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Sensitivity of different hand grip algorithms in classification of body composition status related to health among Lebanese adults

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УНИВЕРЗИТЕТ У БЕОГРАДУ

ФАКУЛТЕТ СПОРТА И ФИЗИЧКОГ ВАСПИТАЊА

Захи Г. Андраос

Сензитивност различитих алгоритама за снагу стиска руке у класификацији статуса телесне композиције у односу на здравље код одраслих Либанаца

Докторска дисертација

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ABBREVIATIONS

HiAP: Health in All Policies

CRP: C-reactive protein

CKD : chronic kidney disease CKD

TUG : Timed Up and Go

OSO: Osteosarcopenic Obesity

CVD : cardiovascular disease

T2D: mellitus

NAFLD : alcoholic fatty liver disease

ASM%: Low appendicular skeletal muscle

NASH : non –alcoholic steatohepatitis

PNPLA3 rs738409: polymorphism

ALMI : appendicular lean mass index

BMI : Body mass index

FMS: Functional Movement Screen

OSTRC :Oslo Sports Trauma Research Center AMS :Athlete Monitoring Systems :

ACWR : Acute Workload Ratio

NHE :Nordic Hamstring Exercise

F_{max}Dom : Force max dominant hand

RFD_{max}Dom: Rate of force development Dominant hand

$IS_{dom:}$ Index of Synergy dominant hand

F_{max}ND: Force max non dominant hand

RFD_{max}ND: Rate of force development non dominant hand

$IS_{ND:}$ Index of synergie non dominant hand

F_{max}SUM: Sum of maximal force

RFD_{max}SUM: Sum of maximal rate of force development

BM: body mass

BH: Body Height

BMI: Body Mass Index

BFM: Body Fat Mass

BFMI: Body Fat Mass Index

PBF: Percent of Body Fat

SMM: Skeletal Muscle Mass

SMMI: Skeletal Muscle Mass Index

PSMM: Percent of Skeletal Muscle Mass

IBC: index of body composition

MFI: Muscle Fat Index

Abstract

Background:
Hand grip strength (HGS) is a widely used, non-invasive indicator of muscular function and overall health status. However, traditional approaches often overlook the sensitivity of various force-based parameters—such as maximal strength, rate of force development (RFD), and interlimb coordination—in predicting body composition and associated health risks. This study aimed to evaluate the discriminative and predictive capacity of different hand grip algorithms in classifying health-related body composition profiles among Lebanese adults.

Methods:
A total of 395 Lebanese adults (242 males and 153 females) participated in this cross-sectional study. Anthropometric and body composition variables were assessed using standardized protocols, including measures such as BMI, percent body fat (%PBF), skeletal muscle mass (SMM), fat-free mass (FFM), visceral fat area (VFA), and the Index of Body Composition (IBC). Neuromuscular performance was evaluated through maximal hand grip force (F_{max}), maximal rate of force development (RFD_{max}), and the Index of Synergy (IS), with both absolute and relative values computed. Discriminant analysis was conducted to classify individuals into health-related clusters, and multiple regression analysis was used to develop predictive models for a Fitness Health-Related Score (FHRS_Index).

Results:
Discriminant analysis demonstrated high classification accuracy (95.5% in males; 94.0% in females), with RFD_{max}_SUM, IS_SUM, and Dominant_F_{rel} emerging as the most sensitive variables. Regression models showed excellent predictive power (R^2 = 1.000) in both sexes. Percentile thresholds (15th percentile) were established to define health risk categories based on the Fact Score Number. Separate predictive equations were developed for both absolute and relative hand grip parameters.

Conclusion:
The findings confirm that specific hand grip variables—especially those related to explosive strength and coordination—are highly sensitive in classifying health-related body composition status. The proposed FHRS_Index and established percentile cut-offs offer a practical tool for early identification of health risk and personalized intervention in clinical and athletic populations.

Keywords: hand grip strength, rate of force development, body composition, health risk, Lebanese adults, discriminant analysis, predictive modeling

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Сажетак

Увод:
Снага стиска шаке (ССШ) је широко коришћен, неинвазиван индикатор мишићне функције и укупног здравственог статуса. Међутим, традиционални приступи често занемарују осетљивост различитих параметара заснованих на мишићној јачини – као што су максимална јачина, брзина развоја силе (РФД) и координација међу екстремитетима – у предвиђању телесног састава и повезаних здравствених ризика. Ова студија је имала за циљ да процени дискриминаторни и предиктивни капацитет различитих алгоритама ССШ у класификацији профила телесног састава у вези са здрављем међу одраслим Либанцима.

Методе:
Укупно 395 одраслих Либанаца (242 мушкарца и 153 жене) учествовало је у овој трансверзалној студији. Антропометријске варијабле и варијабле телесне композиције су процењене коришћењем стандардизованих протокола, укључујући мере као што су БМИ, проценат телесне масти (%ПБФ), маса скелетних мишића (СММ), маса без масти (ФФМ), површина висцералне масти (ВФА) и индекс телесне композиције (ИБЦ). Неуромускуларне перформансе су процењене кроз максималну силу стисака шаке ($Ф_{макс}$), максималну брзину развоја силе ($РФД_{макс}$) и индекс синергије (ИС), при чему су израчунате и апсолутне и релативне вредности. Дискриминантна анализа је спроведена да би се појединци класификовали у кластере повезане са здрављем, а анализа вишеструке регресије је коришћена за развој предиктивних модела за резултат у вези са здрављем фитнеса (ФХРС_Индекс).

Резултати:
Дискриминантна анализа је показала високу тачност класификације (95,5% код мушкараца; 94,0% код жена), при чему су се $РФД_{макс}$_СУМ, ИС_СУМ и Доминант_$Ф_{рел}$ појавиле као најосетљивије варијабле. Регресиони модели су показали одличну предиктивну моћ (R^2 = 1.000) код оба пола. Перцентилни прагови ($15_{ти}$ перцентил) су успостављени у сврху дефинисања категорије ризика по здравље на основу дефинисаног критерија Стандардизованог Скора Резултата. Развијене су засебне предиктивне једначине за апсолутне и релативне параметре теста стиска шаке.

Закључак:
Налази потврђују да су специфичне варијабле теста стиска шаке – посебно оне које се односе на експлозивну снагу и координацију – веома осетљиве у класификацији статуса телесног састава у вези са здрављем. Предложени индекс ФХРС_индекс и утврђене граничне вредности перцентила нуде практичан алат за рану идентификацију здравственог ризика и персонализоване интервенције у клиничкој и спортској популацији.

Кључне речи: снага стиска руке, брзина развоја силе, састав тела, здравствени ризик, одрасли Либанци, дискриминантна анализа, предиктивно моделирање

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INTRODUCTION

Health is a fundamental aspect that significantly impacts individual well-being, societal development, and national security (Golubeva et al., 2022). Research emphasizes the unchanging perception of health as a crucial life domain over time and highlights the intricate relationship between health-related quality of life and overall life satisfaction (Vesić et al., 2022). Additionally, research on elderly populations indicates that health is perceived comprehensively, necessitating preventive care and supportive services to enhance quality of life while considering factors such as chronic diseases and social isolation (Smith et al., 2019).Promoting a healthy lifestyle is vital for personal growth, resilience against harmful influences, and societal advancement, with educational initiatives playing a key role in instilling health knowledge and values among the youth (Abdurakhmonov, 2021). The concept of Health in All Policies (HiAP) underscores the importance of integrating health considerations into public policies to address social determinants, prevent diseases, and enhance population health outcomes (Sihto et al., 2006).

Numerous health indicators are in existence to serve the purpose of either predicting or evaluating our current health condition or status. These indicators encompass a wide range of factors, including the extent of physical activity, such as participation in sports performance tests, analysis of body composition, as well as a diverse array of blood examinations. Furthermore, one can delve into the realm of clinical and laboratory assessments, which encompass examinations like kidney function tests, liver function evaluations, measurements of C-reactive protein (CRP) levels, and analysis of urine composition, all of which contribute significantly to the depth of understanding regarding one's health status. Collectively, these evaluations play a crucial role in facilitating the early identification, continuous monitoring, and effective management of various medical conditions, thereby providing a holistic and thorough assessment of an individual's overall state of health.

Based on the findings reported by Pubmed on 29/5/2024, it is evident that the hand grip test has garnered significant attention as a pivotal tool in the evaluation of both health status and sports performance. The graphical representation depicted in figure 1 underscores the remarkable surge in the number of research studies dedicated to exploring this particular subject matter. Particularly noteworthy is the year 2022, which witnessed a substantial total of 1,123 studies devoted to investigating various facets of the hand grip test. This proliferation of research endeavors sheds light on the profound significance attributed to this assessment tool within the academic and scientific communities. Furthermore, an examination of figure 2 reveals that the hand grip test has been extensively featured in diverse contexts and among various demographic groups. Different populations have utilized this test as a means of establishing benchmarks and guidelines, while others have leveraged it to gauge strength levels and other related parameters. The multifaceted nature of the hand grip test's applications underscores its versatility and relevance across a spectrum of disciplines and populations.

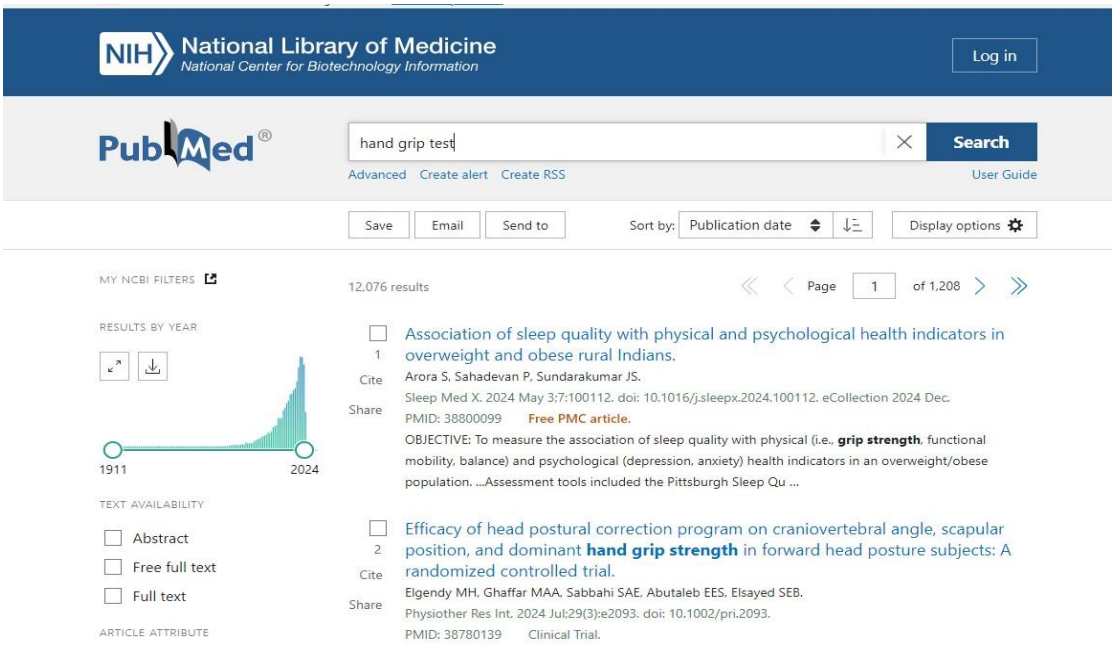


Figure 1: Highlights the significance of the hand grip test in research studies

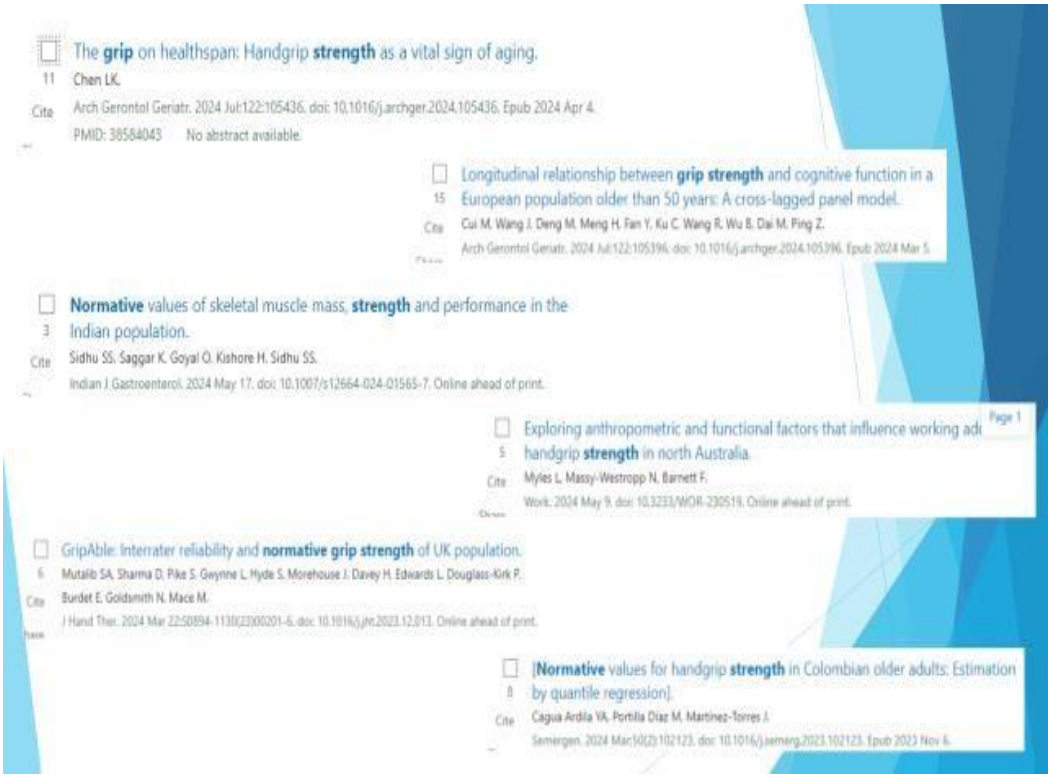


Figure 2: Highlight the Extensive Utilization of the Hand Grip Test Across Diverse Contexts and Demographic Groups

In addition, Handgrip strength assessment is an essential and valuable method utilized in various facets of health evaluation. Recent studies indicate that handgrip strength is associated with cognitive skills, specifically executive function, in people between 45 and 75 years old, highlighting its promise as a swift and economical predictor of cognitive wellness (Vesić et al., 2022). Furthermore, the strength of one's handgrip has been associated with negative health outcomes like mortality and the susceptibility to chronic ailments such as cardiovascular conditions, respiratory issues, cancer, and dementia, establishing it as a notable health indicator (Concha-Cisternas et al., 2022). Additionally, in individuals afflicted with chronic kidney disease (CKD), handgrip strength is correlated with motor skills and the steadiness of gait, functioning as a dependable screening tool prior to more physically demanding evaluations like the Timed Up and Go (TUG) test (Liu et al., 2022). Moreover, the accuracy and precision of handgrip strength assessment have been underscored in the detection of osteosarcopenic obesity (OSO) in elderly women, underscoring its significance as an alternative tool for identifying this particular condition (Dos Santos & Gobbo, 2020). In summary, handgrip strength testing offers a thorough evaluation of upper limb functionality, muscle power, and overall health condition, positioning it as a valuable and adaptable instrument in clinical environments.

That’s why establishing standards for hand grip strength assessments in populations is crucial due to the wide-ranging applications and significant health implications of this test. Given its association with various health outcomes, such as cognitive function, chronic disease susceptibility, and overall physical health, standardized benchmarks ensure accurate and consistent evaluations across different demographic groups. Standards enable healthcare providers to identify deviations from normative values, facilitating early detection of health issues, effective monitoring of disease progression, and timely interventions. Moreover, standardized hand grip strength assessments can enhance the comparability of research findings, contributing to more robust and reliable data in public health studies. This underscores the importance of developing and implementing standardized protocols for hand grip strength testing to maximize its utility in clinical and research settings.

Concerning body composition, a similar pattern can be observed in terms of hand grip strength as depicted in figure 3, showing an exponential growth trajectory from the year 1824 to 2024. The significance of studies focusing on body composition becomes evident through this analysis. While we may assume that we possess comprehensive knowledge on this subject, the data presented here indicates the existence of further insights that necessitate exploration in order to enhance our understanding of body composition. Figure 4 also illustrates the interconnectedness of body composition with various facets such as health, sports, population demographics, and others, underscoring the importance and relevance of this variable in different contexts.

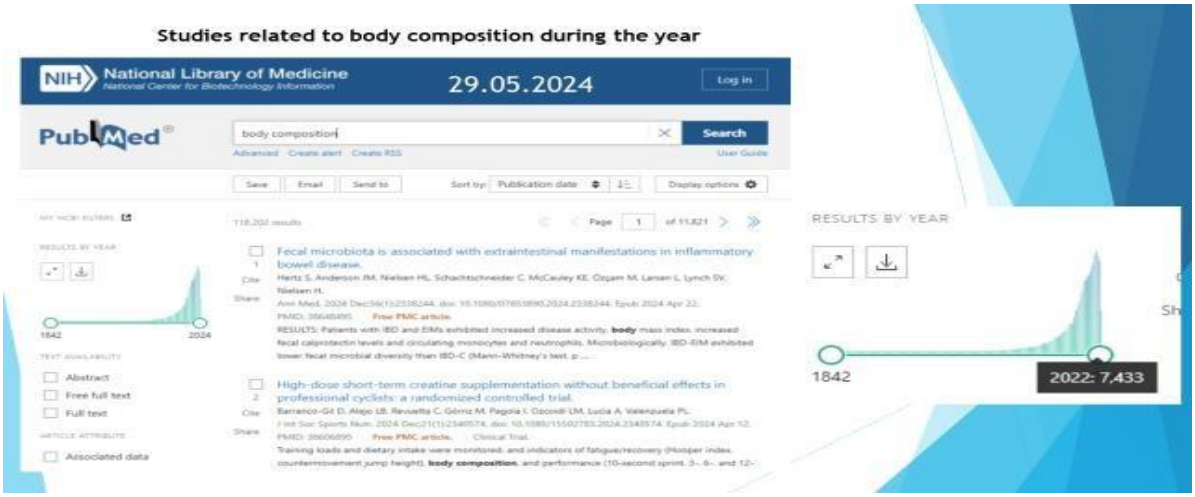


Figure 3: Highlights the significance of body composition in research studies

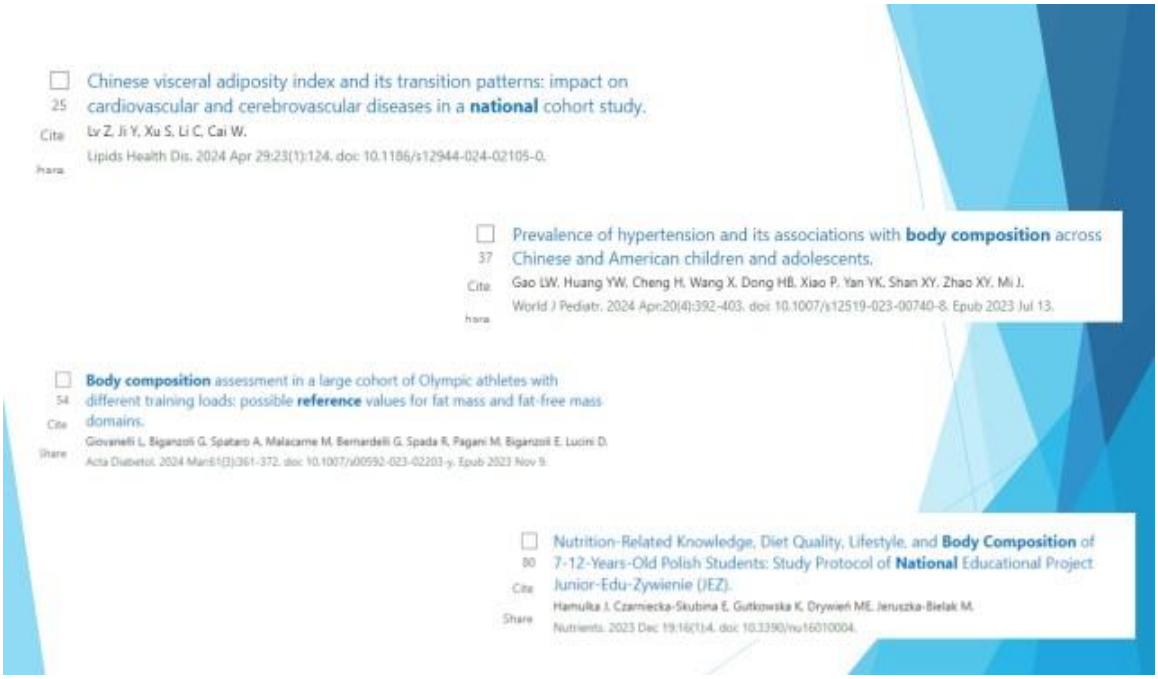


Figure 4: Interconnectedness of Body Composition with Health, Sports, Population Demographics, and Other Contexts

THEORITICAL FRAMEWORK AND DEFINITION

2.1. Body composition

2.1.1. Terms and definition

Body composition pertains to the diverse elements constituting the human body, primarily classified as fat mass (FM) and fat-free mass (FFM), encompassing muscle, bone, and water (Shah & Bilal, 2009; Hemke et al., 2020; Dumuid et al., 2021). It serves as a crucial indicator of health, fitness, and nutritional status, impacting conditions like obesity, sarcopenia, and osteoporosis (Mala et al., 2015). The prevalent twocomponent model, which segregates body mass into FM and FFM, is favored due to its simplicity, while more intricate models such as three- and four-component models enhance accuracy by incorporating additional compartments like bone mineral content and total body water (Zhu & Wang, 2011; Fosbøl & Zerahn, 2015). Different approaches are applied in analyzing body composition, such as hydrostatic weighing, DXA scanning, BIA, and skinfold measurements, each with specific pros and cons (Lim, 2022; Ferreira et al., 2022; Zborowski & Mikulec, 2022). Sophisticated imaging techniques like computed tomography (CT) and magnetic resonance imaging (MRI) provide detailed anatomical information and are employed for measuring specific tissues such as skeletal muscle and intra-abdominal fat. Evaluation of bodily composition is essential in clinical settings for the detection and treatment of disorders like anorexia, obesity, and chronic illnesses, as well as in the realm of sports science for maximizing athletic performance by balancing muscle mass and fat distribution. The statistical methodology for body composition frequently incorporates compositional data analysis, which examines the relative proportions of various body components and their correlations with health outcomes. In general, research on body composition has progressed significantly, offering valuable insights into human health and disease, and remains a crucial domain of research and clinical application.

2.1.2 Diseases related to body composition

Body composition, is a very important element of human well-being, involves the relative distribution of diverse constituents within the physical structure, such as adipose tissue, skeletal muscle, osseous matter, and bodily fluids. The existence of disparities in these constituents can precipitate an array of medical conditions, a phenomenon that has witnessed a surge in occurrence within contemporary society. The intricate interplay of these bodily components underscores the significance of maintaining a harmonious balance for optimal health outcomes.

Obesity is one of the most well-known conditions related to body composition, which has spread widely and rapidly across the world, affecting a large number of people. Obesity is due to the excessive of body fat in human body. (Determinants of obesity in Latin America, 2024).

Obesity has a negative effect on health, significantly increasing the risk of developing numerous conditions, including type 2 diabetes, high blood pressure, abnormal cholesterol levels, and certain types of cancer (Watanabe et al., 2023). Shockingly, the prevalence of obesity is rising, particularly

among children and adolescents, posing a significant public health challenge for the future (González et al., 2024; European Association for the Study of Obesity [EASO], 2023)

Visceral adiposity, which is the accumulation of fat within the abdominal cavity, is a significant factor in disease risk (Raheem et al., 2022). People with higher levels of visceral fat face a greater risk of developing serious health conditions such as type 2 diabetes and cardiovascular disease, compared to those whose fat is distributed more around the periphery of their bodies (Raheem et al., 2022). This type of fat is particularly dangerous because it promotes a pro-inflammatory state, leading to insulin resistance and various metabolic issues.

Additionally, an imbalance in body composition can lead to cardiovascular disease, which is the leading cause of death worldwide. Obesity leads to harmful changes in the heart, including thickening of the heart muscle, enlargement of the heart chambers, and difficulties in both pumping and relaxing the heart. It also impairs the function of blood vessels (Apovian & Gokce, 2012). These changes significantly increase the risk of heartrelated health issues, making it crucial to maintain a healthy body composition.

Furthermore, having exceeding of body fat mass is not only the cause for having diseases, we have also the presence of low skeletal muscle mass that leads to serious various health problems across various age groups and conditions. For older adults having low proportion of skeletal muscle mass will be lead to a decline in cognitive impairment and dementia, potentially due to dysfunctional of myokine secretion, systemic inflammation, impaired insulin metabolism and mitochondrial dysfunction (Oudbier et al., 2022). Also we have Sarcopenia, that is characterized by low muscle mass, that also leads to increase the risk of falls, distal radius fractures, and cardiovascular disease (CVD) in the elderly (OH et al., 2022). In addition, low skeletal muscle mass is a significant risk factor for developing type 2 diabetes mellitus (T2D) and prediabetes, because it affects glucose metabolism and insulin sensitivity (Ibragimova et al., 2022). Patients with non – alcoholic fatty liver disease (NAFLD), Low appendicular skeletal muscle mass (ASM%) is associated with more severe liver conditions, including steatosis, non –alcoholic steatohepatitis (NASH), and liver fibrosis, especially in those carrying the PNPLA3 rs738409 polymorphism (Pan et al., 2022; Kang & Park, 2021). In addition, also more diseases are linked to low level of skeletal muscle mass like subclinical atherosclerosis in NAFLD patients Low skeletal and it can increase the risk of adverse outcomes in cancer patients and may be associated with poorer prognosis and recovery (Looijaard et al., 2021), Plus it is also related to certain inflammatory cytokine levels (Ito et al., 2021). Concerning the children and adolescent population, low muscle mass result in metabolic dysregulation (Alabadi et al., 2023).

Table 1: Health Conditions Related to High Body Fat

Population Group	Condition/Factor	Related Diseases/Health Issues	Impact	Reference
General Population	Obesity	Type 2 Diabetes, High Blood Pressure, Abnormal Cholesterol Levels, Certain Types of Cancer	Increases risk of chronic diseases, reduces quality of life, leads to premature mortality	(Determinants of obesity in Latin America, 2024; Watanabe et al., 2023)
Children and Adolescents	Obesity	Increasing prevalence, Public health challenge	Leads to early onset of chronic diseases, affects growth and development, increases healthcare costs	(Determinants of obesity in Latin America, 2024; Diabetes Conferences, 2023)
General Population	Visceral Adiposity	Type 2 Diabetes, Cardiovascular Disease	Promotes inflammation, insulin resistance, and metabolic syndrome, leading to severe health complications	(Raheem et al., 2022)
Elderly	Obesity	Heart Muscle Thickening, Heart Chamber Enlargement, Pumping and Relaxing Difficulties, Impaired Blood Vessel Function	Causes cardiovascular strain, increases risk of heart failure, and vascular diseases	(Apovian & Gokce, 2012)

This table clearly summarizes the related diseases and impacts of high body fat on human health.

