ipaq.ki.se. If a new translation is undertaken, we highly recommend using the prescribed back translation methods available on the International Physical Activity Questionnaire website. If possible, please consider making your translated version of International Physical Activity Questionnaire available to others by contributing it to the International Physical Activity Questionnaire website. Further details on translation and cultural adaptation can be downloaded from the website.

4. Further Developments of International Physical Activity Questionnaire

International collaboration on International Physical Activity Questionnaire is on-going and an ***International Physical Activity Prevalence Study*** is in progress. For further information see the International Physical Activity Questionnaire website.

5. More Information

More detailed information on the International Physical Activity Questionnaire process and the research methods used in the development of International Physical Activity Questionnaire instruments is available at www.ipaq.ki.se and Booth, M.L. (2000). *Assessment of Physical Activity: An International Perspective*. Research Quarterly for Exercise and Sport, 71 (2): s114-20. Other scientific publications and presentations on the use of International Physical Activity Questionnaire are summarized on the website.

APPENDIX B - INTERNATIONAL PHYSICAL ACTIVITY QUESTIONNAIRE

We are interested in finding out about the kinds of physical activities that people do as part of their everyday lives. The questions will ask you about the time you spent being physically active in the **last 7 days**. Please answer each question even if you do not consider yourself to be an active person. Please think about the activities you do at work, as part of your house and yard work, to get from place to place, and in your spare time for recreation, exercise or sport.

Think about all the **vigorous** activities that you did in the **last 7 days**. **Vigorous** physical activities refer to activities that take hard physical effort and make you breathe much harder than normal. Think *only* about those physical activities that you did for at least 10 minutes at a time.

1. During the **last 7 days**, on how many days did you do **vigorous** physical activities like heavy lifting, digging, aerobics, or fast bicycling?

   _____ **days per week**

   ☐ No vigorous physical activities → ***Skip to question 3***

2. How much time did you usually spend doing **vigorous** physical activities on one of those days?

   _____ **hours per day**

   _____ **minutes per day**

   ☐ Don’t know/Not sure

Think about all the **moderate** activities that you did in the **last 7 days**. **Moderate** activities refer to activities that take moderate physical effort and make you breathe somewhat harder than normal. Think only about those physical activities that you did for at least 10 minutes at a time.

3. During the **last 7 days**, on how many days did you do **moderate** physical activities like carrying light loads, bicycling at a regular pace, or doubles tennis? Do not include walking.

_____ **days per week**

☐ No moderate physical activities → ***Skip to question 5***

4. How much time did you usually spend doing **moderate** physical activities on one of those days?

_____ **hours per day**

_____ **minutes per day**

☐ Don't know/Not sure

Think about the time you spent **walking** in the **last 7 days**. This includes at work and at home, walking to travel from place to place, and any other walking that you have done solely for recreation, sport, exercise, or leisure.

5. During the **last 7 days**, on how many days did you **walk** for at least 10 minutes at a time?

_____ **days per week**

☐ No walking → Skip ***to question 7***

6. How much time did you usually spend **walking** on one of those days?

_____ **hours per day**

_____ **minutes per day**

☐ Don’t know/Not sure

The last question is about the time you spent **sitting** on weekdays during the **last 7 days**. Include time spent at work, at home, while doing course work and during leisure time. This may include time spent sitting at a desk, visiting friends, reading, or sitting or lying down to watch television.

7. During the **last 7 days**, how much time did you spend **sitting** on a **weekday**?

   _____ **hours per day**

   _____ **minutes per day**

   ☐ Don’t know/Not sure

This is the end of the questionnaire, thank you for participating.

VITA

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PRESENTATIONS

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Khosrojerdi A, **Holland N**, Alijanpour E, Bennett HJ, Ringleb SI, "Sex difference in lower extremity joints' kinematics coordination during the gait cycle phases," American Society of Biomechanics, Knoxville, TN, August 2023

Holland N, "Machine Learning to Predict Musculoskeletal Health using Jump Height," PEI-Global GEDC Lightening Round, WEEF&GEDC Conference 2022, Cape Town, South Africa, November 2022

Holland N, Sievert ZA, Bennett HJ, Ringleb SI, "Normalization methodologies involving anticipated cutting tasks," North American Congress on Biomechanics, Ottawa, Ontario, August 2022

Holland N, Sievert ZA, Bennett HJ, Ringleb SI, "Analysis of Normalization Techniques: Surface Electromyography Signals from a Cutting Task of A Hamstring Strength Training Program, 45th meeting of the American Society of Biomechanics, Virtual, August 2021

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