Table 2: Health Conditions Related to Low Skeletal Muscle Mass

Population Group	Condition/ Factor	Related Diseases/Health Issues	Impact	Reference
Older Adults	Low Skeletal Muscle Mass	Cognitive impairment, Dementia, Systemic inflammation, Impaired insulin metabolism, Mitochondrial dysfunction	Leads to reduced cognitive function, increased frailty, higher risk of falls, and metabolic dysregulation	(Oudbier et al., 2022)
Elderly	Sarcopenia (low muscle mass)	Increased risk of falls, Distal radius fractures, Cardiovascular disease (CVD)	Increases risk of fractures and cardiovascular events, reduces mobility and independence	(OH et al., 2022)
All Age Groups	Low Skeletal Muscle Mass	Type 2 Diabetes Mellitus (T2D), Prediabetes	Impairs glucose metabolism and insulin sensitivity, increasing risk of diabetes	(Ibragimova et al., 2022)
Patients with NAFLD	Low Appendicular Skeletal Muscle Mass (ASM%)	Severe liver conditions (steatosis, NASH, liver fibrosis), Subclinical atherosclerosis	Worsens liver conditions and cardiovascular health, increasing morbidity and mortality	(Pan et al., 2022; Kang & Park, 2021)
Cancer Patients	Low Skeletal Muscle Mass	Poorer prognosis and recovery, Increased risk of adverse outcomes	Leads to reduced treatment efficacy, increased complications, and higher mortality	(Looijaard et al., 2021)
General Population	Low Skeletal Muscle Mass	Certain inflammatory cytokine levels	Contributes to systemic inflammation and related chronic conditions	(Ito et al., 2021)
Children and Adolescents	Low Muscle Mass	Metabolic dysregulation	Affects growth and development, increases risk of metabolic syndrome	(Alabadi et al., 2023)

This table summarized the related diseases and health issues associated with low skeletal muscle mass across various populations.

2.2 Hand grip test

2.2.1 Terms and definition

The hand grip test is a widely used method for assessing muscle strength and overall musculoskeletal health (Aydik & Özener, 2023). Hand grip strength (HGS) refers to the maximum force exerted by the hand muscles when gripping an object, measured using a hand grip dynamometer (Sayer et al., 2015). This test evaluates maximal voluntary contraction (MVC) through isometric contraction, providing reliable and valid measurements of muscle strength (Neidenbach et al., 2019). High reliability and validity are crucial, as they ensure consistent and accurate results, making the hand grip test a trusted tool in both clinical and research settings (Savas et al., 2023). Normative data, which represent typical HGS values for specific populations, allow for meaningful comparisons and identification of deviations that may indicate health issues (Dopsaj et al., 2022). In addition, the hand grip test is also a valuable tool for assessing muscle strength in different populations such as adolescents, adults, elderly, and patients with different chronic disease (Ojeda et al., 2021; Luo et al., 2019).

2.2.2 The Importance and Mechanism of Handgrip Strength in Human Interaction and Evolution

The human hand stands out as one of the most unique organs of the human species when it comes to interacting with the surrounding environment (Almécija et al., 2015). Additionally, it holds a crucial role in the successful progression of humans. In the day-today activities, hands serve as the fundamental body parts for carrying out manipulative tasks, being specifically adapted for a variety of motor skills essential for engaging with physical objects (McMillan & Carin-Levy, 2012). This biological aspect explains why the handgrip movement and the strength levels achieved are identified as a constraining factor in all manipulative actions performed by the upper body, irrespective of whether these activities are related to daily routines, professional tasks, or sports engagements (Orr et al., 2017; Zarić et al., 2018; Dopsaj et al., 2019). The hand employs a specific mechanism for grasping handles and handling large, heavy tools through what is known as the power grip, where all fingers are flexed around the objects being held (McMillan & Carin-Levy, 2012). The power grip represents the most basic yet potent grasping motion, making it an ideal posture for assessments, particularly for the arms and cranial regions. Consequently, the handgrip strength test has gained recognition as a widely-used assessment tool that can be easily applied across different population groups (Perna et al., 2016; Orr et al., 2017; Zarić et al., 2018; Trajkov et al., 2018; Dopsaj et al., 2018; Dopsaj et al., 2019).

2.2.3. The Comprehensive Role of Handgrip Strength as a Predictor of Health Outcomes

Handgrip strength measurement has become a widely recognized tool in clinical and research settings for assessing overall muscle strength and physical function (Eckman et al., 2014; Newman et al., 1984; Celis-Morales et al., 2018; Ji et al., 2020). This simple, non-invasive test, conducted using a hand dynamometer, is significantly associated with various clinical conditions such as malnutrition, type 2 diabetes, functional disability, and overall quality of life (Celis-Morales et al., 2018; Eckman et al., 2014; Ji et al., 2020).

Research has extensively studied handgrip strength as a reliable indicator of overall health and disease status. Low handgrip strength is linked to an increased risk of adverse health outcomes, including cardiovascular disease, metabolic syndrome, respiratory disease, and cancer. The strong relationship between handgrip strength and cardiovascular outcomes has been well-documented (Eckman et al., 2014; Celis-Morales et al., 2018). Additionally, handgrip strength is inversely associated with the prevalence of metabolic syndrome, a cluster of conditions that increase the risk of heart disease, stroke, and type 2 diabetes (Eckman et al., 2014; Ji et al., 2020).

Beyond cardiovascular and metabolic conditions, handgrip strength has been linked to respiratory function and cancer prognosis. Lower handgrip strength correlates with poorer respiratory function and higher mortality in individuals with respiratory diseases. It also serves as a prognostic marker for cancer outcomes, with lower grip strength associated with poorer prognosis.

Handgrip strength is an accessible measure that can provide valuable insights into an individual's health status. The literature indicates its potential as a screening tool, especially in settings with limited access to complex medical assessments (Eckman et al., 2014; Rijk et al., 2015; Ji et al., 2020; Celis-Morales et al., 2018).

Handgrip strength (HGS) is a validated measure of overall health, offering significant insights into various health outcomes. HGS is linked to muscle mass and can diagnose malnutrition and predict long-term mortality in patients with cirrhosis (Guo et al., 2023). It is an independent predictor of stroke in middle-aged and older populations, though its association with heart disease varies by region (Li et al., 2023). HGS correlates positively with dietary antioxidant intake, such as vitamin E, selenium, and zinc, which enhance muscle strength in males (Wu et al., 2023). In cancer patients, particularly those with cachexia, reduced HGS is associated with higher mortality and decreased functional status (Hadzibegovic et al., 2024). HGS is a reliable indicator of adverse health outcomes, including mortality, chronic diseases, and dementia, making it a valuable clinical tool (Concha-Cisternas et al., 2023). Among people living with HIV, higher HGS is linked to better body composition and lower cholesterol levels (Gouvêa-e-Silva et al., 2023). In older adults, HGS predicts institutionalization, hospitalization, and death, highlighting its utility in primary healthcare for early identification of at-risk individuals (Santos & Paúl, 2022). HGS and appendicular lean mass index (ALMI) decline with age, influenced by body composition, nutrition, and physical activity (Wen et al., 2023). HGS is also associated with better visual acuity, longer ocular axial length, and lower prevalence of diabetic retinopathy (Bibkov et al., 2023). Stronger HGS correlates with better cognitive functioning, mental health, and brain structure, particularly in subcortical regions and temporal cortices, which may help mitigate cognitive decline during aging (Jiang et al., 2022). Overall, the HGS test is a robust, low-cost measure that provides comprehensive insights into an individual's health status across various domains.

Table 3: Health Outcomes Predicted by Hand Grip Strength Measurements

Predictive Factor	Associated Health Outcomes
Muscle Mass	- Diagnoses malnutrition - Predicts sarcopenia and dynapenia - Indicates risk of falls - Predicts osteoporosis - Linked to overall functional status
Body Fat and Metabolic Health	- Inversely related to body fat percentage - Assesses metabolic syndrome - Indicates risk of obesity and related metabolic disorders
Nutritional Status	- Reflects nutritional status - Correlates with dietary antioxidants like vitamin E, selenium, and zinc
Cardiovascular and Respiratory Health	- Predicts cardiovascular disease - Linked to stroke risk in older populations - Indicates respiratory function and mortality in respiratory diseases
Cancer Prognosis	- Serves as a prognostic marker for cancer outcomes - Associated with mortality and decreased functional status in cancer patients
Chronic Diseases and Dementia	- Indicates risk of chronic diseases - Predicts dementia
HIV-Related Health Outcomes	- Linked to better body composition and lower cholesterol levels in people living with HIV
Geriatric Health	- Predicts institutionalization, hospitalization, and death in older adults
Visual Health	- Associated with better visual acuity - Linked to longer ocular axial length and lower prevalence of diabetic retinopathy
Cognitive Function and Mental Health	- Correlates with better cognitive functioning and mental health - Linked to brain structure in subcortical regions and temporal cortices
Longitudinal Monitoring	- Monitors changes in body composition over time in response to interventions

This table summarizes the various health outcomes that hand grip strength can predict, providing insights into overall human health status.

2.2.4 Hand grip test and body composition

Based on the previous studies discussed in section 2.2.3, it is evident that there is a significant relationship between body composition and hand grip strength. The handgrip strength (HGS) test is a widely recognized and valuable tool for assessing overall health, with strong correlations to various aspects of body composition. Research indicates that HGS is closely linked to muscle mass, serving as an effective metric for diagnosing conditions such as malnutrition and predicting long-term health outcomes in patients (Guo et al., 2023). Studies have shown that handgrip strength is inversely related to the prevalence of metabolic syndrome, highlighting its role in assessing and monitoring body

composition and related health risks (Eckman et al., 2014; Ji et al., 2020). Additionally, HGS correlates positively with dietary antioxidant intake, particularly nutrients like vitamin E, selenium, and zinc, which are essential for maintaining muscle strength and overall body composition (Wu et al., 2023). The decline in HGS and appendicular lean mass index (ALMI) with age further underscores the relationship between muscle strength and body composition, influenced by factors such as nutrition and physical activity (Wen et al., 2023).

Moreover, hand grip strength serves as a significant indicator of muscle mass, acting as a non-invasive marker for muscular health (Aydik & Özener, 2023). It shows an inverse relationship with body fat percentage, particularly in older adults, making it a useful predictor of body fat (Eghbali et al., 2017). Strong hand grip strength is associated with lower risks of obesity and related metabolic disorders, emphasizing its role in health risk assessment (Triana-Reina et al., 2022). It is considered a reliable global health indicator that reflects nutritional status and physical health in various populations (Concha-Cisternas, 2022). Hand grip strength provides a simple, repeatable measure for longitudinal monitoring, allowing for the assessment of changes in body composition over time in response to interventions (Dufner et al., 2020).

In addition, hand grip strength can predict conditions such as sarcopenia, dynapenia, and osteoporosis, as well as the risk of falls (Freitas et al., 2024). This measure is closely related to low muscle mass and high body fat, serving as a comprehensive predictor of various health risks. Overall, the findings from previous studies confirm the integral connection between body composition and hand grip strength, demonstrating that HGS is a robust, low-cost measure that provides comprehensive insights into an individual's health status across various domains.

Table 4: Mutual Diseases and Health Outcomes Predicted by Hand Grip Strength Related to Body Composition

Predictive Factor	Related Diseases/Health Issues	Body Composition
Muscle Mass	- Sarcopenia- Dynapenia- Osteoporosis- Risk of Falls	Low Skeletal Muscle Mass
Body Fat and Metabolic Health	- Obesity- Metabolic Syndrome- Type 2 Diabetes	High Body Fat
Cardiovascu lar and Respiratory Health	- Cardiovascular Disease- Stroke Risk- Respiratory Diseases	High Body Fat
Cancer Prognosis	- Poorer Prognosis and Recovery- Increased Mortality	Low Skeletal Muscle Mass
Chronic Diseases and Dementia	- Chronic Diseases- Dementia	Low Skeletal Muscle Mass
Nutritional Status	- Malnutrition	Low Skeletal Muscle Mass

Based on the information from Tables 1, 2, and 3, we can observe that there are several mutual diseases and health outcomes that can be predicted through the hand grip strength test. The hand grip strength test serves as a reliable indicator for conditions related to body composition, including obesity, sarcopenia, dynapenia, osteoporosis, and the risk of falls. It is also predictive of metabolic syndrome, cardiovascular diseases, type 2 diabetes, respiratory diseases, and cancer prognosis. This

demonstrates the comprehensive utility of hand grip strength measurements in assessing and monitoring a wide range of health conditions linked to both high body fat and low skeletal muscle mass.

2.2.5 Hand grip strength is an indicator for sports performance

Hand grip strength has been shown to be a surprisingly versatile indicator of physical fitness performance, extending far beyond just grip-dependent activities. (Taeymans et al., 2009) found that hand grip strength can predict adult static strength from a young age, particularly in females. This suggests that a strong grip reflects well-developed overall musculature. Furthermore, research suggests that athletes, particularly in sports like wrestling, judo, and rock climbing, may experience enhanced performance with greater hand grip strength. (The Effect of Hand Dimensions, Hand Shape and Some Anthropometric Characteristics on Handgrip Strength in Male Grip Athletes and Non Athletes, 2011) This is logical, as many athletic movements require full-body force transmission, which a strong grip can facilitate. Even in sports like climbing where grip strength is paramount (Cutis & Bollen, 1993) found it's not the sole predictor of success, implying it contributes to a wider foundation of athleticism. This correlation across various disciplines suggests that hand grip strength, while a simple measurement, can offer valuable insight into an individual's overall athletic potential and performance capabilities.

This information underscores the need for further emphasis on this topic, given the existing lack of comprehensive data on the relationship between hand grip strength and various athletic performances (e.g., running, jumping, throwing, change of direction) and different strength exercises (e.g., bench press, deadlift, squat). There is a notable deficiency in accurate information regarding which types of strength movements or athletic performance activities correlate most strongly with hand grip strength or other key parameters of hand grip. Addressing this gap would provide better predictors for sports performance in both children and adults, aiding in the determination of the most suitable sports based on hand grip results. Additionally, this knowledge could play a crucial role in monitoring progress for athletes and children, enabling more effective training and development strategies.

2.2.6 Key parameters of hand grip strength

Recent studies have primarily utilized hand grip maximal force (F_max) as an indicator of health and strength. However, emerging research by Dopsaj et al. (2022) and Chethana et al. (2023) suggests the inclusion of additional parameters to provide a more comprehensive assessment of hand grip strength. These parameters include Explosive Hand Grip Strength (Rate of Force Development, RFD), Relative Hand Grip Strength, Relative Explosive Strength, and the Index of Synergy. Incorporating these metrics for both the dominant and non-dominant hands, as well as their combined sum, offers a more nuanced understanding of hand grip strength. This broader approach can enhance the predictive validity for various health and performance outcomes, thereby providing valuable insights for both clinical and athletic contexts.

2.2.7 Factors affecting hand grip strength

Hand grip strength serves as a crucial indicator of overall physical fitness and has been extensively utilized in clinical and research environments to evaluate various facets of human health and functionality. Numerous factors influence hand grip strength, including age, gender, body composition, ethnicity, and a range of physiological and biomechanical aspects.

One pivotal determinant of hand grip strength is age. Grip strength typically increases during childhood and adolescence, peaks in early adulthood, and gradually diminishes with age (McGrath et al., 2020). This trend is likely linked to changes in muscle mass, muscle fiber composition, and neuromuscular function over the lifespan (Malina et al., 2004).

Gender is another significant factor shaping hand grip strength. Studies have shown that, on average, males exhibit higher hand grip strength compared to females, even after adjusting for variations in body size and composition (Montalcini et al., 2016; Dopsaj et al., 2022). This difference is primarily due to the larger muscle mass and greater muscle fiber cross-sectional area typically observed in males (Ben Mansour et al., 2021; Bandyopadhyay, 2008).

Anthropometric aspects such as height and weight are strongly correlated with hand grip strength. Individuals with greater height and weight generally possess increased muscle mass and muscle cross-sectional area, contributing to enhanced grip strength (Liao, 2016; Kasović et al., 2023). This association is more pronounced in boys than girls, particularly during the adolescent growth phase (Ben Mansour et al., 2021).

Developmental trajectories of hand grip strength may vary depending on an individual's maturation status. Some studies suggest that grip strength is a more reliable predictor of overall static strength in early-maturing and average-maturing females compared to males, implying that hormonal fluctuations and other maturation-related factors may also play a role in grip strength development (Taeymans et al., 2009).

Additionally, ethnicity can influence hand grip strength variations, as genetic and cultural differences may affect muscle development and physical activity levels (McGrath et al., 2020). Body fat percentage is another significant factor, with higher body fat often associated with lower muscle strength due to its detrimental impact on muscle function. Health-related quality of life, encompassing physical, mental, and social well-being, also affects hand grip strength; individuals with higher overall health-related quality of life typically exhibit stronger grip strength due to better overall health and fitness levels (Kang et al., 2021). The size and strength of the forearm muscles are directly related to hand grip strength, as these muscles are primarily responsible for generating the force needed for a strong grip (Abe & Loenneke, 2015).

Neural components also play a crucial role in hand grip strength. Research has shown that stronger grip strength is associated with increased grey matter volume in subcortical regions and temporal cortices of the brain. These brain regions' volumes correlate with better mental health and significantly mediate their relationship with grip strength (Jiang et al., 2022). Additionally, neural tissue mobilization has been found to improve grip strength in patients with cervical radiculopathy (Nair et al., 2017).

In summary, hand grip strength is influenced by a multifaceted interplay of factors, including age, gender, body composition, ethnicity, physiological aspects, and neural components. Understanding

these factors is essential for accurately assessing and interpreting hand grip strength in clinical and research settings.

This table summarizes the factors that affect hand grip strength, highlighting that it is not only muscle mass and body size that play a role but also various other factors such as age, gender, ethnicity, neural components, fitness level, and additional considerations that should be taken into account.

According to the data provided in Table 5, certain factors that affect hand grip strength are within an individual's control. While variables such as age, gender, height, and ethnic background are not modifiable, adopting regular physical activity to increase muscle mass and decrease body fat can improve hand grip strength. Additionally, increasing the thickness of forearm muscles through appropriate workouts can further enhance grip strength. Finally, adopting a nutritious lifestyle by consuming essential nutrients and avoiding high-calorie, low-nutrient foods can also improve hand grip strength.

Table 5: Summary of the factors affecting hand grip strength

Factor	Description
Age	Increases during childhood and adolescence, peaks in early adulthood, declines with age
Gender	Males generally have higher grip strength than females, linked to muscle mass and fiber size
Anthropometric Factors	Height and weight are correlated with grip strength; greater height and weight enhance muscle mass
Maturation Status	Early and average maturation affects grip strength differently, influenced by hormonal changes
Ethnicity	Genetic and cultural differences impact muscle development and physical activity levels
Body Fat Percentage	Higher body fat is associated with lower muscle strength due to its impact on muscle function
Health-Related Quality of Life	Better overall health and fitness levels correlate with stronger grip strength
Forearm-Muscle Characteristics	Size and strength of forearm muscles are crucial for generating grip strength
Neural Components	Grey matter volume in brain regions correlates with grip strength and mental health

Enhancing these conditions can lead to better hand grip strength, which in turn can improve overall well-being. As discussed in previous sections, a low level of hand grip strength is associated with an increased risk of certain diseases, making it a predictor of health and fitness levels. Therefore, increasing hand grip strength can contribute to improved health and fitness.

2.3 Importance of having body composition characteristics for population

According to previous studies that were mentioned above we can know now how much is important the body composition in our life concerning athlete, elderly and general public in order to improve our health and sports performance and to identify early signs of diseases.

Given its comprehensive benefits, implementing body composition assessments as a routine part of health evaluations can significantly contribute to better health management across various

populations. This approach ensures that interventions are tailored to the specific needs of individuals, leading to more personalized and effective healthcare solutions.

Furthermore, having a clear understanding of the body composition characteristics of a population allows for the identification of public health trends and the development of targeted public health campaigns. This knowledge is essential for allocating resources effectively and designing community programs that address specific health risks prevalent in different demographic groups. By recognizing and addressing these trends, healthcare systems can more proactively combat the rising rates of obesity, diabetes, and cardiovascular diseases, ultimately leading to a healthier society.

2.3.1 Analysis of Body Typologies and Age-Related Physical Characteristics

A study was conducted on Kyrgyz women provided important insights into their body types and how they change with age. The research categorized women into four main body types: leptosomatic (20%), mesosomatic (32%), megalosomatic (33%), and indefinite (15%). Within these groups, they identified various body shapes, such as:

- Stenoplastic (66%-77% of the leptosomal group)
- Asthenic thin bone (18%-24%)
- Broad bone (5%-10%)
- Mesoplastic (31%-66%)
- Picnic (34%-69%)

The study also looked at how body measurements change with age, dividing the participants into juvenile, adulthood I, and adulthood II groups. They calculated BMI by dividing body weight in grams by height in centimeters. The researchers differentiated body shapes into categories like asthenic, stenoplastic, mesosomatic-picnic, mesoplastic, and megalosomatic with athletic, sub-athletic, and euriplastic somatotypes. They also noted an indefinite category for those who didn't fit into other groups.

The significance of this study is that it highlights the importance of understanding different body types and how they change with age. This information is crucial for creating personalized medical treatments. It fills a gap in knowledge about body types and variations among Kyrgyz women, providing valuable insights into BMI and fat body mass across different age and body type groups. These findings emphasize the need for personalized medical approaches (Sakibaev et al., 2020).

Another study was conducted on older adults in a retirement village identified four physical typologies: strong sedentary, weak sedentary, overweight active, and lean active. The lean active group, typically younger, had the lowest BMI and body fat percentage, and excelled in gait speed, step count, and all levels of physical activity compared to other groups. They also engaged in more vigorous physical activity and walked significantly more than the sedentary groups. These findings highlight the importance of customizing health programs to fit individual needs, focusing on diet and physical activity based on each typology. Encouraging regular exercise can improve muscle mass, strength, and overall physical function, helping maintain independence and quality of life. Nutrition education sessions can positively influence dietary behaviors, while providing gyms, pools, and social walking groups can promote physical activity, though efforts to increase participation may be needed.

Regular weight checks and assessments of functional strength and mobility can help maintain a healthy BMI and physical function. Understanding and addressing different physical typologies and activity levels can enhance the design of interventions to promote health and well-being in retirement village residents (De Villiers et al., 2019).

A study carried out by Dopsaj et al., 2020 was conducted with the objective of examining the alterations in skeletal muscle mass (SMM) throughout adulthood and aging within a sizable cohort of Serbian adults. The examination involved the evaluation of body composition in 8733 individuals (3370 females and 5363 males) ranging in age from 18 to 79 years. Various metrics, such as protein mass, fat-free mass, and skeletal muscle mass index (SMMI), were employed in the study to scrutinize the correlation between age and muscularity. The results indicated that SMMI and percent skeletal muscle mass (PSMM) are the most responsive parameters to age-related variations, displaying a notable decrease in both genders with advancing age. This investigation emphasizes the significance of monitoring muscle mass for comprehending the aging process and devising strategies that could promote the preservation of muscle health and overall physical well-being. Furthermore, the findings underscore the necessity for gender-specific methodologies in the assessment and management of muscle mass reduction, given the differing trends in decline observed between males and females. Table 6 shows the skeletal muscle mass indicators for the Serbian population.

Table 6: Age-Related Changes in Skeletal Muscle Mass Indicators by Gender for Serbian Population (PM – Protein Mass; PPM – Percent of Protein Mass; SMM – Skeletal Muscle Mass; PSMM – Percent Skeletal Muscle Mass; SMMI – Skeletal Muscle Mass Index, Dopsaj et al., 2020)

Age Group (Years)	Gender	PM (kg)	PPM (%)	SMM (kg)	(PSMM, %)	(SMMI, kg/m²)
18–29.9	Male	14.16 ± 1.76	17.14 ± 1.36	40.73 ± 5.31	49.27 ± 3.96	12.13 ± 1.06
	Female	9.31 ± 1.37	14.76 ± 1.56	26.09 ± 4.17	41.29 ± 4.49	9.03 ± 0.98
30–39.9	Male	14.19 ± 1.81	15.65 ± 1.46	40.78 ± 5.53	44.95 ± 4.28	12.30 ± 1.18
	Female	9.55 ± 1.09	13.95 ± 1.79	26.81 ± 3.31	39.14 ± 5.04	9.37 ± 1.01
40–49.9	Male	14.06 ± 1.71	15.36 ± 1.34	40.40 ± 5.13	44.12 ± 3.88	12.29 ± 1.13
	Female	9.49 ± 1.04	13.43 ± 1.61	26.66 ± 3.13	37.66 ± 4.55	9.46 ± 0.87
50–59.9	Male	13.64 ± 1.65	15.02 ± 1.11	39.12 ± 4.98	43.04 ± 3.17	12.04 ± 0.90
	Female	9.02 ± 1.11	12.54 ± 1.51	25.22 ± 3.34	35.01 ± 4.21	9.29 ± 0.96
60–69.9	Male	13.01 ± 1.72	14.32 ± 1.52	37.24 ± 5.19	40.94 ± 4.30	11.59 ± 1.23
	Female	9.19 ± 1.54	11.86 ± 1.48	25.73 ± 4.66	33.13 ± 4.09	9.67 ± 0.46
70–79.9	Male	11.05 ± 1.59	13.58 ± 0.89	30.91 ± 4.82	37.94 ± 2.68	10.39 ± 1.03
	Female	7.89 ± 0.67	11.84 ± 1.09	21.75 ± 2.05	32.63 ± 3.07	9.09 ± 0.54

This table reflects the data provided in the study, focusing on muscle mass indicators by age group and gender.

A study done by Larsson and his team back in 2015 to check out how bodies are built across different age groups in Swedish grown-ups. They looked at info from four different studies with 1424 folks aged between 20 and 75. They employed something known as dualenergy X-ray absorptiometry

(DXA) to assess body composition. And guess what? The examination illustrated that as individuals get older, their body mass index (BMI) and fat mass (FM) go up, while fat-free mass (FFM) remains approximately the same until the age of 60, at which time it starts to decrease. Basically, this study gives us some useful info about how bodies are made up in Sweden, showing how fat and muscle change with age and why it's important to have health plans that fit different age groups. Table 7 will show us the body composition metrics related to Swedich Population.

Table 7: Body Composition Metrics Across Different Age Groups in Swedish Population (FM – Fat Mass; FMI – Fat Mass Index; FFM – Fat Free Mass; SMM – Skeletal Muscle Mass; SMMI – Skeletal muscle mass Index; Larsson et al., 2015)

Age Group	Gender	FM (kg)	FM %	FMI (kg/m²)	FFM (kg)	FFMI (kg/m²)	SMM (kg)	SMM %	SMMI (kg/m²)
20-29	Males	15.2 ± 7.4	18.9 ± 7.2	4.6 ± 2.2	62.8 ± 6.5	18.9 ± 1.3	33.8 ± 3.9	43.7 ± 3.9	10.2 ± 0.8
30-39		18.9 ± 6.7	22.7 ± 5.9	5.8 ± 2.0	62.6 ± 6.8	19.1 ± 1.5	32.7 ± 3.9	40.7 ± 3.3	10.0 ± 1.0
40-49		20.0 ± 6.7	23.8 ± 5.9	6.2 ± 2.1	62.4 ± 6.0	19.4 ± 1.5	32.7 ± 3.5	39.8 ± 3.5	10.1 ± 0.9
50-61		21.7 ± 7.4	25.2 ± 5.9	6.8 ± 2.2	62.1 ± 6.9	19.5 ± 1.7	32.3 ± 3.8	39.1 ± 3.2	10.1 ± 0.9
75		23.9 ± 6.8	28.8 ± 6.3	7.8 ± 2.3	58.2 ± 7.9	18.9 ± 1.7	29.0 ± 4.3	35.5 ± 3.5	9.4 ± 1.0
20-29	Females	19.1 ± 6.7	29.7 ± 7.0	6.8 ± 2.5	43.8 ± 3.8	15.6 ± 0.8	22.2 ± 2.3	35.6 ± 3.6	7.9 ± 0.6
30-39		21.1 ± 7.1	31.5 ± 6.8	7.6 ± 2.6	44.8 ± 6.0	15.9 ± 1.4	22.4 ± 3.7	34.1 ± 3.9	7.9 ± 0.9
40-49		23.1 ± 8.4	33.0 ± 7.7	8.2 ± 3.1	45.4 ± 7.6	16.0 ± 1.7	22.6 ± 4.6	33.4 ± 4.3	8.0 ± 1.0
50-61		25.8 ± 8.1	36.4 ± 7.2	9.5 ± 3.0	43.8 ± 6.1	16.0 ± 1.5	21.8 ± 3.6	31.6 ± 3.9	7.9 ± 0.9
75		28.2 ± 10.5	38.8 ± 8.1	10.8 ± 3.9	42.4 ± 5.2	16.1 ± 1.5	20.0 ± 2.7	29.0 ± 4.2	7.6 ± 0.7

This Table presents the body composition metrics, including fat mass, fat-free mass, and skeletal muscle mass, across different age groups in the Swedish population for both men and women.

A Research conducted by Dopsaj et al. (2021) explored the variations in body fatness and nutritional status related to age among a substantial cohort of Serbian women aged between 20 and 70 years. The investigation involved the examination of 1937 women through the utilization of multisegmental bioelectrical impedance for the evaluation of body composition parameters like BMI, body fat mass (BFM), percentage of body fat (PBF), body fat mass index (BFMI), and visceral fat area (VFA). The results indicated notable disparities in body composition among different age brackets, with older females displaying elevated levels of body fat accumulation. The escalation in the prevalence of

overweight and obesity with advancing age underscores the significance of monitoring body composition as a strategic approach to tackling public health issues associated with obesity. Table 8 show us the results concerning body composition metrics in Serbian women.

Table 8: Age-Related Body Composition Metrics in Serbian Population for Women *(*BFM – Body Fat Mass; PBF – Percent of Body Fat; BFMI – Body fat Mass Index; Dopsaj et al., 2021)

Age Group (Years)	**BMI (kg/m^2)**	**BFM (kg)**	**PBF (%)**	**BFMI (kg/m^2)**	**VFA (cm^2)**
20-29	22.12 ± 3.65	16.46 ± 8.10	25.17 ± 7.78	5.84 ± 2.89	51.2 ± 31.8
30-39	23.75 ± 4.77	19.70 ± 10.58	26.96 ± 9.49	6.94 ± 3.85	76.0 ± 40.1
40-49	26.11 ± 5.57	24.97 ± 11.93	32.16 ± 9.00	8.95 ± 4.29	106.5 ± 43.9
50-59	27.24 ± 5.03	27.91 ± 10.74	36.40 ± 8.11	10.37 ± 3.97	128.9 ± 40.8
60-69	30.33 ± 6.79	33.09 ± 13.03	40.04 ± 7.35	12.72 ± 4.87	160.7 ± 42.9

This table illustrates the increasing trends in body fatness indicators with age, emphasizing the need for targeted health interventions for different age groups.

A research study carried out by Gába & Přidalová, 2014 was undertaken with the objective of examining alterations in body structure associated with age within the demographic of Czech females spanning from 18 to 89 years of age. The investigation encompassed the evaluation of body fat mass (BFM), fat-free mass (FFM), body fat percentage (%BFM), and visceral adipose tissue (VAT) through the utilization of direct segmental multi-frequency bioelectrical impedance analysis (BSM-BIA). The outcomes of the study demonstrated a rise in BFM, %BFM, and VAT in correlation with advancing age, reaching a peak among women surpassing the age of 70, while FFM exhibited a decline. These findings illuminate noteworthy modifications in body composition in conjunction with the aging process, underscoring the necessity for health interventions tailored to specific age groups. Table 9 shows the Body composition changes in Checz women population.

Table 9: Age-Related Body Composition Changes in Czech Women Population (VFA – Visceral Fat Area; Gába & Přidalová, 2014).

Age Group (years)	BFM (kg)	FFM (kg)	PBF (%)	VFA (cm^2)
18-29	14.7 ± 5.3	46.6 ± 5.3	23.5 ± 5.9	41.1 ± 20.1
30-39	17.3 ± 7.2	46.5 ± 5.7	26.3 ± 7.2	67.0 ± 27.4
40-49	21.0 ± 8.9	48.4 ± 5.9	29.3 ± 7.4	91.6 ± 33.5
50-59	25.3 ± 9.6	45.4 ± 5.8	34.7 ± 7.7	122.5 ± 34.2
60-69	25.9 ± 7.9	44.6 ± 4.7	36.0 ± 6.5	135.8 ± 28.3
>70	27.6 ± 8.8	42.0 ± 5.2	38.8 ± 7.7	155.3 ± 30.3

A study conducted by Martarelli & Pompei (2008) aimed to develop new equations to determine body composition among the Italian population using the body mass index (BMI). The study involved bioelectrical impedance and anthropometric analysis of 764 Italian Caucasian subjects, aged 11 to 80 years. The researchers performed multiple regression analyses to estimate body composition and compared the estimated masses with the measured masses using Bland and Altman plots. The results indicated that the new formulas provided more precise estimates of body composition than the Watson equations, making them suitable for epidemiological studies. These findings are essential for analyzing body composition state and changes within the Italian population. Table 10 shows the body composition parameters for Italian population for both gender.

Table 10: Body composition parameters for Italian population (Martarelli et al., 2008)

Parameter	Males	Females
Sample Size	422	342
Age (years)	32.46 ± 12.19	34.19 ± 14.03
Weight (kg)	77.87 ± 12.29	61.06 ± 12.16
Height (cm)	176.87 ± 8.38	162.84 ± 6.10
BMI	24.90 ± 3.85	23.04 ± 4.64
% Fat Mass	16.7 ± 4.64	28.2 ± 7.97
% Fat-Free Mass	83.7 ± 4.64	71.8 ± 7.97
% Body Cell Mass	41.9 ± 3.51	34.3 ± 4.78
% Total Body Water	60.4 ± 3.2	53.8 ± 5.24
% Underweight (BMI < 18.5)	1.65	3.81
% Normal Weight (BMI 18.5–4.9)	64.45	75.07
% Overweight (BMI 25.0–29.9)	26.06	13.19
% Obese (BMI > 29.9)	6.16	7.33

A research was undertaken by Lissner et al. (2008) with the objective of exploring the secular trends in obesity, dietary patterns, and associated lifestyle elements within two cohorts of Swedish women, aged 38 and 50. The examination involved a comparison of anthropometric indicators and lifestyle variables between individuals born in 1930/1918 and those born in 1966/1954. Data was gathered through anthropometric assessments, dietary recalls, and lifestyle surveys at two distinct time junctures: 1968/69 and 2004/05.

The results revealed noteworthy escalations in body weight, stature, waist circumference, and skinfold measurements among the more recent birth cohorts, notwithstanding consistent levels of body mass index (BMI). Furthermore, alterations in dietary behaviors were documented, characterized by a reduction in fat and sucrose consumption alongside an elevation in carbohydrate and fiber intake. The investigation also identified an uptick in recreational physical activities and perceived stress levels throughout the 36-year timeframe. These outcomes underscore the significance of accounting for both anthropometric variations and lifestyle modifications in the context of addressing obesity and associated health concerns among women. Table 11 shows the comparison of anthropometric measurements for Swedish women aged 38 years and 50 years at two different time periods.

Table 11: Anthropometric Measures in Swedish Women by Age Group and Examination Year (Lissner et al. 2008)

Age Group	Examination Year	Weight (kg)	Height (cm)	BMI (kg/m²)	Waist (cm)	Hip (cm)	Waist-Hip Ratio	Triceps Skinfold (mm)	Subscapular Skinfold (mm)
38	1968/69	63.4 ± 11.2	164.6 ± 5.7	23.4 ± 3.8	71.6 ± 8.2	98.9 ± 7.5	0.73 ± 0.05	16.7 ± 5.9	15.4 ± 7.2
38	2004/05	67.0 ± 13.1	167.3 ± 6.6	23.9 ± 4.3	78.1 ± 10.5	98.7 ± 8.5	0.79 ± 0.07	22.1 ± 8.7	18.1 ± 9.3
50	1968/69	66.2 ± 11.1	163.5 ± 5.6	24.8 ± 3.8	74.8 ± 8.7	100.2 ± 8.0	0.75 ± 0.05	18.2 ± 5.3	18.9 ± 8.2
50	2004/05	68.7 ± 12.1	166.3 ± 6.2	24.8 ± 4.3	82.6 ± 11.1	99.9 ± 8.5	0.83 ± 0.07	24.6 ± 8.8	20.9 ± 9.3

Table 11 illustrates the anthropometric measurements of Swedish women at two different ages, 38 years and 50 years, compared across two time periods, 1968/69 and 2004/05

A study by Gallus et al., 2015 aimed to explore overweight and obesity prevalence in 16 European countries using a Pan-European survey with consistent methods. The research involved a survey in 2010 with 14,685 adults from various countries. Data on height and weight were self-reported for BMI calculation. Results showed 47.6% of European adults were overweight or obese, with higher rates in men. Obesity was more common in Northern Europe (18.0%) than in other regions. The study identified links between obesity and age, education, and smoking. Table 12 shows the prevalence of overweight and obesity in European countries.

Table 12: Prevalence of Overweight and Obesity in 16 European Countries (Gallus et al., 2015)

Country	Total Overweight/Obesity (%)	Total Obesity (%)	Male Overweight/Obesity (%)	Female Overweight/Obesity (%)	Male Obesity (%)	Female Obesity (%)
Czech Republic	56.4	11.7	58.6	39.2	13.7	11.5
England	56.0	20.1	63.9	46.5	24.8	15.5
Finland	61.7	18.9	60.3	47.1	21.9	15.8
France	44.7	12.2	42.7	36.2	11.1	12.7
Hungary	68.9	9.8	68.4	63.0	11.4	8.2
Ireland	55.0	12.2	55.9	38.9	13.5	10.9
Italy	47.4	7.6	46.3	28.7	7.0	8.2
Latvia	52.2	13.8	55.1	50.9	14.9	18.3
Poland	57.1	10.3	58.9	41.2	13.8	10.6
Romania	51.7	16.0	53.0	45.0	15.8	16.9
Spain	61.9	14.0	62.0	48.8	17.7	10.5
Sweden	53.1	10.6	53.2	39.2	11.2	10.6
Albania	43.5	11.1	50.0	36.8	12.8	9.3
Austria	50.0	10.5	49.2	39.6	10.8	10.3
Bulgaria	54.5	13.7	52.7	41.7	13.3	11.2
Croatia	56.4	21.5	62.3	52.7	23.3	19.9

This table provides a clear summary of the prevalence of overweight and obesity in 16 European countries, highlighting significant regional and gender differences.

Another study was conducted about "Body Typology of Lebanese Adults: Initial Cluster Cross-Selection Study" investigated the body typologies of Lebanese adults using a combination of anthropo-morphological characteristics and body composition measured by multichannel bioimpedance. The study included 302 subjects (173 males and 129 females) and utilized K-means cluster analysis to define five specific body type clusters for each sex. The clusters for males were identified as Obese Endomorph, Balanced Mesomorph, Short Endomorph, Short Mesomorph, and Pathological Obese Endomorph, while those for females were Obese Endomorph, Short Endo/Mesomorph, Short Ectomorph, Endomorph, and Balanced Mesomorph. The results highlighted that fat tissue was the primary factor contributing to the distinctions among the clusters, indicating that dietary habits significantly influence body composition differences rather than the level of physical activity (Andraos et al., 2024). Table 13 shows the the body composition characterstics about Lebanese adult population for both gender.

Table 13: body composition characteristics of Lebanese adults for both gender (Andraos et al., 2024)

Characteristic	Male (N = 173)	Female (N = 129)
Body Height (cm)	176.7 ± 6.7	163.4 ± 6.1
Body Mass (kg)	83.8 ± 17.7	64.1 ± 12.4
BMI (kg/m²)	26.7 ± 5.1	24.0 ± 4.3
Body Fat Mass (kg)	19.2 ± 11.8	22.3 ± 8.8
Skeletal Muscle Mass (kg)	36.2 ± 6.47	20.9 ± 4.6
Percent Skeletal Muscle Mass (%)	44.0 ± 6.6	33.0 ± 5.7
Percent Body Fat (%)	21.6 ± 9.0	33.8 ± 7.8
Body Fat Mass Index (kg/m²)	6.2 ± 3.8	8.4 ± 3.3
Skeletal Muscle Mass Index (kg/m²)	11.6 ± 1.7	7.8 ± 1.5
Index of Body Composition (AU)	0.78 ± 0.24	1.40 ± 0.19

This table presents the average body composition characteristics for male and female Lebanese adults as analyzed in the study.

2.3.2 Analysis of Previous Research on Body Composition Characteristics Across Populations

The analysis of various studies on body composition reveals a mutual understanding that monitoring body composition is crucial across different populations. Key findings from these studies highlight the significant impact of age and gender on body composition metrics such as muscle mass, fat mass, and overall obesity levels.

Common Findings Across Studies:

1. **Age-Related Changes**: All studies emphasize the significant changes in body composition with aging. In general, there is a decline in skeletal muscle mass and an increase in fat mass as age advances. For example, Dopsaj et al., 2020 observed a decrease in skeletal muscle mass index (SMMI) and percent skeletal muscle mass (PSMM) with age among Serbian adults.
2. **Gender Differences**: Gender-specific variations are consistently reported. Males tend to have higher muscle mass and lower fat mass compared to females. Studies like those by Larsson et al. ,2015 and Dopsaj et al., 2021 provide evidence of these differences in Swedish and Serbian populations respectively.
3. **Obesity and Health Risks**: Increased body fat percentage and obesity prevalence with age are common findings. Higher levels of body fat, particularly visceral fat, are associated with elevated health risks, including cardiovascular diseases and diabetes. For instance, Gába & Přidalová, 2014 noted increased body fat and visceral adipose tissue in older Czech women

4. **Body typology**: The significance of categorizing individuals based on their body type using composition characteristics has been emphasized in studies by Sakibaev et al., 2020 and Andraos et al., 2024. This method offers valuable insights into the distribution of body types across different populations, facilitating comparisons to identify similarities and differences between nations.

Categorizing individuals according to their body type yields notable advantages. It enables individuals to comprehend the specific attributes of their bodies and determine whether they belong to a less healthy category, motivating them to implement essential lifestyle modifications. Furthermore, this data is beneficial for trainers and coaches, as it permits them to categorize individuals according to their body types and oversee their development over time to monitor any changes or enhancements.

Furthermore, the utilization of these body type classifications is essential for the selection of athletes. It streamlines the process of identifying healthier or more suitable athletes for specific sports by aligning their body types with the demands of the sport. This focused approach enhances the efficacy of training regimes and optimizes athletic performance.

5. **Importance of Customized Health Interventions**: Given the varying body composition characteristics across different demographics, personalized health interventions are essential. These include targeted exercise programs, dietary adjustments, and regular health monitoring to maintain optimal body composition and prevent age-related health issues.

6. **Importance of Body Composition Testing:**

   Implementing routine body composition assessments can significantly enhance health management. Understanding the body composition characteristics of a population helps in identifying public health trends, allocating resources effectively, and designing tailored community health programs. This approach ensures more personalized and effective healthcare solutions, promoting better health outcomes across various age groups and genders.

In summary of all previous finding, figure 5 represent the body composition characteristics of available countries.

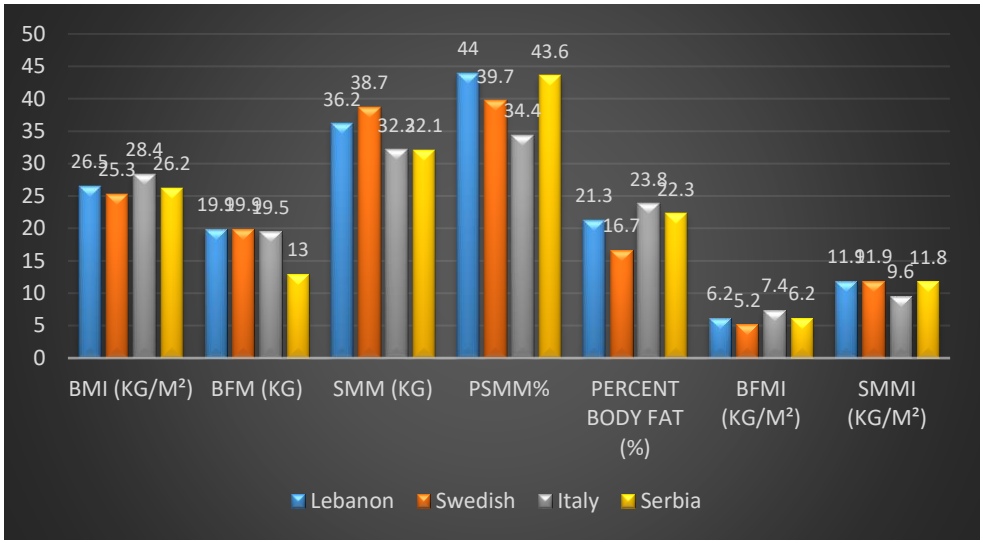


Figure 5: Comparison of Body Composition Metrics Across Lebanese, Swedish, Italian, and Serbian Populations for men

As observed in this figure, there are notable differences in body composition characteristics between various countries. These differences warrant further exploration to understand their underlying causes, which may include dietary habits, levels of physical activity, or ethnic diversity among populations. Investigating these factors is crucial as it could also explain the disparities in sports performance between countries. This topic holds significant importance and merits deeper investigation.

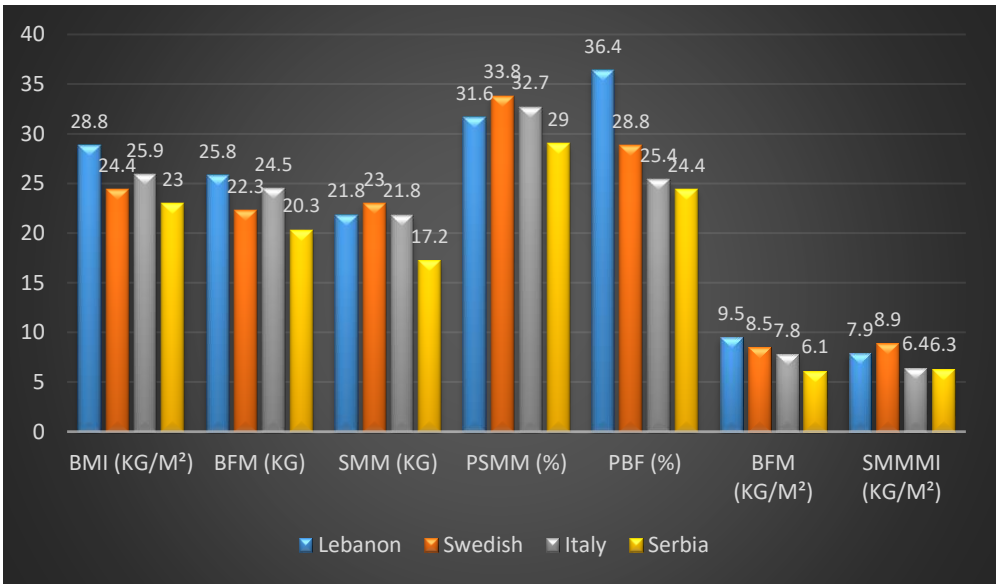


Figure 6: Comparison of Body Composition Metrics Across Lebanese, Swedish, Italian, and Serbian Populations for women

As observed in this figure, there are notable differences in body composition characteristics among women from Lebanon, Sweden, Italy, and Serbia. These differences highlight the need for further exploration to understand the underlying causes. Possible factors contributing to these variations may include dietary habits, levels of physical activity, and genetic or ethnic diversity among the populations. Investigating these aspects is crucial, as they could also explain disparities in sports performance and health outcomes between countries. Understanding these differences can provide valuable insights for designing targeted health and fitness programs, and for enhancing sports training and selection processes based on body composition characteristics.

Based on Figures 1 and 2, it is evident that establishing population-specific norms as well as international standards for body composition is crucial. The observed variations in body composition characteristics across different populations underscore the need for tailored norms. Currently, there is a significant lack of comprehensive information and standards for various body composition variables. This gap highlights the importance of developing robust benchmarks that encompass all body composition characteristics. Such standards are essential not only for the general population but also for different age groups and specific sports. Establishing these norms would provide valuable benchmarks for assessing health and performance, facilitating more precise and effective interventions.

2.4 Comprehensive Predictive Models for health, Injury risk, and performance in Healthcare and sports contexts

2.4.1 Terms and definition

The concept of the health model is a framework that offers a thorough comprehension of an individual's overall wellness, which includes physical, mental, emotional, and social dimensions. Historically, the medical model has held sway in healthcare, concentrating primarily on the existence or lack of disease (Harris, 2010; Larson, 1999). Nonetheless, this limited viewpoint does not fully grasp the complex nature of health. The World Health Organization (WHO) defines health as "a state of complete physical, mental, and social well-being and not merely the absence of disease or infirmity" (Larson, 1999).

2.4.2 Importance of creating predictive health model

In an age characterized by personalized medicine and data-centric methodologies, the ability to forecast an individual's health status or physical capabilities has transitioned from a futuristic notion to a feasible objective with the capacity to transform healthcare and athletic preparation. Envision a realm where healthcare practitioners can foresee and alleviate health hazards before they escalate, and where athletes can utilize customized training regimens optimized for superior performance and injury prevention. This potential for proactive and tailored intervention emphasizes the significant value of constructing precise and insightful predictive models in the realms of health and fitness.

The capacity to precisely anticipate an individual's health status or physical performance harbors significant potential. Robust predictive models could empower healthcare professionals to pinpoint

individuals predisposed to specific conditions, facilitating early intervention and potentially averting future health complexities. In the realm of sports, such models could furnish athletes and coaches with valuable discernments regarding potential strengths and weaknesses, leading to customized training programs optimized for peak performance and injury prevention.

Predictive models also equip individuals with the ability to adopt a proactive stance towards their well-being. By comprehending their individual risk factors and areas for potential enhancement, individuals can make well-informed choices regarding their lifestyle, dietary habits, and workout routines. This transition from reactive to proactive healthcare has the potential to yield improved long-term health results, decreased healthcare expenditures, and a holistic enhancement in quality of life.

2.4.3 Overview of different health models across disciplines

Predictive models for health, injury risk, and performance assessment have become essential tools in modern healthcare and athletic training. These models offer valuable insights into an individual's health status, potential risks, and physical performance, enabling proactive and personalized interventions.

1- Health Prediction Models

1. **Risk Prediction Models for Chronic Diseases:**

Framingham Heart Study Risk Score: This model predicts the risk of developing cardiovascular disease based on factors such as age, cholesterol levels, blood pressure, smoking status, and diabetes status. It typically requires a routine medical check-up and blood tests, which can be completed in a few hours. Costs may vary depending on the healthcare provider, and the individual needs to provide their medical history and lifestyle information (Das et al., 2022).

2. **Predictive Models in Oncology:**

The Gail Model: This model estimates the risk of developing breast cancer based on a woman's personal medical history, family history of breast cancer, and other demographic factors. It is often part of a comprehensive medical evaluation and can take several days to complete, depending on the availability of detailed medical and family history (Euhus et al., 2002).

3. **Models Based on Wearable Health Technology:**

Wearable Devices: These models use data collected from devices such as fitness trackers and smartwatches to predict health events like heart attacks or falls by analyzing changes in heart rate, activity levels, or sleep patterns. The initial cost ranges from $50 to $500 for the devices, with ongoing data collection. Regular use and data syncing are required from the individual (Moller & Kettley, 2017).

2- Injury Risk Prediction Models

1. **Functional Movement Screen (FMS):** The FMS assesses movement patterns to identify asymmetries and limitations that could lead to injury. It involves a series of seven movements scored to identify risk levels. The screening typically takes 15-20 minutes and costs between

$50-$150 per session. Individuals must physically participate in the specific movements (Cook et al., 2014)

2. **Oslo Sports Trauma Research Center (OSTRC) Overuse Injury**

   Questionnaire: This tool tracks symptoms of overuse injuries through a selfreported questionnaire. It is a low-cost method that can be completed in 10-15 minutes, requiring regular participation from the individual (Clarson et al., 2014)

3. **Athlete Monitoring Systems (AMS):** Systems like Catapult and GPSports analyze training load, athletic readiness, and physiological metrics via wearable technology. These systems can predict injury risk by monitoring deviations in training patterns and physical responses. Initial setup costs range from $200 to $2000, with continuous monitoring required (Malone et al., 2017).

4. **Acute Workload Ratio (ACWR):** This model identifies injury risk by comparing the recent training load to the long-term average. It involves ongoing monitoring and calculation based on training data, with minimal cost. Consistent tracking of training loads by the individual is necessary (White., 2024).

5. **Quantitative Movement Analysis:** This model utilizes technologies such as motion capture systems and force plates to analyze biomechanical patterns. It predicts injury risk by identifying biomechanical abnormalities that may predispose athletes to specific injuries. High costs and specialized equipment are involved, with assessments taking several hours (Long & Nelson, 2013).

6. **Nordic Hamstring Exercise (NHE) Performance:** The NHE is a preventive exercise targeting the hamstrings, predicting hamstring injury risk. It requires minimal cost and can be performed in a few minutes, necessitating the individual's physical ability to perform the exercise (Augustsson., 2022).

3- Performance Prediction Models

1. **1 Repetition Maximum (1RM) Test:** This test measures maximum strength for a given exercise by lifting the maximum weight once. It is typically part of gym sessions and can be completed in under an hour, requiring proper technique and safety measures.

2. **Vertical Jump Test:** This test measures explosive leg power by jumping to reach the highest point. It is a low-cost test that takes a few minutes and requires basic physical ability to jump.

3. **Isokinetic Testing:** This test measures muscle strength and endurance using specialized equipment to test muscle strength at various speeds. It involves high costs and specialized equipment, taking up to an hour to complete. Individuals must perform muscle contractions against resistance.

4. **Hand Grip Strength Test:** This test measures hand and forearm strength by squeezing a hand grip dynamometer. It is a low-cost test that takes a few minutes, requiring basic hand strength.

5. **Wingate Test:** This test measures anaerobic power and capacity through an all-out cycling effort for 30 seconds. It involves moderate costs and takes about 30 minutes, including setup. The individual must be able to perform high-intensity exercise.

6. **Functional Movement Screen (FMS):** Similar to its use in injury risk assessment, the FMS evaluates movement patterns to identify functional limitations and injury risk. It takes 15-20 minutes and requires physical participation in movements.
7. **Push-Up Test:** This test measures upper body endurance by performing as many push-ups as possible in a set time. It is a low-cost test that takes a few minutes, requiring basic upper body strength and endurance.

These tests are crucial for assessing sports performance and identifying an athlete's weaknesses to enhance their overall performance. For example, the 1RM (one-repetition maximum) test is used to determine maximal force, which is a critical measure since individuals with lower strength are at a higher risk for conditions such as sarcopenia, dynapenia, and other related diseases. Additionally, tests like the Wingate test and isokinetic testing are also vital for evaluating various aspects of athletic performance and health status. However, these assessments require access to a gym and a laboratory, which can be costly and may not be suitable for individuals of different age groups and training backgrounds.

Each of these models plays a crucial role in predicting health status, injury risk, and performance, providing valuable insights for individuals, healthcare professionals, and athletic coaches. Accurate and insightful predictive models enable proactive and personalized interventions, leading to better health outcomes, reduced injury risks, and optimized athletic performance.

In the article entitled Maximal and Explosive Strength Normative Data for Handgrip Test According to Gender: International Standardization Approach," published in the journal Human Movement in 2022. The research, conducted by a multidisciplinary team from various institutions including Wroclaw University of Health and Sport Sciences, provides percentile standards for handgrip muscle force variables categorized by gender. The table displayed shows detailed percentile values for males and females across different age groups, measuring variables such as maximal muscle force (F_{max}), maximal explosive muscle force (RFD_{max}), and the relative aspect of these measurements. The data is essential for establishing normative benchmarks in handgrip strength, which can be used to assess and compare individual performance against standardized values, aiding in both clinical and sports performance contexts (Dopsaj et al., 2022). Table 14 shows the handgrip muscle strength normative standards for the observed variables by gender.

Table 14 shows normative standards for handgrip muscle strength variables by gender, categorizing performance into superior, excellent, above standard, standard values, below standard, poor, and very poor. This classification provides a comprehensive benchmark for assessing handgrip strength and identifying potential risks for injury based on the observed differences between dominant and non-dominant hands. In addition, seven Lebanese participants were included in this study, making it a significant indicator for understanding more about the Lebanese population. Providing such norms helps to gain insights into the strength, explosive strength, and health of this population, and allows for comparisons with other populations.

Table 14: Handgrip muscle strength normative standards for the observed variables by gender (Dopsaj et al., 2022)

Variables		Superior	Excellent	Above standard	Standard values	Below standard	Poor	Very poor
Males								
F_{max} (N)	D	≥ 703	702–607	606–560	559–465	464–417	416–322	≤ 321
	ND	≥ 658	657–571	570–528	527–441	440–398	397–311	≤ 310
	SUM	≥ 1349	1173–1348	1085–1172	910–1084	821–909	646–820	≤ 645
RFD_{max} (N/s)	D	≥ 4863	4862–4105	4104–3726	3725–2969	2968–2590	2589–1833	≤ 1832
	ND	≥ 4559	4558–3842	3841–3483	3482–2766	2765–2408	2407–1691	≤ 1690
	SUM	≥ 9314	7894–9313	7183–7893	5763–7182	5053–5762	3632–5052	≤ 3631
F_{rel} (N/kg)	D	≥ 8.1	8.1–7.1	7.1–6.6	6.6–5.5	5.5–5.0	5.0–4.0	≤ 4.0
	ND	≥ 7.7	7.7–6.7	6.7–6.2	6.2–5.2	5.2–4.7	4.7–3.7	≤ 3.7
	SUM	≥ 15.7	13.7–15.7	12.8–13.7	10.8–12.8	9.8–10.8	7.9–9.8	≤ 7.9
RFD_{rel} (N/s/kg)	D	≥ 56.7	56.7–48.1	48.1–43.8	43.8–35.2	35.2–30.9	30.9–22.3	≤ 22.3
	ND	≥ 53.5	53.5–45.2	45.2–41.1	41.1–32.8	32.8–28.7	28.7–20.4	≤ 20.4
	SUM	≥ 108.9	92.7–108.9	84.6–92.7	68.4–84.6	60.3–68.4	44.0–60.3	≤ 44.0
Females								
F_{max} (N)	D	≥ 398	397–341	340–312	311–255	254–227	226–170	≤ 169
	ND	≥ 381	380–323	322–295	294–237	236–208	207–150	≤ 149
	SUM	≥ 770.0	769–660	659–605	604–495	494–440	439–330	≤ 329
RFD_{max} (N/s)	D	≥ 2805	2804–2314	2313–2069	2068–1579	1578–1334	1333–843	≤ 842
	ND	≥ 2611	2610–2146	2145–1914	1913–1449	1448–1217	1216–753	≤ 752
	SUM	≥ 5336	5335–4421	4420–3964	3963–3048	3047–2591	2590–1676	≤ 1675
F_{rel} (N/kg)	D	≥ 6.2	6.2–5.3	5.3–4.8	4.8–3.9	3.9–3.5	3.5–2.5	≤ 2.5
	ND	≥ 6.0	6.0–5.0	5.0–4.6	4.6–3.6	3.6–3.2	3.2–2.2	≤ 2.2
	SUM	≥ 12.1	12.1–10.3	9.4–10.3	7.6–9.4	6.7–7.6	4.9–6.7	≤ 4.9
RFD_{rel} (N/s/kg)	D	≥ 43.6	43.6–35.9	35.9–32.0	32.0–24.3	24.3–20.5	20.5–12.8	≤ 12.8
	ND	≥ 40.5	40.5–33.2	33.2–29.6	29.6–22.3	22.3–18.7	18.7–11.4	≤ 11.4
	SUM	≥ 82.9	68.5–82.9	61.3–68.5	46.9–61.3	39.8–46.9	25.4–39.7	≤ 25.4

F_{max} – maximal muscle force, RFD_{max} – maximal explosive muscle force, F_{rel} – relative aspect of maximal muscle force, RFD_{rel} – relative aspect of maximal explosive muscle force, D – dominant hand, ND – non-dominant hand, SUM – summarized for both hands

3. PROBLEM, PURPOSE, AIMS, TASKS, AND SIGNIFICANCE OF THE STUDY

3.1 Defining the Problem

The current evaluation methods for measuring strength, power, and well-being are encountering considerable obstacles due to their complex nature, high expenses, and restricted suitability across various demographics and age ranges. Numerous existing assessments are time-intensive and complex to conduct, rendering them inaccessible to a wide range of individuals. Furthermore, these assessments frequently offer limited insights, focusing solely on one or two facets of an individual's well-being or performance, and do not present a holistic framework that effectively forecasts overall performance, risk of injury, and health condition simultaneously. Moreover, there is a noticeable scarcity of population-specific frameworks tailored to the Lebanese population. This lack of customized predictive frameworks restricts the precision and significance of the available

assessments for this particular demographic, emphasizing the necessity for more comprehensive and targeted evaluation tools that can accommodate the distinct attributes of varied populations.

3.2 Purpose of the Study

To create a national specific and optimized model with prediction algorithms that assess the body and health condition with general physical performance status of a person for both gender that is very specific for Lebanese population.

3.3 Aims of the Study

- to develop and evaluate algorithms based on hand grip parameters to assess body composition (nutritional status) and different health risks.
- we will create specific predictive algorithms sensitive according to gender and health status, possible to be apply individually for each participant. Using regression analysis, we will derive a predictive formula, which can be applied in future testing (scores algorithm system).
- This process will result in 12 algorithms, with 6 tailored for each gender. We will then identify which algorithm is most sensitive to body composition variables by examining the correlation between each algorithm and various body composition metrics.
- This will allow us to determine the best algorithm for assessing individual health status and identifying those at risk of diseases related to body composition.

3.4 Tasks of the Study

Based on the defined problem, purpose and aims of the study, this research will be conducted through the following tasks:

-Develop protocols for evaluating hand grip strength and explosive strength in various demographics in Lebanon.

-Collect data on hand grip strength, explosive strength, and body composition metrics from Lebanese individuals.

-Design algorithms using hand grip parameters to assess health risks and body composition, tailoring them to gender and health status.

-Conduct regression analysis to create predictive formulas and validate them statistically.

-Develop 6 algorithms, 3 for each gender, and determine the most accurate in predicting health risks

-Test algorithms on collected data and refine them for better predictive accuracy.

-Establish normative data for hand grip and explosive strength in Lebanese population by age and gender.

-Create a risk assessment framework to identify individuals at risk of health issues related to body composition.

-Offer recommendations for interventions and training programs based on predictive analysis to reduce injury risks.

-Disseminate study findings through publications and collaborations with health professionals. divide this paragraph by bullets

3.5 Significance of the Study

The significance of the study can be recognized in relation to the following three outcomes:

1. Addressing Limitations of Current Testing Methods: Develop more efficient and widely applicable algorithms to overcome the limitations of existing tests for strength, power, and health measurements, which are often time-consuming, costly, and not suitable for diverse populations and age groups.
2. Comprehensive Health and Performance Prediction: Current tests usually provide limited information by focusing on one or two health aspects. This study will create algorithms that predict overall performance, injury risk, and health status simultaneously, offering a more holistic assessment tool.
3. Population-Specific Models for the Lebanese Population: There is a lack of predictive models tailored specifically to the Lebanese population. This study will develop and validate models that are relevant and accurate for this demographic, enhancing the effectiveness of health assessments and interventions in this specific population.

4. HYPOTHESES

Based on the literature foundation and literature analysis as well as on defined problem, purpose, aim and tasks of the dissertation, the following hypotheses are defined:

The defined general hypothesis is –

- **HG** – Algorithms developed using hand grip parameters can accurately predict body composition status related to health with a statisticaly significant reliability and validity considering the gender at Lebanese adults.

The supporting hypotheses are defined as follow **-**

H 1– The predictive formula derived from regression analysis of hand grip parameters will be effective in future assessments for assessing strength, explosiveness and power for individual.

H 2 –There will be a significant difference in the sensitivity of the algorithms based on gender, with some algorithms being more accurate for males and others for females.

H 3 – The most sensitive algorithm, identified through correlation with body composition variables, will be able to accurately assess the health status and predict the risk of diseases related to body composition.

H 4 –The correlation between hand grip strength scores and body composition metrics will be strong enough to use these algorithms as a reliable tool in clinical and fitness settings for health risk assessments.

5. METHODS

5.1 Design of the Study

This research is a cross selection design, population study and non-experimental study.

5.2 Sample Characteristics

The research will encompass healthy adult males and females from Lebanon, ranging in age from 19 to 68 years. Eligibility criteria will mandate the absence of hormonal disorders or injuries that could impede hand grip test performance. The study cohort will encompass individuals with varying levels of physical activity, including athletes, active persons, and sedentary individuals.

A substantial group of 395 subjects will be enlisted, with a specific focus on enrolling more than 242 men and 153 women. Geographical diversity will be ensured by recruiting participants from different regions within Lebanon. Moreover, individuals must demonstrate pure Lebanese lineage, indicating not only birth in Lebanon but also having Lebanese ancestry up to the grandparental level. The upper age threshold of 68 years has been chosen to correspond with the typical retirement age in Lebanon.

This heterogeneous and all-encompassing sample is intended to provide a comprehensive insight into hand grip strength and associated health indicators across diverse segments of the Lebanese population. The research was realized according to the regulations of the Declaration of Helsinki and with the permission of the Ethics Committee at the University of Belgrade Faculty of Sport and Physical Education (02 No. 484-2).

5.3 Data Collection and Testing Procedures

This study will be conducted over a period of two months, from June 30 to August 30, operating five days per week from 7 am to 5 pm. Participants will be informed to abstain from eating and drinking for two hours before the test, and physical activity will be forbidden 24 hours prior to the test. The tests will be conducted at the L3S Laboratory, Antonine University, Baabda, Lebanon. All tests will be completed on the same day and will be divided into four steps:

1. Step 1: Completing a questionnaire on paper.
2. Step 2: Measuring body height.

3. Step 3: Conducting body composition measurements.
4. Step 4: Performing the hand grip test.

A Certified nutritionist and four assistants, who are Master's students in sport sciences from Antonine University, will be recruited for data collection. They will be trained one week prior to the test to ensure accuracy and consistency. The training will include entering data on a laptop, operating the testing devices, and delivering standardized verbal instructions to participants.

Additionally, a pilot study will be conducted to familiarize the students with the testing procedures and to identify and rectify any potential errors during the tests. This comprehensive preparation aims to ensure the reliability and validity of the data collected throughout the study.

5.3.1. Questionnaires

The questionnaires will contain the following variables:

1. Origin
2. Gender
3. Age
4. Profession
5. Social status
6. Geographic position in Lebanon
7. Number of exercise sessions per week
8. Minutes per session

A master's student, who will be trained for this task, will ask the participants these questions and fill in the answers on the questionnaire paper. Afterward, the data will be entered into an Excel sheet. The questionnaire document is included in the appendix.

5.3.2. Body Height and Body composition

Physical evaluations were conducted in the Laboratory of the 3S: Sport, Health, and Society (L3S) at the university, adhering to established protocols (Dopsaj et al., 2020; Rakić et al., 2022; Dopsaj et al., 2023). An accredited nutrition specialist oversaw the physical assessments, encompassing measurements of weight, height, and bioelectrical impedance analysis (BIA). Body mass (BM) was assessed with a precision of 0.1 kg, with participants attired in lightweight indoor apparel and barefoot, utilizing a BIA device. Height measurements (BH), taken shoeless, were recorded with a portable digital height gauge (Campry, China) to the nearest 0.1 cm. Each metric was captured twice, and the mean of the two readings was documented. Bioimpedance analysis (i30, Mediana, Korea) was employed to calculate body composition parameters. In addition to BM and BH, the variables scrutinized in this study included: BMI - body mass index, quantified in kg/m^2; BFM - body fat mass, and SMM - skeletal muscle mass, gauged in kg; PBF - percentage of body fat mass, and PSMM –

percentage of skeletal muscle mass, expressed in %; BFMI - body fat mass index, and SMMI - skeletal muscle mass index, measured in kg/m^2; IBC – index of body composition, denoted in Index Units (Dopsaj et al., 2020; Dopsaj et al., 2023).

5.3.3. Hand grip test

The protocol for conducting the isometric handgrip test will adhere to standardized procedures and utilize appropriate equipment. A handgrip device equipped with a fixed strain gauge from Sports Medical Solutions, All4gym d.o.o., Serbia, will be employed to assess the mechanical attributes of isometric handgrip strength (Markovic et al., 2020). Participants will be seated upright in a chair, extending one arm to hold the measuring device as per guidelines established in prior literature (Zarić et al., 2018; Dopsaj et al., 2019; Trajkov et al., 2018; Marković et al., 2020; Marković et al., 2018). Previous studies have demonstrated the high reliability of the handgrip test, with Intraclass Correlation coefficients for F_{max} ranging from 0.938 to 0.977, and from 0.903 to 0.971 for RFD_{max} (Ćopić & Trajkov, 2018).

Prior to the commencement of handgrip testing, a detailed verbal description of the procedures will be provided. Each participant will conduct two preliminary measurements for familiarization, using both hands randomly, at a moderate level of exertion. Following a 2-minute rest period, the handgrip test will be conducted, focusing on the power grip known for its strength. Participants will be instructed to apply maximum and rapid pressure on the device upon the researcher's cue, sustaining the grip for at least 2 seconds, with verbal motivation offered throughout (Dopsaj et al., 2019; Marković et al., 2020; Marković et al., 2018).

Testing of handgrip strength in both dominant and non-dominant hands will occur twice, in a randomized sequence, with a 1-minute gap between each trial. Throughout the evaluation, participants will be directed to keep their arms close to their body, with the tested arm slightly abducted (around 5–10 cm) without contact with the body or chair. Data on F_{max} and RFD_{max} will be captured during each trial using a laptop, with F_{max} assessed as the peak muscle force achieved, and RFD_{max} derived from the steepest slope of the force-time curve (Knezevic et al., 2014; Dopsaj et al., 2019).

The initiation of muscle contraction will be identified as the point at which the force-time curve's first derivative surpasses the baseline by 3% of its maximum value. The strain gauge employed in the handgrip assessment will be linked to a force reader with an accuracy of ± 0.1 N. Data will be sampled at 500 Hz and filtered using a fourth-order Butterworth filter with a cut-off frequency of 10 Hz. RFDmax will be determined by analyzing the instantaneous slope of the force-time relationship within the designated time frame (Knezevic et al. 2014; Dopsaj et al., 2019).

For data collection and analysis, a customized software-hardware system tailored for isometric measurements (Sports Medical Solutions Isometrics, ver. 3.4.0) will be utilized. Results of all measurements will be documented in a dedicated database, and the superior outcome will be selected for subsequent data processing and statistical evaluation.

6. VARIABLES

This study involved a comprehensive set of variables to evaluate hand grip strength, neuromuscular function, body composition, and training characteristics among Lebanese adults. Demographic and anthropometric variables included age, sex, body height (BH), body mass (BM), body mass index (BMI), fat-free mass (FFM), fat mass (FM), skeletal muscle mass (SMM), percent skeletal muscle mass (%SMM), percent body fat (%PBF), fat mass index (FMI), muscle-fat index (MFI), and visceral fat area (VFA). The Index of Body Composition (IBC) was calculated as the ratio between percent body fat (%PBF) and body mass index (BMI).

To assess neuromuscular performance, several hand grip strength parameters were measured, including maximal isometric hand grip force (F_{max}) for the dominant hand, non-dominant hand, right and left hands individually, and the total sum (F_{max}_SUM). Relative force (F_{rel}), calculated by normalizing F_{max} to body mass, was recorded for the dominant and non-dominant hands and as a total sum (F_{rel}_SUM). Explosive strength was evaluated through the rate of force development (RFD_{max}), measured bilaterally for the right and left hands, for the dominant and non-dominant hands, and as a total sum (RFD_{max}_SUM). Relative RFD (RFD_{rel}), normalized to body mass, was similarly calculated for each hand and as a sum (RFD_{rel}_SUM). The Index of Synergy (IS), reflecting neuromuscular coordination between limbs, was computed for the dominant side (D IS), non-dominant side (ND IS), left (IS L), right (IS R), and as a total sum (IS_SUM).

Training-related variables included total weekly training volume (in minutes), number of exercise sessions per week, and the average duration of a single training session. Collectively, these variables were selected for their relevance to muscular performance, neuromuscular coordination, and health-related body composition, forming the basis for the discriminative and predictive models applied in this research.

7. STATISTICAL PROCEDURES

The statistical analysis for this study will involve several key methods and tools to ensure comprehensive and accurate evaluation of the data.

1. Descriptive Statistics:

    - Descriptive statistics, including the mean, standard deviation, coefficient of variation, and maximal and minimal variable values, will be calculated to summarize the data.

2. Confidence Intervals:

    - A 95% confidence interval for the mean will be computed, providing lower and upper bound reference values to assess the precision of the estimates.

3. Factor Analysis:
    - Factor analysis will be employed to optimize the explored research space for key parameters of body composition and hand grip strength (HG). This method will support the testing of Specific Hypotheses 1, 2, 3, and 4.
4. ANOVA and MANOVA:
    - Univariate (ANOVA) and Multivariate (MANOVA) analyses will be utilized to compare differences between gender and defined groups based on specific criteria. These analyses will address the General Hypothesis of the study.
5. ROC Curve Analysis:
    - Receiver Operating Characteristic (ROC) curve analysis will be conducted to determine cut-off values for all analyzed variables, considering optimal sensitivity and specificity criteria. This analysis will contribute to testing the General Hypothesis and Specific Hypothesis 1.
6. Regression Analysis:
    - Correlation, linear, or multiple regression analyses will be performed to determine relationships between observed variables. These analyses will also be used for modeling specific predictive algorithms (predictive formulas) for all observed parameters related to body composition and HG.

      This approach will support the testing of Specific Hypotheses 3 and 4.
7. Software Tools:
    - All statistical analyses will be conducted using the SPSS Win Statistics 26.0 software package and Excel 2016 to ensure accurate and efficient data processing.

8. RESULTS

8.1. Descriptive and comparative results or explored variables accordg to samples

Table 15 present the descriptive statistics of anthropometric, body composition, and training variables in the Lebanese population by sex. The data demonstrate a high level of accuracy and reliability, as evidenced by the coefficient of variation (CV), which ensures the consistency of measurements. The mean values of coefficient of variations for males are 34.92%, and for females 32.92% indicate acceptable variability tendencies, while the mean value of standard error of the mean (SEM%) for males was 2.24% and for females 2.68% further confirms the acceptable accuracy of measurement for our dataset. These measures highlight the robustness of the collected data, making it suitable for meaningful analysis and interpretation.

Table 15: Descriptive Statistics of Anthropometric, Body Composition, and Training Variables in the Lebanese Population by Sex

Variables	Mean	SD	CV%	SEM%	Min	Max
Males						
Age (years)	32.29	13.88	42.99	2.74	18	81
BH (cm)	177.22	7.20	4.06	0.26	158	200
BM (kg)	82.81	14.49	17.50	1.12	53.6	145.3
BMI (kg/m^2)	26.33	4.00	15.19	0.97	16.92	42.45
FFM (kg)	64.76	8.85	13.67	0.88	44.2	95.8
FMI (kg/m^2)	5.75	2.79	48.52	3.08	1.08	14.46
BFM (kg)	18.05	8.84	48.98	3.13	3.3	49.5
SMM (kg)	35.86	5.72	15.95	1.04	24.3	58.2
PSMM (%)	43.78	5.68	12.97	0.85	24.79	56.21
PBF (%)	20.98	7.73	36.84	2.35	5.59	40.99
SMMI (kg/m^2)	11.38	1.45	12.74	0.84	7.8	17.01
IBC (AU)	0.93	0.38	40.86	2.65	0.24	2.62
MFI (AU)	2.62	1.66	63.36	4.08	0.71	9.81
Duration training per week (min)	309.57	356.84	115.27	7.40	0	2520
Females						
Age (years)	32.53	14.52	44.64	3.62	18	73
BH (cm)	163.67	6.01	3.67	0.30	149	183
BM (kg)	64.47	12.16	18.86	1.54	39.4	113.4
BMI (kg/m^2)	24.08	4.43	18.40	1.51	16	40.56
FFM (kg)	42.69	5.74	13.45	1.10	30.35	61.75
FMI (kg/m^2)	8.17	3.38	41.37	3.38	2.58	20.56
BFM (kg)	21.78	8.80	40.40	3.31	6.6	57.2
SMM (kg)	20.76	4.52	21.77	1.79	11	33
PSMM (%)	32.46	5.72	17.62	1.44	20.74	50
PBF (%)	32.78	7.88	24.04	1.97	13.64	50.69
SMMI (kg/m^2)	7.72	1.50	19.43	1.59	4.52	11.2
IBC (AU)	1.25	0.31	24.80	2.01	0.65	2.09
MFI (AU)	1.09	0.48	44.04	3.62	0.44	3.67
Duration training per week (min)	224.79	288.77	128.46	10.40	0	1440

Table 16: Descriptive statistics of handgrip strength, rate of force development, relative values, and index of synergy among male and female participants

Variables	Mean	Std. Deviation	CV	SEM	Min	Max
Males						
F_{max}_SUM (N)	952	166.61	17.5	1.13	568	1690
RFD_{max}_SUM (N/s)	5773	1291.08	22.4	1.44	2699	11457
DHG_F_{max} (N)	492	85.16	17.3	1.11	289	871
NDHG_F_{max} (N)	459	87.81	19.1	1.23	254	819
DHG_RFD_{max} (N/s)	2989	667.93	22.3	1.44	1503	5630
NDHG_RFD_{max} (N/s)	2784	680.63	24.5	1.57	1196	5827
DHG_F_{rel} (N/kg)	6.04	1.07	17.7	1.14	3.28	8.95
NDHG_F_{rel} (N/kg)	5.64	1.09	19.4	1.25	2.73	8.53
DHG_RFD_{rel} (N/s/kg)	36.72	8.45	23.0	1.48	16.14	58.43
NDHG_RFD_{rel} (N/s/kg)	34.21	8.51	24.9	1.60	11.87	56.99
F_{rel}_SUM (N)	11.68	2.09	17.9	1.15	6.02	16.63
RFD_{rel}_SUM (N/s)	70.93	16.26	22.9	1.47	31.29	111
IS_SUM (S^{-1})	6.078	0.90	14.78	0.01	2.78	8.11
DHG_ IS (S^{-1})	6.088	0.95	15.61	0.010	2.5	8.7
NDHG_IS (S^{-1})	6.075	1.01	16.59	0.011	2.24	8.63
Females						
F_{max}_SUM (N)	526	106.13	20.16	1.63	254	844
RFD_{max}_SUM (N/s)	3051	888.20	29.11	2.35	752	5284
DHG_F_{max} (N)	273	54.12	19.80	1.60	126	433
NDHG_F_{max} (N)	253	56.13	22.19	1.79	128	429
DHG_RFD_{max} (N/s)	1586	457.21	28.82	2.33	425	2717
NDHG_RFD_{max} (N/s)	1465	457.06	31.20	2.52	327	2647
DHG_F_{rel} (N/kg)	4.34	0.97	22.27	1.80	2.1	7.06
NDHG_F_{rel} (N/kg)	4.01	0.94	23.45	1.90	2.14	7.21
DHG_RFD_{rel} (N/s/kg)	25.15	7.58	30.13	2.44	6.67	46.84
NDHG_RFD_{rel} (N/s/kg)	23.16	7.32	31.61	2.56	5.46	47.07
F_{rel}_SUM (N)	8.34	1.84	22.07	1.78	4.24	14.19
RFD_{rel}_SUM (N/s)	48.31	14.44	29.89	2.42	12.55	93.9
IS_SUM (S^{-1})	5.753	1.07	18.64	1.51	2.77	7.9
DHG_IS (S^{-1})	5.77	1.1	19.07	1.54	2.56	7.55
ND_IS (S^{-1})	5.747	1.18	20.50	1.66	2.53	8.41

DHG_F_{max}: Dominant hand grip maximum force; NDHG_F_{max}: Non-dominant hand grip maximum force; SUM_F_{max}: Sum of dominant and non-dominant hand grip maximum force; DHG_RFD_{max}: Dominant hand grip maximum rate of force development; NDHG_RFD_{max}: Non-dominant hand grip maximum rate of force development; SUM_RFD_{max}: Sum of dominant and non-dominant hand grip RFDmax; DHG_Frel: Dominant hand grip relative force (N/kg); NDHG_F_{rel}: Non-dominant hand grip relative force (N/kg); SUM_F_{rel}: Sum of dominant and non-dominant hand grip relative force; DHG_RFD_{rel}: Dominant hand grip relative rate of force development (N/s/kg); NDHG_RFD_{rel}: Non-dominant hand grip relative rate of force development (N/s/kg); SUM_RFD_{rel}: Sum of dominant and non-dominant hand grip relative RFD; IS: Index of synergy.

Table 17: Final cluster centers of anthropometric, body composition, training, handgrip strength, and health-related variables among males participants (n = 242).

Variables	Cluster Group Males n= 242				
	Group 1 n= 23 (9.5%)	Group 2 n= 57 (23.5%)	Group 3 n= 83 (34.2%)	Group 4 n= 78 (32.23%)	Group 5 n = 1 (0.41%)
Age (years)	30.22	37.20	29.40	32.51	23.00
BH (cm)	180.9	173.9	178.4	177.2	185.0
BM (KG)	94.1	78.7	83.4	81.1	145.3
BMI (kg/m^2)	28.55	25.99	26.27	25.80	42.45
FFM (kg)	72.61	60.66	66.74	62.95	95.80
FMI (kg/m^2)	6.48	5.99	5.30	5.74	14.46
BFM (Kg)	21.47	18.05	16.67	18.11	49.50
SMM (kg)	40.68	32.85	37.44	34.68	58.20
PSMM (%)	43.75	42.17	45.22	43.49	40.06
PBF (%)	22.00	22.22	19.46	21.24	34.07
SMMI (kg/m^2)	12.42	10.82	11.75	11.01	17.01
IBC (AU)	.94	.94	.90	.94	.80
MFI (Muscle-Fat Index)	2.26	2.25	2.94	2.67	1.18
weekly amount of training (min)	275.1	204.6	421.5	279.6	135.0
F_{max}_L (N)	559.6	391.9	505.5	429.3	819.0
F_{max}_R (N)	587.9	423.7	531.7	463.6	871.0
RFD_{max}_L (N/s)	3841	1923	3206	2616	5827
RFD_{max}_R (N/s)	4054	2177	3375	2821	5630
F_{max}_SUM (N)	1147	816	1037	893	1690
RFD_{max}_SUM (N/s)	7894	4100	6581	5437	11457
IS L (S^{-1})	6.91	5.03	6.41	6.17	7.11
IS R (S^{-1})	6.91	5.25	6.43	6.15	6.46
IS_SUM (S-1)	6.91	5.15	6.41	6.15	6.78
Dominant HG_F_{max} (N)	586.7	423.2	534.9	465.0	871.0
Non Dominant HG_F_{max} (N)	560.8	392.5	502.2	427.9	819.0
Dominant HG_RFD_{max} (N/s)	4048	2158	3394	2820	5630
Non Dominant HG_RFD_{max} (N/s)	3847	1943	3187	2616	5827
D IS (S^{-1})	6.92	5.21	6.42	6.13	6.46
ND IS (S^{-1})	6.90	5.07	6.42	6.19	7.11
Dominant_F_{rel} (N/kg)	6.39	5.47	6.51	5.85	5.99
NonDominant_F_{rel} (N/kg)	6.11	5.08	6.11	5.40	5.64
Dominant_RFD_{rel} (N/s/kg)	44.17	28.22	41.41	35.70	38.75
NonDominant_RFD_{rel} (N/s/kg)	42.12	25.61	38.81	33.20	40.10
F_{rel}_SUM (N/kg)	12.50	10.55	12.62	11.25	11.63
RFD_{rel}_SUM (N/s/kg)	86.29	53.83	80.22	68.90	78.85
Health_Score /100	70.99	29.65	60.63	48.05	83.54

Table 18: ANOVA results showing between-cluster differences in anthropometric, body composition, training, handgrip strength, and health-related variables among male participants.

Variables	Cluster		Error		F	Sig.
	Mean Square	df	Mean Square	df		
Age	564.798	4	186.476	237	3.029	.018
BH	275.158	4	48.123	237	5.718	.000
BM	2012.421	4	179.535	237	11.209	.000
BMI	100.601	4	14.558	237	6.910	.000
FFM	980.166	4	63.272	237	15.491	.000
FMI	27.011	4	7.462	237	3.620	.007
BFM	354.244	4	73.636	237	4.811	.001
SMM	466.568	4	25.431	237	18.347	.000
PSMM (%)	84.722	4	31.473	237	2.692	.032
PBF (%)	119.863	4	58.803	237	2.038	.090
SMMI	24.059	4	1.734	237	13.873	.000
IBC	.025	4	.152	237	.167	.955
MFI (Muscle-Fat Index)	5.379	4	2.729	237	1.971	.100
weekly training in mn	448982.961	4	121906.494	237	3.683	.006
F_{max}_L	216592.958	4	4004.163	237	54.092	.000
F_{max}_R	203532.700	4	4203.632	237	48.418	.000
RFD_{max}_L	23536220.607	4	81194.207	237	289.876	.000
RFD_{max}_R	21300629.576	4	87237.598	237	244.168	.000
F_{max}_SUM	839409.349	4	14061.582	237	59.695	.000
RFD_{max}_SUM	89572844.369	4	183245.484	237	488.813	.000
IS L	22.143	4	.667	237	33.217	.000
IS R	16.419	4	.633	237	25.923	.000
IS_SUM	18.894	4	.502	237	37.633	.000
Dominant HG_F_{max}	207399.431	4	3874.128	237	53.534	.000
Non Dom. HG_F_{max}	212701.904	4	4249.952	237	50.048	.000
Dominant HG_RFD_{max}	21996317.642	4	82410.904	237	266.910	.000
Non Dom. HG_RFD_{max}	22811067.370	4	86079.981	237	264.999	.000
D IS	17.147	4	.629	237	27.242	.000
ND IS	21.328	4	.673	237	31.675	.000
Dominant_F_{rel}	10.600	4	.985	237	10.758	.000
NonDominant_F_{rel}	11.568	4	1.020	237	11.346	.000
Dominant_RFD_{rel}	1827.064	4	41.796	237	43.713	.000
NonDominant_RFD_{rel}	1881.667	4	41.829	237	44.985	.000
F_{rel}_SUM	44.218	4	3.685	237	12.000	.000
RFD_{rel}_SUM	7411.447	4	143.747	237	51.559	.000
Health_Score/100	11127.203	4	79.709	237	139.597	.000

Table 16 presents the descriptive statistics of handgrip strength, rate of force development, relative values, and index of synergy among male and female participants. The data demonstrate a high level of accuracy and reliability, as evidenced by the coefficient of variation (CV), which reflects the consistency of measurements across individuals. The mean CV for males (19.73%) and females (24.59%) indicates acceptable variability for physiological data. Additionally, the standard error of the mean (SEM) for males (1.07) and females (1.99) further supports the precision of the measurements. These values confirm the robustness and reliability of the dataset, providing a solid foundation for subsequent statistical analyses and interpretation.

Table 17 presents the final cluster centers for the five distinct groups identified through k-means cluster analysis among male participants (n = 242). Each cluster represents a unique profile based on anthropometric, body composition, handgrip performance variables, training load, and overall health score. Cluster 1 (9.5%) is characterized by elevated BMI, fat mass, and muscle mass, reflecting a heavier yet muscular profile. Cluster 2 (23.5%) includes older individuals with lower body weight, muscle mass, and handgrip strength, possibly indicating a less trained or deconditioned group. Cluster 3 (0.41%) represents a unique individual profile, combining very high body mass, fat mass, and skeletal muscle mass, along with the highest strength and health score values among all groups. Cluster 4 (32.2%) demonstrates moderate body composition with average performance metrics, while Cluster 5 (34.2%) is distinguished by higher training volume, muscle mass, and overall better health and strength scores, representing the fittest subgroup.

Table 18 reports the ANOVA results comparing the clusters. Significant differences ($p < 0.05$) were observed across clusters for the majority of the analyzed variables, including age, body height, body mass, BMI, fat-free mass (FFM), skeletal muscle mass (SMM), skeletal muscle mass index (SMMI), fat mass (BFM), and muscle-fat index (MFI). Additionally, significant between-group differences were found in all handgrip strength and rate of force development (RFD) parameters (e.g., Fmax, RFD_{max}, Frel, RFD_{rel}), as well as in the symmetry indexes (IS) and total training volume. Notably, the Health Score also differed significantly between clusters ($F = 139.597$, $p < .001$), with Cluster 3 showing the highest score (83.54) and Cluster 2 the lowest (29.65). These results indicate meaningful segmentation of the male population based on physiological, strength, and health-related characteristics, supporting the relevance of cluster-based profiling in evaluating health and performance status.

Table 19 presents the final cluster centers for the five distinct groups identified through k-means cluster analysis among male participants (n = 151). Each cluster reflects a unique profile based on anthropometric, body composition, training, handgrip strength, and health-related variables. Cluster 1 (38.4%) includes younger participants with elevated BMI and the highest fat and muscle mass levels, indicating a heavier yet muscular profile with the highest training volume and health score. Cluster 2 (26.5%) is characterized by older individuals with lower body mass, FFM, and grip strength, reflecting a deconditioned or less trained group. Cluster 3 (7.95%) shows a high training volume, balanced muscle-fat profile, and intermediate strength and health indicators. Cluster 4 (17.9%) exhibits the lowest muscle mass, strength, and training volume, as well as the poorest health score (24.01), identifying it as the most compromised group. Cluster 5 (9.3%) presents a leaner profile with lower body mass and fat levels, moderate muscle mass, and strength, but with a suboptimal training load and health score, suggesting an undertrained but lean phenotype.

Table 19: Final cluster centers of anthropometric, body composition, training, handgrip strength, and health-related variables among Females participants

Variables	Cluster Group Females n= 151				
	Group 1 n= 58 (38.4%)	Group 2 n= 40 (26.5%)	Group 3 n = 12 (7.95%)	Group 4 n= 27 (17.88%)	Group 5 n= 14 (9.27%)
Age	23.27	36.11	29.09	34.68	33.60
BH	163.0	164.0	166.2	159.3	163.8
BM	71.2	64.7	66.3	63.4	61.5
BMI	26.75	24.08	23.99	24.94	22.97
FFM	47.31	42.69	45.54	39.47	40.98
FMI	8.96	8.21	7.56	9.41	7.70
BFM	23.91	21.98	20.75	23.90	20.57
SMM	24.33	20.58	23.41	18.89	19.01
PSMM (%)	35.34	32.00	35.44	30.26	31.18
PBF (%)	32.40	32.98	30.75	36.05	32.35
SMMI	9.19	7.65	8.43	7.42	7.07
IBC	1.17	1.20	1.17	1.44	1.28
MFI (Muscle-Fat Index)	1.28	1.02	1.30	.94	1.04
weekly training in min	324.5	177.6	404.3	109.0	178.9
F_{max}_L	364.5	248.6	290.5	201.3	234.0
F_{max}_R	366.4	275.0	309.5	212.8	252.0
RFD_{max}_L	2342	1538	1863	777	1287
RFD_{max}_R	2404	1671	2031	918	1354
F_{max}_SUM	731	524	600	414	486
RFD_{max}_SUM	4746	3209	3894	1695	2641
IS L	6.46	6.25	6.47	3.96	5.56
IS R	6.58	6.14	6.62	4.44	5.46
IS_SUM	6.52	6.19	6.54	4.20	5.51
Dominant HG_F_{max}	366.4	274.2	309.8	213.8	254.5
Non Dominant HG_F_{max}	364.5	249.4	290.3	200.3	231.5
Dominant HG_RFD_{max}	2404	1670	2030	912	1358
Non Dominant HG_RFD_{max}	2342	1539	1864	783	1283
D IS	6.58	6.16	6.60	4.39	5.41
ND IS	6.46	6.23	6.49	4.00	5.62
Dominant_F_{rel}	5.27	4.36	4.76	3.48	4.25
NonDominant_F_{rel}	5.25	3.97	4.44	3.27	3.85
Dominant_RFD_{rel}	34.76	26.54	31.22	14.98	22.89
NonDominant_RFD_{rel}	33.80	24.53	28.65	12.87	21.36
F_{rel}_SUM	10.53	8.33	9.20	6.75	8.11
RFD_{rel}_SUM	68.55	51.06	59.87	27.85	44.25
Health Score/100	74.84	52.80	65.26	24.01	44.31

Table 20: ANOVA results showing between-cluster differences in anthropometric, body composition, training, handgrip strength, and health-related variables among Females participants.

Variables	Cluster		Error		F	Sig.
	Mean Square	df	Mean Square	df		
Age	501.401	4	203.354	146	2.466	.048
BH	172.976	4	32.002	146	5.405	.000
BM	250.207	4	146.794	146	1.704	.152
BMI	37.307	4	19.432	146	1.920	.110
FFM	221.211	4	28.085	146	7.876	.000
FMI	16.709	4	11.416	146	1.464	.216
BFM	65.111	4	78.787	146	.826	.510
SMM	147.072	4	17.271	146	8.516	.000
PSMM (%)	145.836	4	29.925	146	4.873	.001
PBF (%)	103.574	4	61.865	146	1.674	.159
SMMI	15.079	4	1.934	146	7.795	.000
IBC	.337	4	.088	146	3.807	.006
MFI (Muscle-Fat Index)	.664	4	.224	146	2.967	.022
weekly training in min	421228.234	4	74866.197	146	5.626	.000
F_{max}_L	66472.690	4	1367.899	146	48.595	.000
F_{max}_R	62312.764	4	1428.087	146	43.634	.000
RFD_{max}_L	6767880.603	4	29095.654	146	232.608	.000
RFD_{max}_R	6900856.642	4	23367.528	146	295.318	.000
F_{max}_SUM	255860.213	4	4702.918	146	54.405	.000
RFD_{max}_SUM	27275288.376	4	59805.875	146	456.064	.000
IS L	28.510	4	.649	146	43.928	.000
IS R	21.168	4	.607	146	34.897	.000
IS_SUM	24.293	4	.490	146	49.591	.000
Dominant HG_F_{max}	60634.675	4	1384.432	146	43.798	.000
Non Dominant HG_F_{max}	68040.510	4	1386.851	146	49.061	.000
Dominant HG_RFD_{max}	6922886.323	4	24369.842	146	284.076	.000
Non Dominant HG_RFD_{max}	6739806.924	4	28359.441	146	237.657	.000
D IS	22.155	4	.597	146	37.129	.000
ND IS	27.472	4	.662	146	41.496	.000
Dominant_F_{rel}	8.509	4	.737	146	11.547	.000
NonDominant_F_{rel}	9.511	4	.644	146	14.762	.000
Dominant_RFD_{rel}	1276.666	4	23.661	146	53.956	.000
NonDominant_RFD_{rel}	1273.496	4	19.521	146	65.237	.000
F_{rel}_SUM	35.620	4	2.534	146	14.059	.000
RFD_{rel}_SUM	5092.351	4	72.828	146	69.923	.000
Health score/100	8259.335	4	59.113	146	139.721	.000

Table 20 displays the ANOVA results comparing the five clusters. Significant between-group differences ($p < .05$) were observed for the majority of analyzed variables. These include age, body height, fat-free mass (FFM), skeletal muscle mass (SMM), percentage of skeletal muscle mass (PSMM), skeletal muscle mass index (SMMI), index of body composition (IBC), muscle-fat index (MFI), and weekly training volume. Most notably, significant differences were found in all handgrip strength (F_{max}, Frel) and rate of force development (RFD_{max}, $RFDr_{el}$) parameters, as well as in the synergy indexes (IS) for both dominant and non-dominant hands. The Health Score also varied significantly across groups ($F = 139.721$, $p < .001$), with Cluster 1 demonstrating the highest overall

score (74.84) and Cluster 4 the lowest (24.01). These findings confirm meaningful segmentation within the female population, highlighting the diversity in strength, training engagement, and health outcomes, and reinforcing the utility of clustering in profiling physiological and performance status.

8.2. Results of Factor Analyses for Fitness Health Risk Score (FHRS_Index)

Table 21 shows results of Kaiser-Meyer-Olkin Measure and Bartlett's Test of Sphericity for Male and Female Participants in relation to the tested samples as a function of gender.

In both cases, the results of the KMO analysis showed that the defined score has a statistically significant variance reliability (Table 7, for females KMO = 0.59, p = 0.000; for males KMO = 0.475, p = 0.000).

Table 21: Kaiser-Meyer-Olkin Measure and Bartlett's Test of Sphericity for Male and Female Participants

		Male	Female
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.509	.475
Bartlett's Test of Sphericity	Approx. Chi-Square	237.6	173.41
	df	3	3
	Sig.	.000	.000

On the Table 22 was shown the results of extracted communalities of Body Composition and Training Variables among Male and Female Participants as a variable which represent basic varianse for defining criteria variable of Fitness Health Risk Score index (FHRS_index)

Table 22: Communalities of Body Composition and Training Variables among Male and Female Participants for FHRS_index

		Male	Female
	Initial	Extraction	Extraction
BMI	1.000	.736	.899
PBF (%)	1.000	.861	.948
weekly amount of training in min	1.000	.332	-.441
Extraction Method: Principal Component Analysis.			

Table 23 shows the results of the Total Variance Explained by Principal Component Analysis (factor analysis) which defined the FHRS_index in relation to the tested samples as a function of gender (female and male, respectivaly).

Table 23: Total Variance Explained by Principal Component Analysis for Male and Female Participants

Gender	Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
		Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
Male	1	1.929	64.287	64.287	1.929	64.287	64.287
	2	.841	28.043	92.330			
	3	.230	7.670	100.000			
Female	1	1.902	63.384	63.384	1.902	63.384	63.384
	2	.921	30.713	94.097			
	3	.177	5.903	100.000			
Extraction Method: Principal Component Analysis.							

In both cases of analysed samples (male and female), one factor was defined, which proves that the given variables belonged to the same space (definied FHRS_index) and in men, common variances were explained 64.287, and in women 63.384% of cumulative variance (Table 23).

Table 24 shows the results of the structure of defined factors which represent the FHRS_index (Component Matrix) in relation to the tested samples as a function of gender (females and males, respectively).

Table 24: Principal Component Analysis: Total Variance Explained and Component Loadings for Males and Females participants

	Males	Females
	Component 1	Component 1
BMI	.858	.899
PBF (%)	.928	.948
weekly training in min	-.576	-.441
Extraction Method: Principal Component Analysis.		

In both cases, the matrix of components for both males and females had the same factor structure, where the most important (strongest) variable in defining FHRS_index was PBF (%), which mean that amount of body fat is the strongest predictor of fitness health risk factor independent of gender considering Lebanesse population (Table 10, Male 0.928, Females 0.948). The next most important variable was BMI (Male 0.858, Female .899), while the weakest predictor was the amount of exercise/physical activity per week (Male -.576, Female -.441).

8.3. General Results of Discriminant Analysis for males and females

Table 25 presents the results of Box's M test for both male and female participants, indicating that the assumption of equality of covariance matrices was violated in both groups ($p < .001$). Nevertheless, as recommended in large-sample multivariate designs, the discriminant analyses continued using the pooled within-group covariance matrices for the non-singular cases

Table 25: Box's M Test of Equality of Covariance Matrices for Males and Females

Gender	Box's M	F (Approx.)	Df1	Df2	Sig.
Males	3327.152	2.633	975	52380.929	.000
Females	2910.506	3.259	600	20893.258	.000

This outcome is anticipated due to the natural heterogeneity in age, training background, and physical activity levels within the Lebanese adult population. Such variability reinforces the ecological validity of the discriminant analysis by reflecting real-world population characteristics.

Table 26 summarizes the eigenvalues, percentage of explained variance, cumulative variance, and canonical correlations associated with each discriminant function extracted from the analysis for both males and females. These values indicate the relative importance and discriminative power of each function in classifying individuals into distinct health-related groups.

Table 26: Summary of Eigenvalues, Explained Variance, and Canonical Correlations for Discriminant Functions in Lebanese Males and Females

	Males				**Females**			
Function	Eigenvalue	%of Variance	Cumulative %	Canonical Correlation	Eigenvalue	%of Variance	Cumulative %	Canonical Correlation
1	9.345	80.2%	80.2%	0.950	11.687	84.1%	84.1%	0.960
2	1.831	15.7%	95.9%	0.804	1.160	8.4%	92.5%	0.733
3	0.305	2.6%	98.6%	0.483	0.862	6.2%	98.7%	0.680
4	0.167	1.4%	100.0%	0.378	0.183	1.3%	100.0%	0.393

The first discriminant function for both males and females accounted for the vast majority of explained variance (80.2% and 84.1%, respectively), with high canonical correlations (.950 for males and .960 for females), indicating a strong association between the discriminant scores and group membership. This highlights the dominant role of the primary function in differentiating health status across clusters, particularly through explosive strength and neuromuscular efficiency variables.

Table 27 presents the Wilks' Lambda values and associated chi-square tests for the discriminant functions in both male and female participants. These tests assess whether each canonical function significantly contributes to the discrimination between predefined groups. A lower Wilks' Lambda value indicates better discriminatory power of the corresponding function, and statistical significance ($p < .05$) suggests that the function adds value in classifying individuals based on the input variables.

Table 27: Wilks' Lambda and Chi-Square Statistics for the Significance of Discriminant Functions in Males and Females

Sex	Function(s)	Wilks' Lambda	Chi-square	df	Sig
Males	1 through 4	0.029	804.958	100	.000
	2 through 4	0.279	291.356	72	.000
	3 through 4	0.711	77.814	46	.002
	4	0.920	19.092	22	.640
Females	1 through 4	0.017	555.592	96	.000
	2 through 4	0.210	211.348	69	.000
	3 through 4	0.454	106.983	44	.000
	4	0.846	22.739	21	.358

8.4. Discriminative Structure metrics and modeling for Males

The significant Wilks' Lambda values for the first three discriminant functions in both males and females indicate that these functions explain a meaningful amount of variance between health-related clusters. The non-significant result for Function 4 suggests it contributes little additional discriminatory power.

Table 28 presents the structure matrix, showing pooled within-group correlations between each predictor variable and the four standardized canonical discriminant functions for the males. These correlations indicate the relative contribution of each variable to the respective discriminant function, with variables having the highest absolute correlations in each function marked with an asterisk.

Function 1 exhibited strong positive loadings from multiple neuromuscular performance variables, notably RFDmax_SUM (.921), Dominant HG_RFDmax (.700), RFDmax_L (.694), and RFDmax_R (.675), indicating that this function primarily represents explosive strength potential and capacity.

Function 2 was characterized by body composition variables, particularly BMI (–.193), BM (–.185), and SMMI (–.153), suggesting this axis reflects nutritive-related anthropometric measures and overall body size status.

Function 3 showed notable negative correlations with IS_SUM (–.319) and IS L (–.313), indicating that it captures aspects of neuromuscular coordination or asymmetry.

Function 4 was primarily defined by Dominant HG_Fmax (.418), Dominant_Frel (.416), D IS (–.405), and IS R (–.392), suggesting this function represents maximal strength potential and symmetry-based performance.

Collectively, this structure matrix highlights how each canonical function is driven by distinct groups of variables, enabling the discriminant functions to differentiate clusters based on performance, body composition, and neuro-muscular coordination measures.

Table 28: Structure Matrix of Discriminant Function Loadings for males

	Function			
	1	2	3	4
RFD_{max}_SUM	**.921***	-.131	-.028	.028
Dom HG_RFD_{max}	.700*	-.077	.028	-.064
RFD_{max}_L	.694*	-.106	-.087	.136
RFD_{max}_R	.675*	-.088	.047	-.096
NonDomHG_RFD_{max}	.670*	-.116	-.066	.101
RFD_{rel}_SUM	.315*	.162	.049	.104
NonDom_RFD_{rel}	.294*	.140	.027	.128
Dominant_RFD_{rel}	.288*	.160	.064	.064
SMM	.167*	-.137	-.002	.052
FFM	.147*	-.128	.027	-.005
BMI	.059	**-.193***	-.047	-.073
BM	.100	-.185*	-.086	-.133
SMMI	.142	-.153*	.058	.140
MFI	.035	.070*	.011	.000
IS_SUM	.224	.130	**-.319***	-.197
IS L	.229	.130	-.313*	-.209
IBC	-.018	.030	-.092*	.076
Dominant HG_F_{max}	.283	-.152	.110	**.418***
Dominant_F_{rel}	.126	.075	.158	.416*
D IS	.235	.141	-.185	-.405*
IS R	.230	.141	-.192	-.392*
F_{rel}_SUM	.140	.074	.192	.386*
F_{max}_SUM	.309	-.159	.158	.383*
F_{max}_R	.271	-.154	.126	.382*
ND IS	.262	.154	-.285	-.333*
F_{max}_L	.303	-.140	.169	.327*
NonDom_F_{rel}	.142	.067	.210	.326*
Non Dom HG_F_{max}	.292	-.144	.183	.297*
BFM	.019	-.171	-.160	-.204*
Week of training in min	.066	.049	.160	.202*
PSMM (%)	.058	.075	.053	.183*
PBF (%)	-.024	-.100	-.104	-.178*
average/single session	.053	.031	.170	.171*
Exerc_per_WEEK	.065	.044	.058	.166*
FMI	.002	-.162	-.125	-.165*
Age	-.071	-.004	-.051	-.133*
BH	.091	.007	-.081	-.111*

In conclusion the structure matrix showed that Function 1 was strongly associated with RFD_{max}_SUM, RFD_{max}_R, and RFD_{max}_L, indicating that explosive strength, specifically the rate of force development, was the most important factor distinguishing clusters. This suggests that individuals with higher RFD values possess superior neuromuscular performance and are likely to belong to the healthier, more athletic clusters. Explosive strength is critical for executing fast, powerful movements, and is widely considered a key indicator of functional capacity and reduced health risk. Function 2 primarily loaded on fat mass-related variables (BMI, BM and SMMI), while Function 3 was related to training frequency and Synergy indexes (IS_SUM). Function 4 was associated with relative strength measures (Dominant HG_$F_{max,}$ SUM, Dominant_F_{rel}), but contributed less overall.

Finally, based on the results of the discriminant analysis for men, it can be concluded that the following variables most strongly represent the defined factors: RFD_{max}_SUM, BMI, IS_SUM and Dominant HG_F_{max}.

Table 29: Group Centroids for the Canonical Discriminant Functions for males

Functions at Group Centroids - Males				
Cluster Number of Case	Function			
	1	2	3	4
1	4.415	-.200	.382	.483
2	-4.608	-1.220	.696	.063
3	1.399	.497	.174	-.338
4	-1.435	.357	-.659	.121
5	12.250	-16.723	-2.845	-1.047
Unstandardized canonical discriminant functions evaluated at group means				

Table 29 shows the within-group covariance values of the four canonical discriminant functions for each male cluster. It highlights the internal variability and how the discriminant functions are related within each group.

Figure 7: Canonical Discriminant Function Plot of Male Participants by Cluster Membership

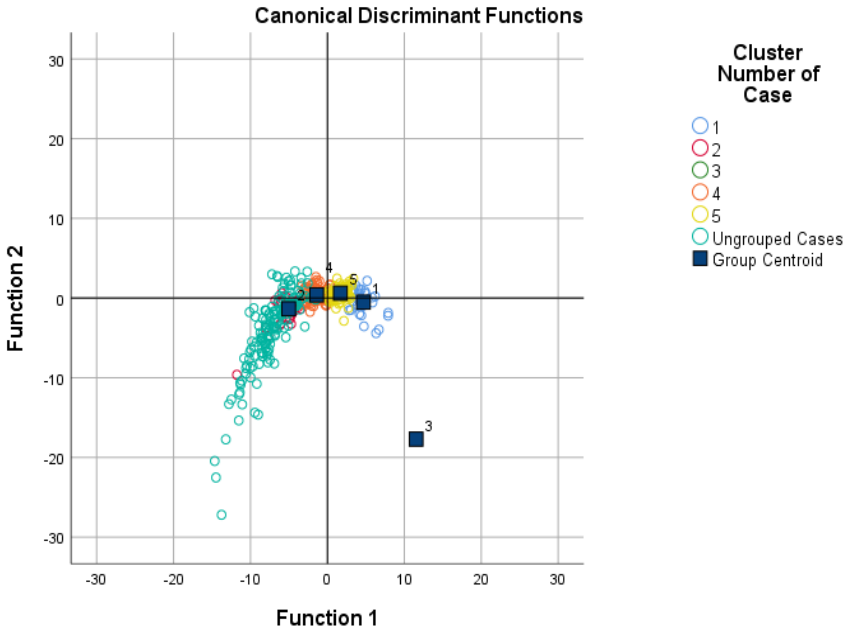


Figure 7 illustrates the distribution of male participants (n = 242) across five clusters derived from discriminant analysis, plotted on the first two canonical discriminant functions. Each colored circle represents an individual case assigned to a cluster, and the dark blue squares indicate the group centroids, which correspond to the average position of each cluster in the canonical space. The results showed that the maximum value for the centroid position of the group 3 for the most important

function - Function 1, was positioned at the value of 12.250, while the minimum value of the centroid of the group 2 was positioned at the value of the centroid of – 4.608.

Table 30: Discriminative analysis clasification results for males

Classification Results - Males								
		Cluster Number of Case	Predicted Group Membership					Total
			1	2	3	4	5	
Original	Count	1	**32**	0	5	0	0	37
		2	0	**37**	0	2	0	39
		3	0	0	**85**	1	0	86
		4	0	1	2	**78**	0	81
		5	0	0	0	0	1	1
	%	1	**86.5**	.0	13.5	.0	.0	100.0
		2	.0	**94.9**	.0	5.1	.0	100.0
		3	.0	.0	**98.8**	1.2	.0	100.0
		4	.0	1.2	2.5	**96.3**	.0	100.0
		5	.0	.0	.0	.0	100.0	100.0
b. 95.5% of original grouped cases correctly classified.								

Based on the results of Table 30, it can be claimed that the discriminative analysis defined the classes of subsamples of men with a very high percentage of accuracy (95.5%), which confirms the high accuracy of the defined structure of the extracted factors, and shows that the first extracted variables are highly informative in terms of defining the criteria for establishing the final algorithms of the model.

8.5. Final algorithm modeling for males by Multiple Regresional Analysis

Table 31 shows the results of the strength of the summary regression model for predicting health outcomes in lebanese males according to 4 factor of Discriminant Analysis

Table 31: Regression Model Summary for Predicting Health Score in Lebanese Males

	Model R	R^2	Adj. R^2	Std. Error of the Estimate
1	1.000	1.000	1.000	.00296

This model demonstrates an excellent fit, with an R^2 of 1.000, indicating that the selected predictors explain 100% of the variance in the health score for Lebanese males. The negligible standard error of estimate (0.00296 of point score number) confirms the precision of the predictions. These results suggest that the chosen variables are extremely powerful in modeling health status in this population.

Table 32: Regression Coefficients for Health Score Prediction Model in Lebanese Males according to the 4 factors of discriminant analysis

Model MALE		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-52.70537	.005		-11682.719	0.000
	RFD_{max}_SUM	.00632	.000	.503	18769.392	0.000
	BMI	-.49435	.000	-.118	-5564.869	0.000
	IS_SUM	7.82413	.000	.428	20661.926	0.000
	Dominant_F_{rel}	5.30915	.000	.344	14645.669	0.000

All predictors significantly contribute to the model ($p < .001$). The most influential variable is RFD_{max}_SUM ($\beta = 0.503$), reflecting the importance of rate of force development in male health status. IS_SUM and Dominant_F_{rel} also show strong positive effects, highlighting the contribution of isometric strength and relative force in the dominant hand. BMI is negatively associated, suggesting that higher body mass index may reduce the health score. These findings support the integration of neuromuscular and body composition variables in health assessments.

Based on the obtained Multiple Regresion Analysis (MRA) results, it can be claimed that the prediction algorithm for classification Fittness Health Related Score (FHRS_index), as a measure for assessing hand grip and body composition status related to health amog Lebanese adult male has the following equation:

FHRS_Index_MALES = -52.70537 + (RFD_{max}_SUM • 0.00632) – (BMI • 0.49435) + (IS_SUM • 7.82413) + (Dominant_F_{rel} • 5.30915)

8.6. Practitioner Modeling Based on Handgrip Variables for Males

Table 33: Regression Model Summary for Predicting Health Score from Absolute Handgrip Variables in Lebanese Males

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	1.000	1.000	1.000	.00283

This model demonstrates an excellent fit, with an R^2 of 1.000, indicating that the selected predictors explain 100% of the variance in the health score for Lebanese males. The negligible standard error of estimate (0.00283 of point score number) confirms the precision of the predictions. These results suggest that the chosen variables are extremely powerful in modeling health status in this population.

Table 34: Regression Coefficients for Predicting Health Score from Absolute Handgrip Variables in Lebanese Males

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-38.15473	.001		-36041.345	.000
	F_{max}_SUM	.05221	.000	.538	32811.127	.000
	RFD_{max}_SUM	.00673	.000	.538	32775.442	.000

Both predictors are highly significant ($p < .001$), with equal standardized coefficients ($\beta = 0.538$), indicating that handgrip strength and explosive strength equally contribute to predicting the health score. This model highlights the importance of absolute neuromuscular performance in health profiling for males.

Based on the obtained Multiple Regression Analysis (MRA) results, it can be claimed that the prediction algorithm for the classification of the Fitness Health-Related Score (FHRS_Index), as a measure for assessing absolute handgrip strength and explosive force related to health among Lebanese adult males, is expressed by the following equation:

FHRS_Index_MALES (Absolute) = –38.15473 + (Fmax_SUM • 0.05221) + (RFDmax_SUM • 0.00673)

Table 35: Regression Model Summary for Predicting Health Score from Relative Handgrip Variables in Lebanese Males

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	1.000[b]	1.000	1.000	.00287

This model predicts the health score from relative handgrip values (adjusted for body mass). The R^2 value of 1.000 and very low error (0.00287) confirm the model's exceptional ability to predict health status using normalized performance indicators.

Table 36: Regression Coefficients for Predicting Health Score from Relative Handgrip Variables in Lebanese Males

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-36.19711	.001		-34458.522	.000
	F_{rel}_SUM	4.17251	.000	.533	30077.230	.000
	RFD_{rel}_SUM	.53289	.000	.530	29920.497	.000

Both relative handgrip strength and relative rate of force development are strong, significant predictors of the health score ($p < .001$). Their near-equal contributions ($\beta \approx 0.53$) show that relative neuromuscular capacity is crucial for understanding health in relation to body size.

Based on the obtained Multiple Regression Analysis (MRA) results, it can be claimed that the prediction algorithm for the classification of the Fitness Health-Related Score (FHRS_Index), as a measure for assessing relative handgrip strength and explosive force adjusted for body mass among Lebanese adult males, is expressed by the following equation:

FHRS_Index_MALES (Relative) = –36.19711 + (Frel_SUM • 4.17251) + (RFDrel_SUM • 0.53289)

8.7. Discriminative Structure metrics and modeling for Females

Table 37: Structure Matrix of Discriminant Function Loadings for females

	Function			
	1	2	3	4
RFD_{max}_SUM	**.881***	.058	-.008	.020
RFD_{max}_L	.726*	.038	-.019	.091
RFD_{max}_R	.677*	.053	.005	-.055
$RFDr_{el}$_SUM	.368*	.205	.157	.057
NonDominant_RFD_{rel}	.360*	.186	.132	.103
F_{max}_SUM	.343*	-.214	.047	.288
F_{max}_L	.327*	-.297	.023	.308
Dominant_RFD_{rel}	.322*	.193	.158	.008
F_{max}_R	.304*	-.102	.062	.224
FFM	.142*	-.125	.072	.039
IS L	.294	**.495***	-.015	-.162
IS_SUM	.315	.434*	-.031	-.214
IS R	.260	.282*	-.036	-.212
SMMI	.109	-.235*	.064	-.209
weekly training in min	.118	-.120	**.631***	.149
Exerc_per_WEEK	.134	-.073	.457*	-.067
MFI (Muscle-Fat Index)	.071	-.096	.400*	.054
avg/signle session	.098	-.136	.353*	.165
PSMM (%)	.093	-.091	.295*	-.181
PBF (%)	-.046	-.070	-.283*	-.106
BFM[b]	-.006	-.123	-.242*	.003
FMI[b]	-.019	-.134	-.239*	-.014
BMI	.021	-.187	-.187*	.003
IBC	-.097	-.071	-.180*	-.019
BM	.058	-.144	-.145*	.019
BH	.094	.119	.134*	.003
F_{rel}_SUM	.167	.007	.161	**.242***
Dominant_F_{rel}	.152	.069	.185	.234*
NonDominant_F_{rel}	.169	-.059	.123	.230*
SMM	.130	-.175	.123	-.190*

Table 37 presents the structure matrix, which shows the pooled within-group correlations between each predictor variable and the four standardized canonical discriminant functions for the females. Variables with the highest absolute correlations in each function are marked with an asterisk (*), reflecting their dominant role in defining the respective canonical functions.

Function 1 is driven by neuromuscular performance indicators, especially RFD_{max}_SUM (.881), RFD_{max}_L (.726), and RFD_{max}_R (.677), representing explosive strength potential. Function 2 is characterized by isometric strength variables (IS_L, IS_SUM, IS_R), and structural indicators (SMMI), reflecting aspects of muscle coordination and body structure. Function 3 is associated with physical activity frequency (weekly training, sessions/week) and body composition metrics (MFI, PSMM%), identifying lifestyle and morphological differentiation.

Function 4 includes variables related to relative strength (F_{rel}_SUM, Dominant_F_{rel}, NonDominant_F_{rel}), but its contribution is less prominent, in line with its non-significance in Wilks' Lambda test.

Table 38: Group Centroids for the Canonical Discriminant Functions for Females

Functions at Group Centroids - Females				
Cluster Number of Case	Function			
	1	2	3	4
1	-1.199	.704	-.015	.427
2	1.919	.818	-.383	-.544
3	3.696	-.662	2.882	-.058
4	-5.229	-1.387	-.058	-.283
5	6.400	-2.012	-1.202	.381
Unstandardized canonical discriminant functions evaluated at group means				

Table 38 displays the average discriminant scores (centroids) of each cluster on the four canonical functions. Clusters 3 and 5 show extreme positive values on Function 1, reinforcing their distinct profiles in explosive strength. Cluster 4 presents the most negative Function 1 value, suggesting an opposing performance profile. Function 3 sharply distinguishes Cluster 3 due to high training frequency and PSMM%, whereas Function 2 separates Clusters 1 and 2 based on isometric capacity.

Figure 8: Canonical Discriminant Functions Plot for Female Participants

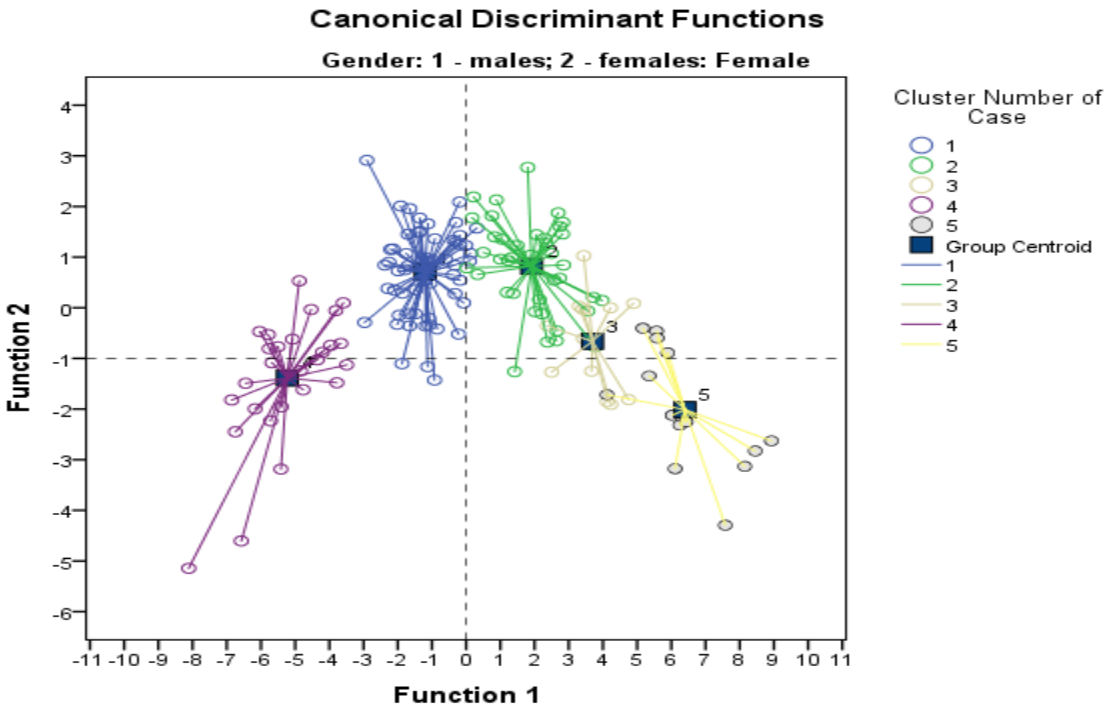


Figure 8 shows the distribution of female participants (n = 151) across five clusters in the canonical space. Function 1 explains 84.1% and Function 2 adds 8.4% of the between-group variance. Strong separation is evident between Clusters 5 (right extreme) and 4 (left extreme), corresponding to high vs. low neuromuscular performance. Minimal overlap between clusters demonstrates excellent discriminant capability.

Table 39: Discriminative analysis clasification results for males

		Cluster Number of Case	Predicted Group Membership					Total
			1	2	3	4	5	
Original	Count	1	**58**	0	0	0	0	58
		2	4	**35**	1	0	0	40
		3	0	3	**9**	0	0	12
		4	1	0	0	**26**	0	27
		5	0	0	0	0	14	14
	%	1	**100.0**	.0	.0	.0	.0	100.0
		2	10.0	**87.5**	2.5	.0	.0	100.0
		3	.0	25.0	**75.0**	.0	.0	100.0
		4	3.7	.0	.0	**96.3**	.0	100.0
		5	.0	.0	.0	.0	100.0	100.0
b. 94.0% of original grouped cases correctly classified.								

This table shows how accurately the discriminant functions classified participants into their original clusters. The overall classification accuracy is high (94.0%), demonstrating that the model effectively distinguishes between the five health-related clusters among Lebanese females. Particularly strong

classification is seen in Clusters 1, 4, and 5 (100% or near), while Cluster 2 shows minor misclassification (10%).

Table 40: Regression Model Summary for Predicting Health Score in Lebanese Females

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	1.000[b]	1.000	1.000	.00300

Table 36 indicates a perfect model fit, with $R^2 = 1.000$ and negligible standard error (.00300), suggesting that the selected predictors from the discriminant functions fully account for the variance in the health score among Lebanese females.

Table 41: Regression Coefficients for Health Score Prediction (Discriminant-Based Variables)

Model Female		Unstandardized Coefficients		Standardized Coefficients	t
		B	Std. Error	Beta	
1	(Constant)	-29.97808	.002		-17993.723
	RFDmax_SUM	.00810	.000	.431	16780.752
	IS L	4.77076	.000	.338	15583.340
	weekly training in min	.01452	.000	.253	15937.386
	Frel_SUM	2.92873	.000	.325	17329.634

All variables contribute significantly ($p < .001$) to predicting female health score. RFD_{max}_SUM is the most influential ($\beta = 0.431$), followed by IS_L and F_{rel}_SUM. Weekly training volume reinforces the behavioral impact on health. Together, these variables confirm the importance of explosive power, isometric strength, and training volume in health profiling.

Based on the obtained Multiple Regression Analysis (MRA) results, it can be claimed that the prediction algorithm for the classification of the Fitness Health-Related Score (FHRS_Index), as a measure for assessing neuromuscular performance and training-related indicators among Lebanese adult females, is expressed by the following equation:

FHRS_Index_FEMALES (Discriminant-Based) = –29.97808 + (RFD_{max}_SUM • 0.00810) + (IS_L • 4.77076) + (Weekly Training • 0.01452) + (F_{rel}_SUM • 2.92873)

8.8. Practitioner Modeling Based on Handgrip Variables for Females

On the Table 42 and 43 the results of the regression model for practitioners are shown defined for basic apsolute hand grip variables for female sample.

Table 42: Regression Model Summary (Absolute Handgrip Strength Only)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	1.000[b]	1.000	1.000	.00294

This model evaluates health status using only absolute strength variables (F_{max}_SUM and RFD_{max}_SUM), showing perfect predictive accuracy with minimal error (.00294), validating its use in practical assessments.

Table 43: Regression Coefficients (Absolute Handgrip Strength)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-24.14104	1.731		-13.946	.000
	F_{max}_SUM	.07640	.005	.465	14.259	.000
	RFD_{max}_SUM	.01091	.001	.556	17.048	.000

Both predictors are statistically significant ($p < .001$). RFD_{max}_SUM has a slightly higher standardized coefficient ($\beta = 0.556$) than F_{max}_SUM ($\beta = 0.465$), indicating that explosive handgrip strength is the strongest contributor to predicting health score in females. The model confirms that absolute strength and power measures are essential in evaluating health status in Lebanese women.Based on the obtained Multiple Regression Analysis (MRA) results, it can be claimed that the prediction algorithm for the classification of the Fitness Health-Related Score (FHRS_Index), as a measure for assessing absolute handgrip strength and explosive power among Lebanese adult females, is expressed by the following equation:

FHRS_Index_FEMALES (Absolute) = –24.14104 + (F_{max}_SUM • 0.07640) + (RFD_{max}_SUM • 0.01091)

On the Table 44 and 45 the results of the regression model for practitioners are shown defined for basic relative hand grip variables for female sample.

Table 44: Regression Model Summary (Relative Handgrip Strength Only)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.988[b]	.976	.975	2.68550

This model predicts the health score using relative handgrip variables (normalized to body mass). The R^2 value of 0.976 indicates that the model explains 97.6% of the variance in the health score. While slightly lower than the absolute model, this still represents excellent predictive capability, especially in adjusting for body size, with a reasonably low standard error (2.68550).

Table 45: Regression Coefficients (Relative Handgrip Strength Only)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-20.11100	1.018		-19.750	.000
	F_{rel}_SUM	4.60987	.203	.495	22.706	.000
	RFD_{rel}_SUM	.64475	.026	.543	24.907	.000

Both relative handgrip strength and relative rate of force development significantly predict the health score ($p < .001$). The standardized beta values (F_{rel}_SUM: $\beta = 0.495$; RFD_{rel}_SUM: $\beta = 0.543$) show that both variables contribute meaningfully, with a slight edge for explosive relative strength. This model validates the importance of normalized neuromuscular indicators in assessing health across different body sizes in females.Based on the obtained Multiple Regression Analysis (MRA) results, it can be claimed that the prediction algorithm for the classification of the Fitness Health-Related Score (FHRS_Index), as a measure for assessing relative handgrip strength and explosive force adjusted for body mass among Lebanese adult females, is expressed by the following equation:

FHRS_Index_FEMALES (Relative) = –20.11100 + (F_{rel}_SUM • 4.60987) + (RFD_{rel}_SUM • 0.64475)

8.9. Percentile-Based Classification of Health Risk Status Using Fact Score Number Among Lebanese Males and Females

On the Table 46 percentile standards for defined Score number values ar calculated as a criteria decision values.

Table 46 presents the combined percentile distribution of the health score (Fact Score Number) for both male (n = 242) and female (n = 153) participants, calculated through descriptive frequency analysis in SPSS. The distribution includes key percentile values (5th, 10th, 15th, 20th, 80th, 85th, 90th, and 95th), allowing for sex-specific comparisons.

For both sexes, the 15th percentile was selected as a statistical threshold to identify individuals potentially at health risk. Among males, a score of 33.30 or lower corresponds to the 15th percentile, and thus individuals falling below or at this value were classified as being at health risk, while those above were categorized as having a lower health risk. Similarly, for females, the 15th percentile score was 30.05, serving as the cut-off to distinguish between higher and lower health risk categories.

Table 46: Percentile Distribution of Health Score (Fact Score Number) Among Male & Females Participants

		Males_Fact_Score_NUMBER _percent n = 242	Females_Fact_Score_NUMBER _percent n = 153
Percentiles	5	17.1050	21.5020
	10	26.5200	24.6460
	15	**33.2975**	**30.0540**
	20	36.1200	38.1100
	80	63.8300	62.7980
	85	66.6725	65.9760
	90	69.8750	69.9940
	95	73.2100	75.7900

This percentile-based classification provides an empirically grounded and population-specific method to evaluate health risk, supporting its use as a screening tool in identifying individuals who may require further assessment or intervention based on their neuromuscular performance and health-related fitness score.

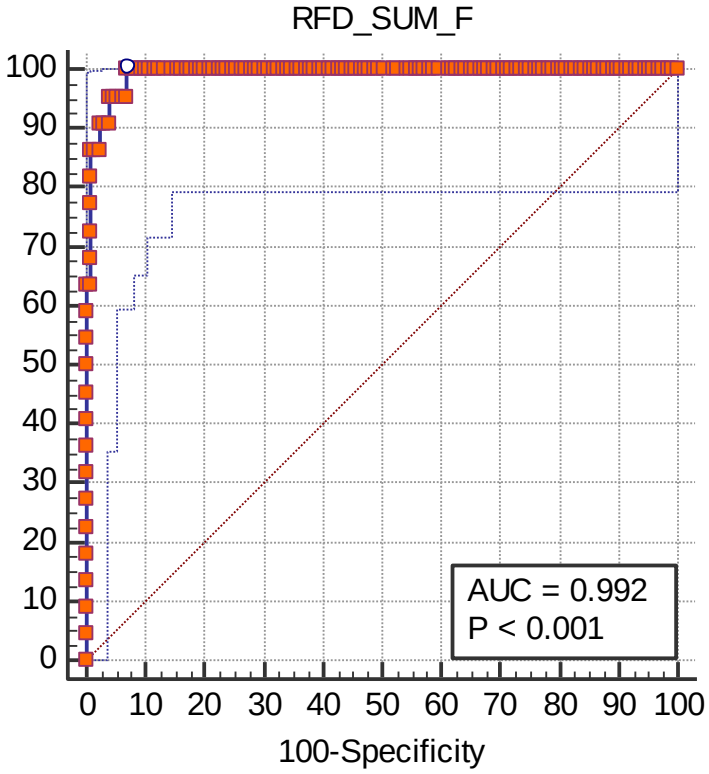
8.10. Results of ROC Curve Analysis for Females

The analysis begins with the female cohort, examining the diagnostic performance of the primary discriminative factors identified through the predictive models to classify health risk profiles.

8.11. Female – Fitnes Health Risk Score Index (FHRS_Index) Classification vs RFD_{max}_SUM

Figure 9 shows the results of the ROC curve in relation to predictive sensitivity and specificity for body composition related Healt Risk Classification in female sample according to RFD_{max}_SUM variable as a explosive strength body potential.

Figure 9: ROC Curve of RFD_{max}_SUM for Predicting body composition Health Risk Classification in Female Participants



This ROC curve illustrates the diagnostic accuracy of RFD_{max}_SUM in classifying health risk status related to body composition among female participants. The Area Under the Curve (AUC) is very high - 0.992, indicating excellent to near-perfect discrimination. The AUC value signifies that the HG test with maximal force strength, as a body fitness potential, and defined criteria index of health related to body composition correctly distinguishes between at-risk and low-risk individuals in 99.2% of cases.

The results indicating high sensitivity (true positive rate) across a wide range of thresholds while maintaining a very low false positive rate (1 - specificity). The associated p-value < 0.001 confirms that the model's performance is statistically significant and unlikely due to chance.

These results demonstrate that RFD_{max}_SUM is a highly reliable predictor of health risk classification related to body composition in females and can be considered a powerful screening metric in body status with fitness health and strength-performance profiling.

Table 47: ROC Curve Summary Cut-off values standars for RFD_{max}_SUM in Female Participants

Variable	RFD_SUM_F
Classification variable	Female_Clases
Sample size	151
Positive group	22 (14.57%)
Negative group	129 (85.43%)

Female_Clases = 1
Female_Clases = 0

Area under the ROC curve (AUC)

Area under the ROC curve (AUC)	0.992
Standard Error	0.00490
95% Confidence interval	0.962 to 1.000
95% Bootstrap CI	0.976 to 0.998
z statistic	100.397
Significance level P (Area=0.5)	<0.0001

Youden index

Youden index J	0.9302
95% Confidence interval	0.8781 to 0.9612
Associated criterion	≤2413
95% Confidence interval	≤2206 to ≤2413
Sensitivity	100.00
Specificity	93.02

This table presents the ROC curve analysis of the variable RFD_{max}_SUM used to predict Body composition related with fitness health risk status among female participants (N = 151). Of the total sample, 22 individuals (14.57%) were classified as "at risk" (Female_Classes = 1), and 129 individuals (85.43%) as "low risk" (Female_Classes = 0).

The Area Under the Curve (AUC) was 0.992, with a standard error of 0.00490, and a 95% confidence interval ranging from 0.962 to 1.000. The bootstrap confidence interval (based on 1000 iterations) confirmed similar precision (95% CI: 0.976 to 0.998). The p-value < 0.0001 indicates that the discriminative ability of this test is highly significant, and the observed AUC differs from random classification (AUC = 0.5).

The Youden Index was 0.9302, identifying the optimal cut-off point at ≤ 2413 N/s, with 100.0% sensitivity (i.e., all at-risk females correctly identified) and 93.02% specificity (i.e., 93% of low-risk females correctly excluded). The confidence interval for the criterion (≤ 2206 to ≤ 2413 N/s) reflects high precision of defined Cut-offs values for explosive strength capacity for adult Lebanese females.

Table 48: Diagnostic classifications standards at Fixed Sensitivity and Specificity Thresholds for RFD_{max}_SUM in Female Participants

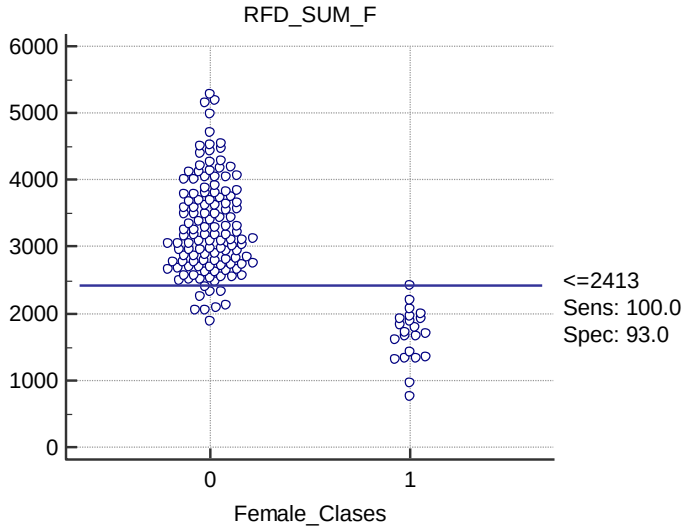
Estimated specificity at fixed sensitivity			
Sensitivity	Specificity	95% CI	Criterion
80.00	99.22	93.02 to 100.00	≤1947.6
90.00	97.67	89.15 to 100.00	≤2068.2
95.00	96.12	88.37 to 99.22	≤2198.2
97.50	93.02	85.27 to 96.90	≤2403.65
99.00	93.02	85.27 to 96.90	≤2409.26
Estimated sensitivity at fixed specificity			
Specificity	Sensitivity	95% CI	Criterion
80.00	100.00	100.00 to 100.00	≤2688.6
90.00	100.00	95.45 to 100.00	≤2512.6
95.00	95.45	54.55 to 100.00	≤2281.65
97.50	90.91	0.00 to 0.00	≤2073.025
99.00	86.36	0.00 to 0.00	≤2012.47

The summary tables show high diagnostic performance even at varying fixed thresholds. For example:

- At 95% sensitivity, specificity remains 96.12%.
- At 95% specificity, sensitivity is still 95.45%.
- At 90% specificity, sensitivity is maximized at 100.00% (criterion: ≤2512.6).

These results confirm that RFD_{max}_SUM is a highly effective variable for health risk screening in females, offering both high sensitivity and excellent specificity, especially around the optimal cut-off.

Figure 10: Classification Scatter Plot of RFD_{max}_SUM by Health Risk Status in Female Participants



This scatter plot visually confirms the excellent classification performance of RFD_{max}_SUM as observed in the ROC analysis. All individuals in the "at risk" group (Class 1) fall below the cut-off of 2413, while nearly all individuals in the "low risk" group (Class 0) fall above this threshold.

The cut-off line (horizontal) clearly separates the two groups, yielding:

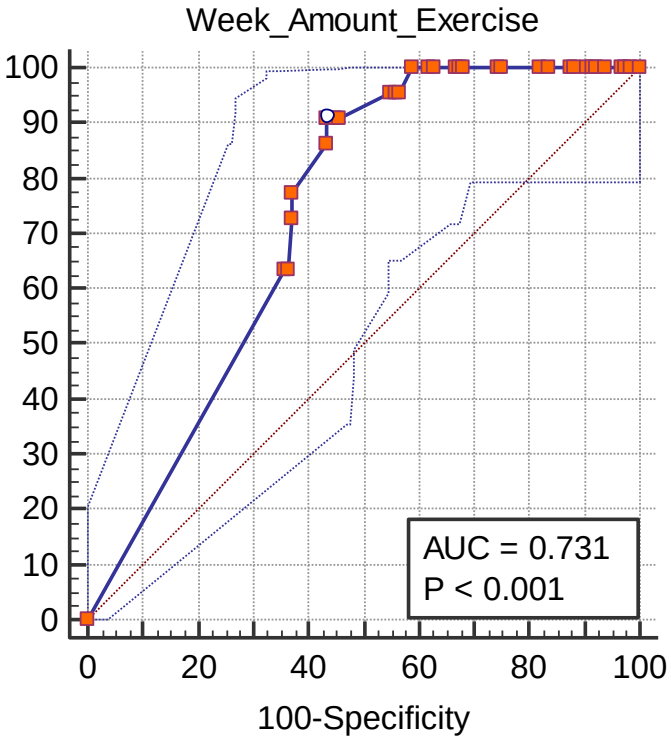
- Sensitivity = 100.0% (all at-risk individuals correctly identified)
- Specificity = 93.0% (only 7% of low-risk individuals misclassified)

The strong vertical separation between classes emphasizes the variable's near-perfect discriminative power, with high clinical potential of defined Cut-off criteria. These findings support the use of RFDmax_SUM as a reliable predictor of health status in female participants, both statistically and visually.

8.12. Female – Fitnes Health Risk Score Index (FHRS_Index) Classification vs Weekly Amount of Exercise

Figure 11 shows the results of the ROC curve in relation to predictive sensitivity and specificity for body composition related Healt Risk Classification in female sample according to Weekly Amount of Exercise variable as a explosive strength body potential.

Figure 11: ROC Curve of Weekly Amount of Exercise for Predicting Health Risk in Female Participants



This figure displays the ROC curve for the variable weekly amount of exercise, used to classify health risk status among females. The AUC of 0.731 indicates a moderate level of discriminative clasification power.

The curve shows that as specificity increases (fewer false positives), the gain in sensitivity (true positives) plateaus, reflecting a trade-off between over-classification and under-detection. The significance level ($p < 0.001$) confirms that the classification ability of this variable is statistically meaningful.

Despite its clinical relevance, the moderate AUC suggests that weekly amount of exercise, when used in isolation, is less effective than strength-based markers for accurately identifying health risk status. It may still serve as a useful complementary factor in a broader predictive model.

Table 49: ROC Curve Summary and Diagnostic Performance Metrics for Weekly Amount of Exercise in Female Participants

Variable	Week_Amount_Exercise
Classification variable	Female_Clases
Sample size	151
Positive group	22 (14.57%)
Negative group	129 (85.43%)

[a] Female_Clases = 1
[b] Female_Clases = 0

Area under the ROC curve (AUC)

Area under the ROC curve (AUC)	0.731
Standard Error	0.0393
95% Confidence interval	0.652 to 0.800
95% Bootstrap CI	0.633 to 0.791
z statistic	5.875
Significance level P (Area=0.5)	<0.0001

Youden index

Youden index J	0.4750
95% Confidence interval	0.3358 to 0.5891
Associated criterion	≤135
95% Confidence interval	≤70 to ≤240
Sensitivity	90.91
Specificity	56.59

This table presents the results of the ROC curve analysis evaluating the classification performance of the variable weekly amount of exercise (in minutes per week) in distinguishing between at-risk and low-risk health status among female participants (N = 151). A total of 22 individuals (14.57%) were categorized as at risk (Female_Classes = 1), while 129 individuals (85.43%) were considered low risk (Female_Classes = 0).

The area under the ROC curve (AUC) was 0.731, indicating moderate discriminative power for accuracy. The standard error was 0.0393, with a 95% confidence interval ranging from 0.652 to 0.800. Bootstrap analysis further confirmed this result with a BCa 95% CI of 0.633 to 0.791. The AUC was significantly greater than 0.5 ($z = 5.875$, $p < 0.0001$), confirming that the model has a statistically significant ability to classify health risk status better than chance, but at lower clinical values.

The Youden index was 0.4750, identifying an optimal cut-off point of ≤135 minutes per week. This threshold yielded a sensitivity of 90.91%, indicating that the model correctly identifies the majority of at-risk individuals. However, the specificity was 56.59%, reflecting moderate capacity to correctly exclude low-risk individuals. The 95% CI for the cut-off value ranged from ≤ 70 to ≤ 240 minutes per week, indicating some variability in the threshold precision.

These findings suggest that weekly physical activity level may serve as a complementary indicator of health risk in females. However, due to its moderate specificity, it may be less suitable as a stand-alone screening tool compared to neuromuscular strength indicators.

Table 50: Diagnostic classifications standards at Fixed Thresholds for Weekly Amount of Exercise in Female Participants

Estimated specificity at fixed sensitivity			
Sensitivity	Specificity	95% CI [a]	Criterion
80.00	60.93	50.08 to 70.34	≤85
90.00	56.59	41.55 to 67.86	≤132
95.00	45.89	27.70 to 58.91	≤178
97.50	42.36	26.43 to 53.49	≤231.75
99.00	41.60	27.50 to 52.71	≤236.7
Estimated sensitivity at fixed specificity			
Specificity	Sensitivity	95% CI [a]	Criterion
80.00	63.64	0.00 to 0.00	≤0
90.00	63.64	0.00 to 0.00	≤0
95.00	63.64	0.00 to 0.00	≤0
97.50	63.64	0.00 to 0.00	≤0
99.00	63.64	0.00 to 0.00	≤0

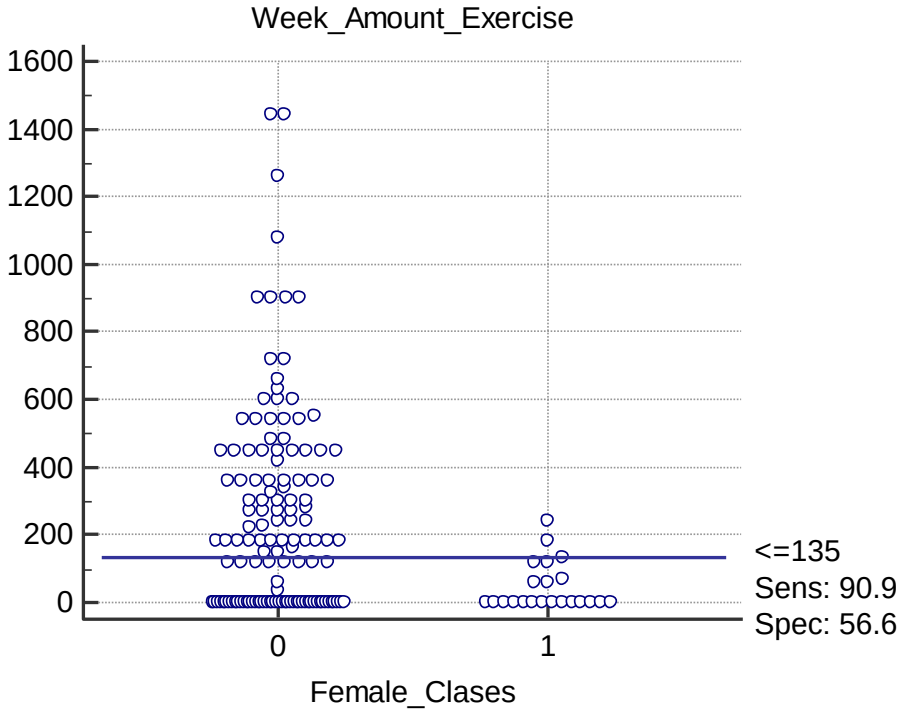
This table summarizes the diagnostic trade-offs between sensitivity and specificity for various fixed thresholds using weekly amount of exercise (minutes per week) as a predictor of health risk among females.

As sensitivity increases, specificity decreases—indicating a trade-off in diagnostic performance. At a sensitivity of 80%, specificity was 60.93%, which dropped to 45.89% at 95% sensitivity, and further to 41.60% at 99% sensitivity. Corresponding cut-off values ranged from ≤85 to ≤236.7 minutes per week, indicating that higher sensitivity is associated with more lenient (higher) thresholds and reduced ability to correctly exclude low-risk individuals.

Across all levels of fixed specificity (from 80% to 99%), sensitivity remained constant at 63.64%. Interestingly, the associated cut-off values were consistently ≤0, suggesting that beyond a certain threshold, weekly amount of exercise loses its discriminatory utility in this modeling context. Moreover, the 95% confidence intervals for sensitivity were undefined (0.00 to 0.00), indicating possible limitations in model calibration or sample distribution at extreme specificity constraints.

These results emphasize that while weekly exercise duration contributes moderately to classification performance, it lacks stability and precision at the extremes of sensitivity or specificity, highlighting the importance of multivariate models when evaluating health risk.

Figure 12: Classification Scatter Plot of Weekly Amount of Exercise by Health Risk Status in Female Participants



The figure displays the distribution of weekly exercise duration (in minutes) by health risk class. The horizontal line at 135 minutes/week represents the optimal cut-off point identified by ROC analysis.

This scatter plot illustrates how the variable weekly amount of exercise differentiates between low-risk (Class 0) and at-risk (Class 1) female participants. The cut-off value of ≤135 minutes per week, as derived from ROC curve analysis.

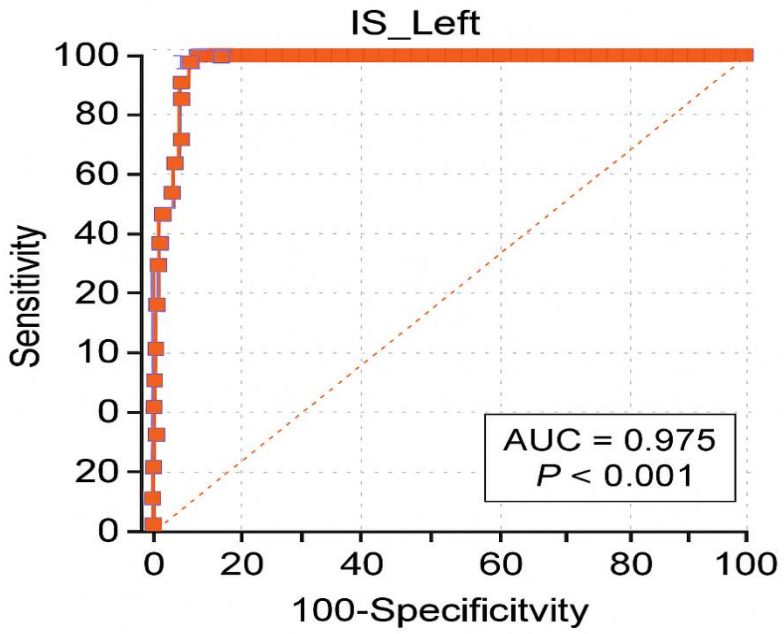
- The sensitivity at this threshold is 90.9%, indicating that nearly all at-risk individuals engage in 135 minutes or less of physical activity per week.
- The specificity is 56.6%, showing a moderate ability to correctly classify low-risk individuals.

While the majority of at-risk individuals (Class 1) are concentrated below the 135-minute mark, there is substantial overlap with low-risk individuals (Class 0), many of whom also report low weekly activity. This visual pattern confirms the moderate predictive utility of this variable - supporting its value in identifying at-risk individuals but highlighting its limited precision in excluding false positives.

8.13. Female – IS_Left Classification vs RFD_{max}_SUM

Figure 13 shows the results of the ROC curve in relation to predictive sensitivity and specificity for body composition related Healt Risk Classification in female sample according to IS_Left variable as a as a neuro-mechanical indicator for contractile potential capacity od non-dominant hand.

Figure 13: ROC Curve of IS_Left for Predicting Health Risk in Female Participants



This ROC curve assesses the diagnostic accuracy of the left-hand Index of Synergy (IS_Left), as a neuro-mechanical indicator for contractile potential capacity of non-dominant hand, for classifying female participants by health risk. The AUC is 0.975 ($p < 0.001$), indicating excellent discriminative capability.

This figure displays the ROC curve for IS_Left, a neuromuscular coordination measure, as a predictor of health risk status among females. The Area Under the Curve (AUC) is 0.975, reflecting outstanding diagnostic accuracy. An AUC this high indicates that the variable almost perfectly separates at-risk from low-risk individuals.

The curve follows a steep upward trajectory near the Y-axis, suggesting:

- High sensitivity (true positive rate) is maintained even at low false positive rates.
- The statistical significance ($p < 0.001$) confirms that the performance is not due to chance.

These results validate IC_Left as a highly reliable single-variable marker for identifying females at elevated health risk. Its excellent performance makes it well-suited for inclusion in clinical screening tools or predictive health algorithms, particularly in settings where neuromuscular function is a concern.

Table 51: ROC Curve Summary and Diagnostic Metrics for IS_Left in Female Participants

Variable	IS_Left
Classification variable	Female_Clases
Sample size	151
Positive group	22 (14.57%)
Negative group	129 (85.43%)

[a]Female_Clases = 1
[b] Female_Clases = 0

Area under the ROC curve (AUC)

Area under the ROC curve (AUC)	0.975
Standard Error	0.0107
95% Confidence interval	0.936 to 0.993
95% Bootstrap CI	0.946 to 0.990
z statistic	44.456
Significance level P (Area=0.5)	<0.0001

Youden index

Youden index J	0.8837
95% Confidence interval	0.8062 to 0.9225
Associated criterion	≤5.07
95% Confidence interval	≤4.88 to ≤5.07
Sensitivity	100.00
Specificity	88.37

This table presents the ROC analysis for the variable IS_Left (Index of Synergy – Left) in predicting body status with fitness health related with health risk classification among female participants (N = 151), of whom 22 (14.57%) were categorized as "at risk" (Female_Clases = 1), and 129 (85.43%) as "low risk" (Female_Clases = 0).

The Area Under the Curve (AUC) was 0.975, reflecting excellent discriminatory ability of the IS_Left measure. The standard error was 0.0107, and the 95% confidence interval ranged from 0.936 to 0.993, indicating precision in the estimation. The bootstrap confidence interval (BCa) based on 1000 iterations further confirmed this robustness (95% CI: 0.946 to 0.990). The result was statistically significant ($z = 44.456$, $p < 0.0001$), confirming the model's performance was well above chance level.

The Youden index ($J = 0.8837$) identified the optimal cut-off value for classification at ≤5.07. The 95% CI for the threshold ranged from ≤ 4.88 to ≤ 5.07. At this cut-off:

- Sensitivity = 100.00%: all at-risk individuals were correctly identified.
- Specificity = 88.37%: nearly nine out of ten low-risk individuals were accurately excluded.

These results confirm that IS_Left is one of the most powerful and reliable predictors of health risk in female participants, combining perfect sensitivity with very high specificity. This measure may be confidently integrated into clinical and field-based screening protocols aimed at early risk detection, particularly when evaluating neuromuscular coordination or asymmetry-based health indicators.

Table 52: Estimated Specificity and Sensitivity at Fixed Thresholds for IS_Left in Female Participants

Estimated specificity at fixed sensitivity			
Sensitivity	Specificity	95% CI [a]	Criterion
80.00	93.80	86.17 to 98.45	≤4.586
90.00	93.80	87.60 to 98.45	≤4.712
95.00	91.47	82.95 to 96.12	≤4.879
97.50	88.37	79.14 to 93.02	≤5.0535
99.00	88.37	79.14 to 93.02	≤5.0634
Estimated sensitivity at fixed specificity			
Specificity	Sensitivity	95% CI [a]	Criterion
80.00	100.00	100.00 to 100.00	≤5.524
90.00	95.45	59.09 to 100.00	≤4.909
95.00	72.73	40.91 to 95.45	≤4.499
97.50	68.18	0.00 to 0.00	≤4.3345
99.00	63.64	0.00 to 0.00	≤4.0635

This table summarizes the trade-offs between sensitivity and specificity at different fixed levels of performance when using the IS_Left variable to predict health risk status among female participants.

The model maintains very high specificity even at elevated sensitivity thresholds:

- At 80% and 90% sensitivity, specificity remains at 93.80%, indicating excellent accuracy in excluding false positives.
- At 95% sensitivity, specificity is still high at 91.47%.
- Even at 97.5% and 99.0% sensitivity, specificity remains stable at 88.37%, with cut-off values around ≤5.05–5.06.

This performance highlights the variable's robust diagnostic strength, showing minimal trade-off even at high sensitivity.

- At 80% specificity, sensitivity reaches 100.00%, indicating perfect detection of at-risk individuals.
- At 90% specificity, sensitivity remains high at 95.45% (cut-off ≤4.909).
- Sensitivity begins to decline at 95% specificity (72.73%), and further at 97.5% and 99.0%, though still within acceptable clinical ranges.

These results underscore that IS_Left is a balanced and highly efficient variable, offering both excellent sensitivity and specificity across a broad range of thresholds. This makes it ideal for integration into health risk screening protocols where both minimizing false negatives and false positives are essential.

The figure illustrates the distribution of IS_Left values among female participants categorized as low risk (Class 0) or at risk (Class 1). The cut-off value of ≤5.07 yields 100.0% sensitivity and 88.4% specificity.

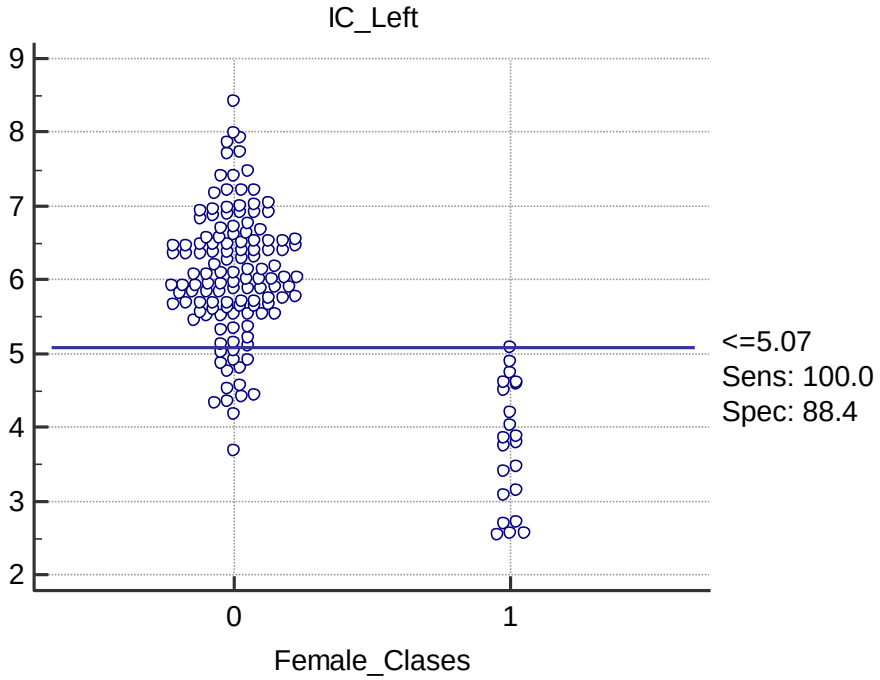
This scatter plot displays individual IS_Left scores in relation to participants' health risk classification. The horizontal line at 5.07 represents the optimal cut-off point identified via ROC analysis.

• All participants classified as at risk (Class 1) fall below the threshold, producing 100.0% sensitivity, meaning that no at-risk individual was missed.

• The majority of low-risk individuals (Class 0) are positioned above the cut-off, with some overlap below, resulting in specificity of 88.4%.

This visual distribution reinforces the strong discriminative power of IS_Left, validating its ability to perfectly identify at-risk individuals while maintaining a high rate of accurate classification for low-risk participants. It confirms IS_Left as a highly effective screening marker for health risk detection in female populations.

Figure 14: Classification Scatter Plot of IS_Left by Health Risk Status in Female Participants



8.14. Female – F_{rel}_SUM Classification vs RFD_{max}_SUM

Figure 14 shows the results of the ROC curve in relation to predictive sensitivity and specificity for body composition related Healt Risk Classification in female sample according to F_{rel}_SUM variable as a relative strength body potential.

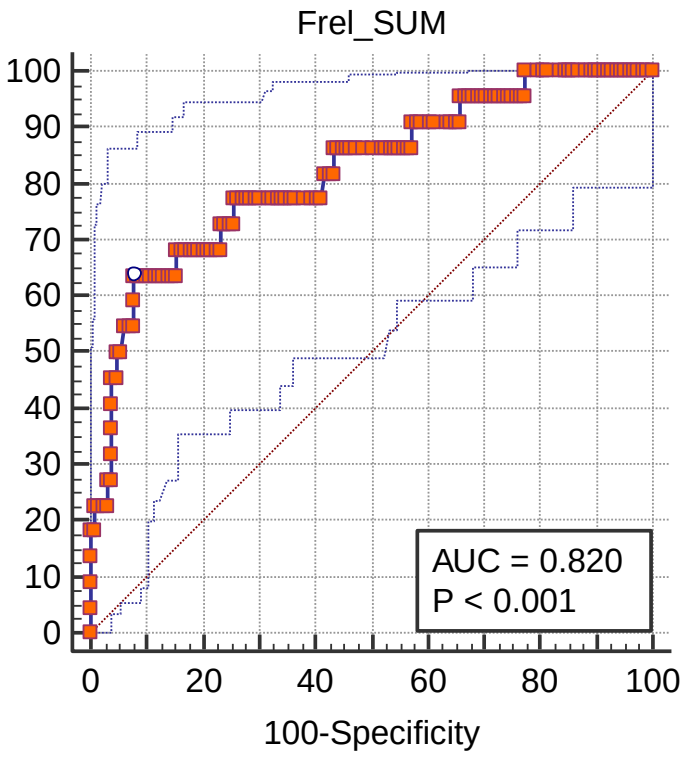
The ROC curve evaluates the discriminative ability of relative force (F_{rel}_SUM) to classify health risk status among females. The AUC is 0.820, indicating good diagnostic accuracy ($p < 0.001$).

This ROC curve demonstrates the classification performance of the relative force sum (F_{rel}_SUM) in distinguishing between at-risk and low-risk health status in female participants. The Area Under the Curve (AUC) is 0.820, suggesting good discriminative accuracy. This indicates that in 82% of all possible at-risk vs. low-risk pairings, the test correctly ranks the at-risk participant as having a lower relative force.

The curve shows a consistent ascent with a leftward shift, which reflects favorable balance between sensitivity and specificity. The curve lies well above the reference line (diagonal), and the significance level ($p < 0.001$) confirms that the classification ability is not due to chance.

These findings support the use of F_{rel}_SUM as a strong predictor of health risk in females. Although not as powerful as RFD_{max}_SUM, its performance is still robust enough to be included in multi-variable predictive models.

Figure 15: ROC Curve of F_{rel}_SUM for Predicting Health Risk in Female Participants



This table summarizes the results of the ROC curve analysis for Frel_SUM (Relative Force Sum) in predicting health risk classification among female participants (N = 151). Within the sample, 22 individuals (14.57%) were categorized as "at risk" (Female_Clases = 1), and 129 individuals (85.43%) were classified as "low risk" (Female_Clases = 0).

The Area Under the Curve (AUC) was 0.820, indicating good diagnostic performance. The standard error was 0.0530, and the 95% confidence interval ranged from 0.750 to 0.878, supported by a bootstrap CI of 0.704 to 0.911. The z-statistic was 6.041, and the p-value < 0.0001, confirming that the classification ability of F_{rel}_SUM is highly significant and superior to random guessing.

The optimal cut-off point was determined as ≤6.48 N/kg, based on the Youden index (J = 0.5588). The 95% confidence interval for this criterion ranged from ≤6.01 to ≤8.38. At this threshold:

- Sensitivity was 63.64%, meaning the model correctly identified nearly two-thirds of individuals at risk.
- Specificity was 92.25%, reflecting a high rate of correctly identifying individuals not at risk.

These findings suggest that F_{rel}_SUM is a highly specific marker for health risk classification in females. While its sensitivity is moderate, the high specificity makes it particularly valuable in minimizing false positives. As such, it serves as an effective tool for identifying healthy individuals with a high degree of certainty and could be integrated as a supporting variable in multifactorial health screening algorithms.

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Table 53: ROC Curve Summary and Diagnostic Performance Metrics for F_{rel}_SUM in Females

Variable	Frel_SUM
Classification variable	Female_Clases
Sample size	153
Positive group	23 (14.57%)
Negative group	130 (85.43%)

Female_Clases = 1; Female_Clases = 0

Area under the ROC curve (AUC)

Area under the ROC curve (AUC)	0.820
Standard Error	0.0530
95% Confidence interval	0.750 to 0.878
95% Bootstrap CI	0.704 to 0.911
z statistic	6.041
Significance level P (Area=0.5)	<0.0001

Youden index

Youden index J	0.5588
95% Confidence interval	0.3548 to 0.7107
Associated criterion	≤6.48
95% Confidence interval	≤6.01 to ≤8.38
Sensitivity	63.64
Specificity	92.25

Table 54 : Diagnostic classifications standards at Fixed Thresholds for F_{rel}_SUM in Female Participants

Estimated specificity at fixed sensitivity			
Sensitivity	Specificity	95% CI	Criterion
80.00	58.45	26.36 to 85.45	≤8.212
90.00	42.64	16.51 to 74.41	≤8.954
95.00	34.11	15.49 to 58.91	≤9.289
97.50	22.48	11.63 to 35.66	≤9.989
99.00	22.48	11.63 to 35.66	≤9.9956
Estimated sensitivity at fixed specificity			
Specificity	Sensitivity	95% CI	Criterion
80.00	68.18	45.45 to 86.36	≤7.266
90.00	63.64	40.91 to 86.36	≤6.529
95.00	50.00	18.18 to 77.27	≤6.019
97.50	22.73	0.00 to 0.00	≤5.2245
99.00	22.73	0.00 to 0.00	≤4.9983

This Table presents the trade-off between sensitivity and specificity when using different threshold criteria for F_{rel}_SUM (Relative Force Sum) in classifying health risk status among female participants.

As sensitivity increases from 80% to 99%, specificity progressively decreases:

- At 80% sensitivity, specificity is 58.45%, with a cut-off of ≤8.212 N/kg.
- At 90% sensitivity, specificity drops to 42.64%, and further to 22.48% at 97.5%–99.0% sensitivity, with increasingly higher cut-off values (up to ≤9.996 N/kg).

These results highlight the difficulty of maintaining high sensitivity without compromising the model's ability to exclude false positives. Beyond a sensitivity of 95%, specificity falls below 35%, suggesting weaker reliability of this variable at high sensitivity thresholds.

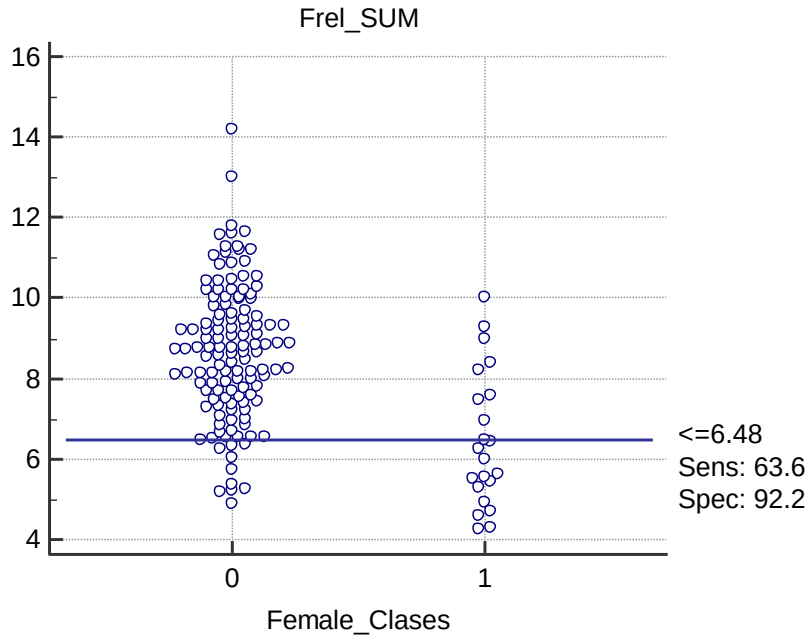
When specificity is held constant:

- At 80% specificity, sensitivity is 68.18% (cut-off ≤7.266 N/kg).
- At 90% specificity, sensitivity is 63.64% (cut-off ≤6.529 N/kg).
- At 95% specificity, sensitivity drops to 50.00%, and declines sharply to 22.73% at 97.5% and 99% specificity (cut-offs ≤5.22 and ≤5.00, respectively).

These results show that while high specificity thresholds are achievable, they come at the expense of greatly reduced sensitivity. Therefore, although F_{rel}_SUM is reliable for identifying individuals without health risk, it is less effective in detecting all at-risk cases under strict classification thresholds.

These performance characteristics reinforce the interpretation that F_{rel}_SUM is a highly specific but moderately sensitive predictor, and its greatest utility lies in minimizing false positives in screening.

Figure 16: Classification Scatter Plot of Frel_SUM by Health Risk Status in Female Participants



The plot illustrates the distribution of Frel_SUM values across low-risk (Class 0) and at-risk (Class 1) females. The optimal cut-off of ≤6.48, indicated by the horizontal line, yields a sensitivity of 63.6% and a specificity of 92.2%.

This figure presents the individual data points for F_{rel}_SUM (relative force output) by health classification among female participants. The threshold of ≤6.48 N/kg was determined from the ROC analysis to provide the most effective balance of sensitivity (63.6%) and specificity (92.2%).

- Most low-risk individuals (Class 0) score above the cut-off, confirming the variable's strong ability to rule out false positives.
- A subset of at-risk individuals (Class 1) also fall above the threshold, reflecting the variable's moderate sensitivity - i.e., some true positives are missed.

This visualization reinforces the interpretation that F_{rel}_SUM is a highly specific predictor for identifying low-risk individuals, while its use in isolating all at-risk cases may be limited unless combined with other indicators.

8.15 Results of ROC Curve Analysis for Males

Following the female-specific scientific model, the next section presents the male predictive model based on the top four discriminative factors.

Figure 17 presents the ROC curve results showing the predictive sensitivity and specificity of RFDmax_SUM in relation to health risk classification among the male sample, highlighting its effectiveness as a neuromuscular performance indicator of explosive strength capacity.

8.16 Male – Fitnes Health Risk Score Index (FHRS_Index) Classification vs RFD_{max}_SUM

Figure 17 : ROC Curve of RFD_{max}_SUM Males for Predicting Health Risk in Male Participants

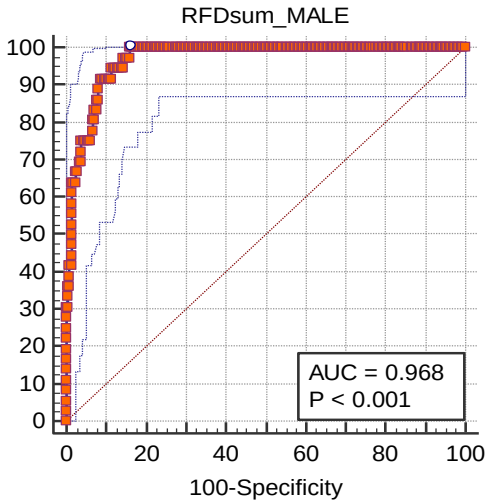


Figure 17 shows the Receiver Operating Characteristic (ROC) curve for the variable RFDsum_MALE, used to classify health risk status among male participants. The curve demonstrates excellent discriminative performance, with an Area Under the Curve (AUC) of 0.968, indicating that RFDsum_MALE is highly effective in distinguishing between at-risk and low-risk individuals. The curve's steep trajectory toward the upper-left corner reflects a favorable balance between high sensitivity and specificity, and the result is statistically significant ($p < 0.001$).

Table 55: ROC Curve Summary and Diagnostic Performance Metrics for RFDsum_MALE in Male Participants

Variable	RFDsum_MALE
Classification variable	Male_Classification
Sample size	242
Positive group	36 (14.75%)
Negative group	208 (85.25%)

Male_Classification = 1; Male_Classification = 0

Area under the ROC curve (AUC)

Area under the ROC curve (AUC)	0.968
Standard Error	0.00996
95% Confidence interval	0.938 to 0.986
95% Bootstrap CI	0.941 to 0.984
z statistic	47.023
Significance level P (Area=0.5)	<0.0001

Youden index

Youden index J	0.8413
95% Confidence interval	0.7548 to 0.8809
Associated criterion	≤4936
95% Confidence interval	≤4737 to ≤4936
Sensitivity	100.00
Specificity	84.13

Table 55 shows the ROC curve for RFD_{sum}_MALE, and this table provides the corresponding diagnostic metrics for predicting body status with fitness health related with health in male participants (N = 242). Among them, 36 individuals (14.75%) were classified as "at risk" (Male_Classification = 1), and 208 (85.25%) as "low risk" (Male_Classification = 0).

The analysis revealed an Area Under the Curve (AUC) of 0.968, indicating excellent diagnostic accuracy. The standard error was 0.00996, and the 95% confidence interval (CI) ranged from 0.938 to 0.986, with a bootstrap CI of 0.941 to 0.984. The AUC value was significantly greater than 0.5 ($z = 47.023$, $p < 0.0001$), confirming that the variable discriminates well between at-risk and low-risk individuals.

The Youden index (J = 0.8413) identified the optimal classification threshold at ≤4936, with a 95% CI between ≤4737 and ≤4936. At this cut-off:

- Sensitivity = 100.00%, meaning all at-risk males were correctly identified.
- Specificity = 84.13%, indicating that the majority of low-risk individuals were correctly excluded.

These results confirm RFD_{sum}_MALE as a highly sensitive and specific variable for detecting health risk in males. The perfect sensitivity ensures no false negatives, while the high specificity limits false positives, making it a robust marker for inclusion in health screening models, particularly those assessing neuromuscular strength and explosive capacity.

Table 56: Diagnostic classifications standards at Fixed Thresholds for RFD_{sum}_MALE in Male Participants

Estimated specificity at fixed sensitivity			
Sensitivity	Specificity	95% CI	Criterion
80.00	93.27	86.39 to 97.60	≤4528.6
90.00	91.63	84.62 to 96.15	≤4593.4
95.00	85.58	76.01 to 91.83	≤4886.8
97.50	84.13	76.92 to 89.42	≤4918.9
99.00	84.13	76.92 to 89.42	≤4929.16
Estimated sensitivity at fixed specificity			
Specificity	Sensitivity	95% CI [a]	Criterion
80.00	100.00	97.22 to 100.00	≤5149.4
90.00	91.67	68.49 to 100.00	≤4647.8
95.00	75.00	55.56 to 90.00	≤4357
97.50	66.67	0.00 to 0.00	≤4167.2
99.00	41.67	0.00 to 0.00	≤3775.72

This table summarizes the diagnostic performance of RFDsum_MALE at various fixed sensitivity and specificity thresholds, allowing for assessment of the classification model's behavior under different clinical or research priorities in male participants.

Specificity at Fixed Sensitivity Levels - When sensitivity is fixed at high values (i.e., prioritizing detection of at-risk individuals):

- At 80% sensitivity, specificity is 93.27%, with a cut-off of ≤4528.6.
- At 90% sensitivity, specificity remains high at 91.63%.
- As sensitivity increases to 95% and above, specificity gradually decreases, reaching 84.13% at 97.5% and 99% sensitivity.

This indicates that RFDsum_MALE maintains a strong ability to exclude low-risk individuals even when sensitivity is prioritized—an important feature in screening tools that aim to minimize missed risk cases.

Sensitivity at Fixed Specificity Levels - When prioritizing specificity (i.e., reducing false positives):

- At 80% specificity, the model achieves 100.00% sensitivity, meaning no at-risk individuals are missed.
- At 90% specificity, sensitivity remains high at 91.67%, with a cut-off of ≤4647.8.
- Sensitivity decreases to 75.00% at 95% specificity, and further declines at 97.5% (66.67%) and 99% (41.67%), showing that increasing specificity results in more at-risk individuals being missed.

These results confirm that RFDsum_MALE offers an excellent balance of sensitivity and specificity, particularly within the 80–95% range. This makes it highly applicable in health screening contexts where either minimizing false negatives or false positives is critical depending on the operational or clinical objectives.

Figure 18. Classification Scatter Plot of RFDsum_MALE by Health Risk Status in Male Participants

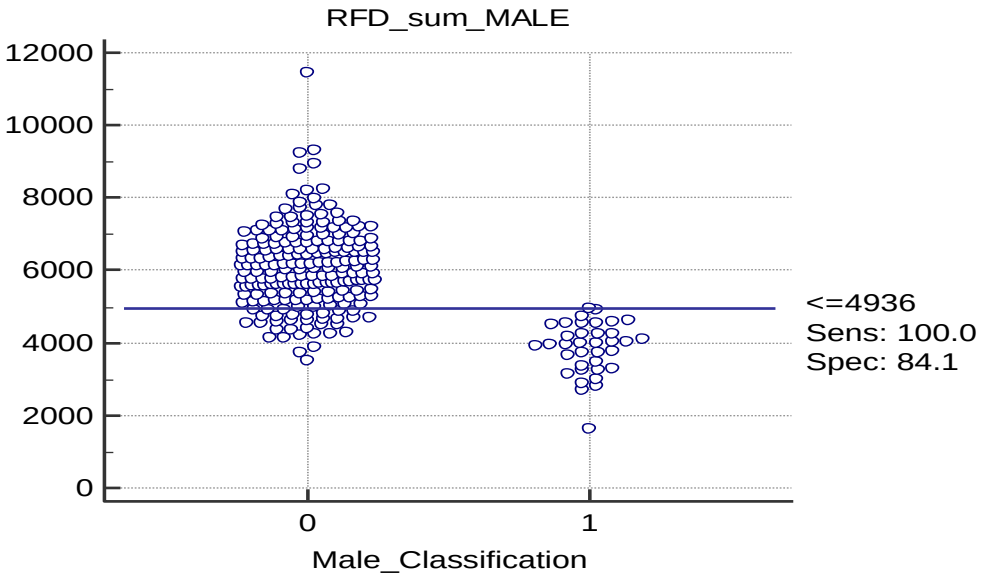


Figure 18 presents the classification performance of the total rate of force development (RFD_{sum}_MALE) in relation to health risk classification among male participants. The horizontal line at 4936 represents the optimal cut-off point determined through ROC curve analysis.

- All individuals categorized as at risk (Class 1) fall below the threshold, supporting the finding of 100.0% sensitivity—no at-risk participant was misclassified.
- Most low-risk individuals (Class 0) score above the threshold, resulting in a specificity of 84.1%, indicating that the majority of healthy participants were accurately classified.

The clear vertical separation between the two groups visually confirms high clinical potential of defined cut – off criteria. The excellent discriminatory ability of RFD_{sum}_MALE and reinforces its role as a robust neuromuscular marker for identifying individuals at health risk within a male population.

Figure 19 illustrates the ROC curve analysis for the BMI variable in the male sample, depicting its sensitivity and specificity in predicting body composition-related health risk, with BMI serving as a general anthropometric indicator of nutritional status.

Figure 19. ROC Curve of BMI for Predicting Health Risk in Male Participants

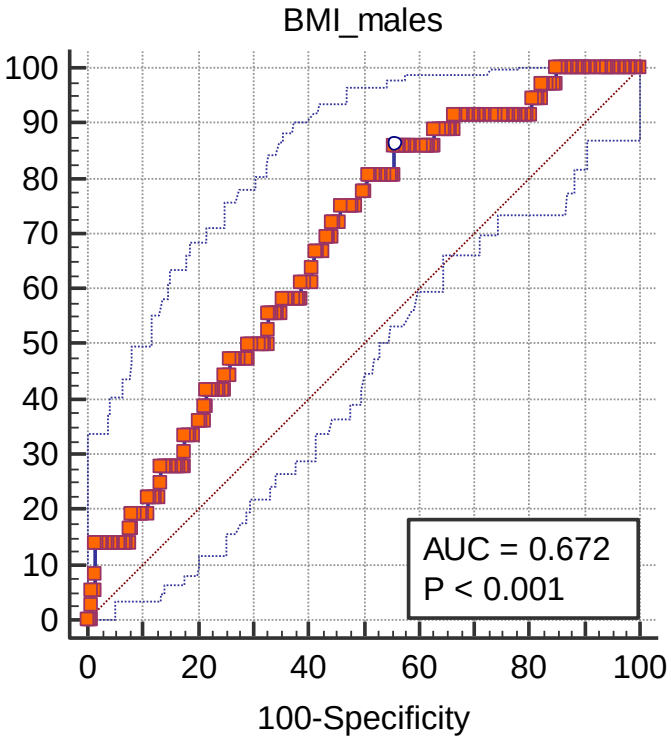


Figure 19 displays the Receiver Operating Characteristic (ROC) curve for Body Mass Index (BMI) as a classifier of health risk in male participants. The Area Under the Curve (AUC) is 0.672, suggesting a modest level of diagnostic accuracy.

The curve shows a moderate deviation from the diagonal, meaning BMI performs better than chance, but with noticeable overlap between classes. The p-value < 0.001 confirms that the classification performance is statistically significant.

Although BMI is widely used as a general health indicator, its moderate AUC in this analysis suggests it is less effective as a stand-alone classifier for health risk in this sample of males. It may contribute value when used in multivariate predictive models, but it lacks the discriminative power of performance-based neuromuscular variables such as RFD_{sum}_MALE.

Table 57 : ROC Curve Summary and Diagnostic Performance Metrics for BMI in Males Participants

Variable	BMI_males
Classification variable	Male_Classification
Sample size	242
Positive group	36 (14.87%)
Negative group	206 (85.12%)

Male_Classification = 1; Male_Classification = 0

Area under the ROC curve (AUC)

Area under the ROC curve (AUC)	0.672
Standard Error	0.0449
95% Confidence interval	0.609 to 0.730
95% Bootstrap CI	0.568 to 0.748
z statistic	3.821
Significance level P (Area=0.5)	0.0001

Youden index

Youden index J	0.3034
95% Confidence interval	0.1397 to 0.3910
Associated criterion	>25.19
95% Confidence interval	>21.99 to >26
Sensitivity	86.11
Specificity	44.23

Table 57 illustrates the ROC curve of Body Mass Index (BMI) in relation to health risk classification among male participants (N = 242), where 36 individuals (14.87%) were classified as at risk (Male_Classification = 1) and 208 (85.12%) as low risk (Male_Classification = 0).

The Area Under the Curve (AUC) was 0.672, indicating modest discriminative power. The standard error was 0.0449, with a 95% confidence interval ranging from 0.609 to 0.730, and a bootstrap CI of 0.568 to 0.748. The z-statistic was 3.821, and the test reached statistical significance (p = 0.0001), suggesting that BMI performs better than chance in differentiating health risk status, albeit with limitations.

The Youden index was 0.3034, identifying the optimal classification threshold at >25.19, with a 95% CI between >21.99 and >26.00. At this criterion:

- Sensitivity was 86.11%, indicating good ability to detect at-risk individuals.
- Specificity was 44.23%, showing poor capacity to exclude low-risk individuals.

These results imply that although BMI is widely recognized and easy to obtain, it exhibits limited precision for identifying health risk in this male population. It may still be useful as a supporting indicator but should not be used in isolation for classification purposes, particularly in populations where body composition may be influenced by muscle mass or athletic training.

Table 58: Estimated Specificity and Sensitivity at Fixed Thresholds for BMI in Male Participants

Estimated specificity at fixed sensitivity			
Sensitivity	Specificity	95% CI	Criterion
80.00	49.13	32.21 to 61.16	>25.592
90.00	33.65	12.69 to 50.00	>24.08
95.00	17.79	10.58 to 38.46	>22.402
97.50	14.90	8.17 to 20.19	>22.035
99.00	14.90	8.17 to 20.19	>22.008
Estimated sensitivity at fixed specificity			
Specificity	Sensitivity	95% CI	Criterion
80.00	35.56	16.67 to 52.78	>29.092
90.00	19.44	8.33 to 36.11	>31.906
95.00	13.89	5.56 to 27.78	>32.546
97.50	13.89	0.00 to 0.00	>33.596
99.00	5.56	0.00 to 0.00	>34.6036

This table displays the performance trade-offs between sensitivity and specificity for the variable Body Mass Index (BMI) when used to classify health risk in male participants, based on fixed decision thresholds.

Specificity at Fixed Sensitivity Levels - When attempting to maintain higher sensitivity, specificity decreases markedly:

- At 80% sensitivity, specificity is 49.13%, with a cut-off of >25.59.
- At 90% sensitivity, specificity drops to 33.65%, and continues decreasing to 14.90% at 97.5% and 99% sensitivity (cut-offs ranging between >22.035 and >22.008).

These findings suggest that in order to ensure that most at-risk individuals are captured by the BMI threshold, a large number of false positives (low-risk individuals misclassified as at risk) must be accepted.

Sensitivity at Fixed Specificity Levels - Conversely, when trying to increase specificity:

- At 80% specificity, sensitivity is only 35.56% (cut-off >29.09).
- At 90% specificity, sensitivity falls to 19.44%, and drops to 5.56% at 99% specificity (cut-off >34.60).

This demonstrates that using higher BMI thresholds to avoid misclassifying low-risk individuals results in many at-risk individuals being missed, highlighting the variable's low sensitivity under strict classification settings.

Overall, these results reinforce that BMI shows poor classification efficiency in this male population when high precision is required. It may have limited standalone value, particularly in contexts where

muscle mass could obscure the interpretation of body composition. Its contribution is best suited to multifactorial models rather than as an independent screening variable.

Figure 20. Classification Scatter Plot of BMI by Health Risk Status in Male Participants

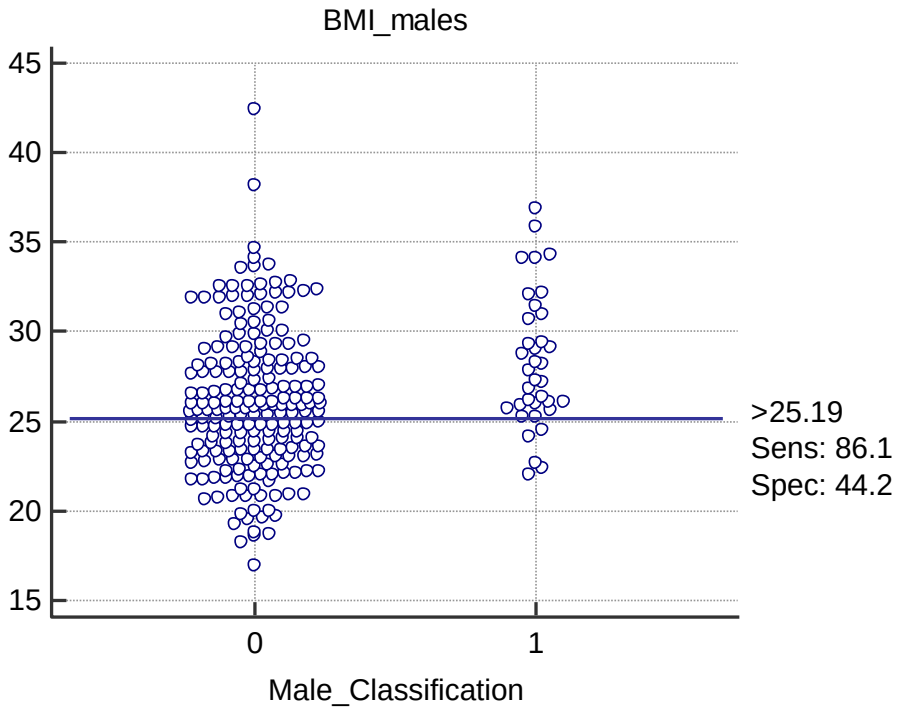


Figure 20 presents the classification performance of Body Mass Index (BMI) in relation to health risk status among male participants. The horizontal line at 25.19 represents the optimal threshold derived from ROC curve analysis.

- The majority of at-risk individuals (Class 1) fall above the threshold, resulting in 86.1% sensitivity, meaning most individuals at risk are correctly identified.
- However, a substantial portion of low-risk individuals (Class 0) also fall above the cut-off, leading to a low specificity of 44.2%, indicating a high rate of false positives.

This visual representation underscores BMI's limited discriminative power in this male population. Although it is relatively effective in identifying individuals at risk (good sensitivity), it performs poorly in excluding healthy individuals, likely due to BMI's inability to distinguish between fat and lean mass in physically active or muscular populations.

These findings highlight the importance of interpreting BMI cautiously and preferably in combination with other physiological or performance-based variables when used in health risk classification models.

Figure 21 displays the ROC curve results for IS_SUM in male participants, illustrating its diagnostic accuracy in predicting health risk based on neuromuscular coordination capacity across both limbs, with IS_SUM serving as a global index of bilateral synergy.

Figure 21 : ROC Curve of IS_SUM (Average) for Predicting Health Risk in Male Participants

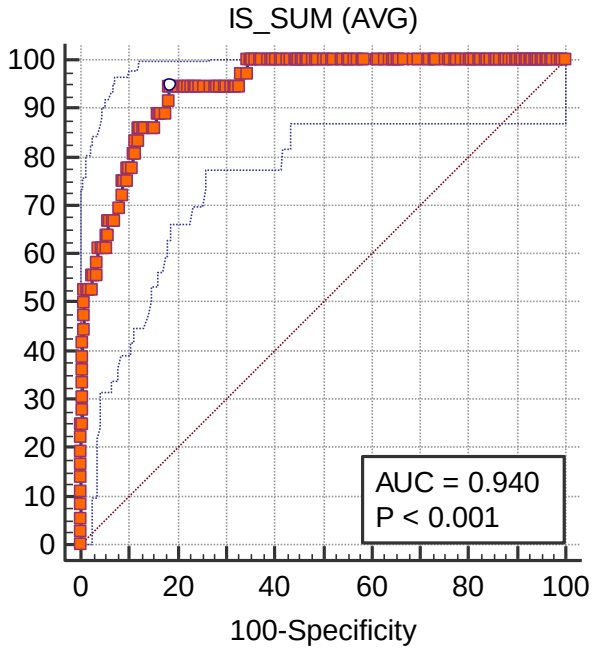


Figure 21 presents the Receiver Operating Characteristic (ROC) curve for IS_SUM (Average Index of Synergy from both hands) in predicting health risk classification among male participants.

- The Area Under the Curve (AUC) is 0.940, reflecting excellent diagnostic performance.
- The curve ascends sharply and remains close to the top-left corner of the plot, indicating a favorable balance between sensitivity and specificity.
- The result is statistically significant ($p < 0.001$), confirming that the predictive performance of IS_SUM is well above chance.

This finding supports the use of bilateral neuromuscular synergy as a powerful and objective indicator of health status in males. IS_SUM demonstrates strong capacity to differentiate between at-risk and low-risk individuals and may serve as a central variable in multi-indicator screening models for physical or functional health assessment.

Table 59: ROC Curve Summary and Diagnostic Performance Metrics for IS_SUM in Male Participants

Variable	IS_SUM
Classification variable	Male_Classification
Sample size	242
Positive group	35 (14.75%)
Negative group	207 (85.25%)

Male_Classification = 1
Male_Classification = 0

Area under the ROC curve (AUC)

Area under the ROC curve (AUC)	0.940
Standard Error	0.0170
95% Confidence interval	0.903 to 0.966
95% Bootstrap CI	0.896 to 0.967
z statistic	25.941
Significance level P (Area=0.5)	<0.0001

Youden index

Youden index J	0.7618
95% Confidence interval	0.6203 to 0.8317
Associated criterion	≤5.71
95% Confidence interval	≤5.55 to ≤6.05
Sensitivity	94.44
Specificity	81.73

Table 59 shows the ROC curve for the variable IS_SUM (Index of Synergy – SUM), used to classify health risk among male participants (N = 242). Within the sample, 35 participants (14.75%) were categorized as "at risk" (Male_Classification = 1), while 207 participants (85.25%) were classified as "low risk" (Male_Classification = 0).

The Area Under the Curve (AUC) was 0.940, indicating excellent diagnostic accuracy in body status with fitness health & strength performance profiling. The standard error was 0.0170, with a 95% confidence interval ranging from 0.903 to 0.966, and a bootstrap confidence interval (based on 1000 iterations) ranging from 0.896 to 0.967. The performance of the model is statistically robust and significantly better than random (AUC = 0.5), as confirmed by the z-statistic = 25.941 and $p < 0.0001$.

The Youden index (J = 0.7618) identified the optimal classification threshold at ≤5.71, with a 95% confidence interval for the criterion ranging between ≤5.55 and ≤6.05. At this threshold:

- Sensitivity was 94.44%, correctly identifying the vast majority of at-risk individuals.
- Specificity was 81.73%, indicating a strong ability to exclude those who are not at risk.

These results confirm that IS_SUM is a highly effective and reliable marker for health risk classification in males. Its excellent balance of sensitivity and specificity supports its use as a central

variable in health screening and functional assessment models, especially those targeting neuromuscular performance and coordination.

Table 60: Diagnostic classifications standards at Fixed Thresholds for IS_SUM in Male Participants

Estimated specificity at fixed sensitivity			
Sensitivity	Specificity	95% CI	Criterion
80.00	89.04	78.93 to 94.71	≤5.408
90.00	82.02	60.81 to 89.61	≤5.678
95.00	67.21	56.74 to 84.13	≤6.022
97.50	65.38	57.69 to 81.73	≤6.041
99.00	65.38	57.69 to 81.73	≤6.0464
Estimated sensitivity at fixed specificity			
Specificity	Sensitivity	95% CI	Criterion
80.00	94.44	80.56 to 100.00	≤5.756
90.00	77.78	55.56 to 91.67	≤5.378
95.00	61.11	41.67 to 77.78	≤5.064
97.50	55.56	0.00 to 0.00	≤4.748
99.00	52.78	0.00 to 0.00	≤4.614

This table summarizes the classification performance of the variable IS_SUM_AVG in male participants by examining the diagnostic trade-offs between sensitivity and specificity at various fixed thresholds.

Specificity at Fixed Sensitivity Levels - The ability to exclude false positives remains high, even as sensitivity increases:

- At 80% sensitivity, specificity is 89.04%, with an optimal cut-off of ≤5.408.
- At 90% sensitivity, specificity is still robust at 82.02%, and at 95% sensitivity, it remains acceptable at 67.21%.
- Specificity stabilizes around 65.38% for higher sensitivity levels (97.5–99%), showing that IS_SUM_AVG maintains relatively high specificity even when sensitivity is prioritized.

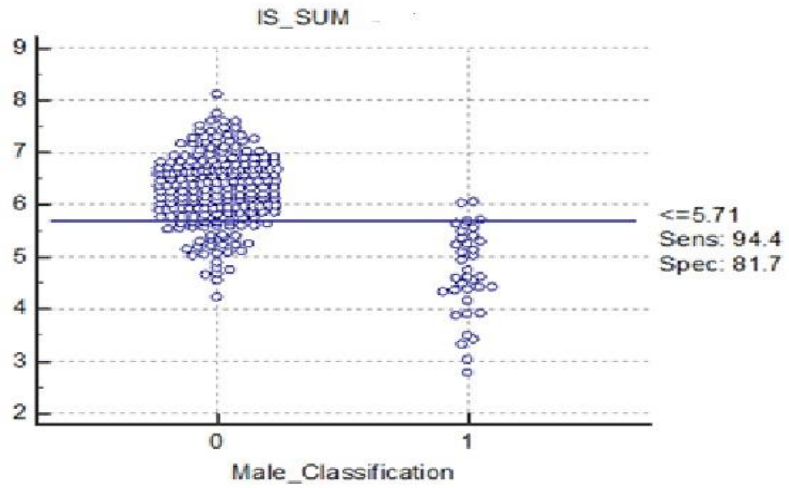
Sensitivity at Fixed Specificity Levels - When the classification prioritizes high specificity:

- At 80% specificity, the sensitivity is 94.44%, indicating very strong ability to detect at-risk individuals.
- At 90% specificity, sensitivity is 77.78%, and remains moderate (61.11%) even at 95% specificity.
- At 97.5% and 99% specificity, sensitivity decreases to 55.56% and 52.78%, respectively, showing that more at-risk cases may be missed under stringent thresholds.

Overall, these results indicate that IS_SUM_AVG offers a well-balanced diagnostic profile, with both high sensitivity and specificity across a wide range of thresholds. Its robust classification accuracy supports its use as a reliable tool for screening and risk stratification in male populations, particularly in functional or neuromuscular health assessments.

Figure 22 illustrates the individual IS_SUM values plotted against health risk classifications for male participants. The horizontal threshold line at 5.71, derived from ROC curve analysis, represents the optimal cut-off for differentiating at-risk from low-risk individuals.

Figure 22: Classification Scatter Plot of IS_SUM by Health Risk Status in Male Participants



- Most at-risk individuals (Class 1) fall below the threshold, leading to a high sensitivity of 94.4%, meaning the majority of individuals with elevated health risk were accurately identified.
- A large proportion of low-risk individuals (Class 0) score above the threshold, resulting in a specificity of 81.7%, reflecting a strong ability to correctly classify healthy individuals.

This scatter plot confirms the excellent discriminative ability of IS_SUM. The relatively low overlap between the two groups highlights its value as a neuromuscular coordination marker for detecting health risk. Its performance makes it a high clinical potential of defined cut – off criteria.

Figure 23 presents the ROC curve analysis for Dominant HG_Fmax in the male sample, illustrating its diagnostic accuracy in classifying health risk based on maximal voluntary contraction strength of the dominant hand.

Figure 23 presents the ROC curve for Dominant HG_Fmax, representing the maximal isometric handgrip strength of the dominant hand used to classify health risk status among male participants.

- The Area Under the Curve (AUC) is 0.633, indicating a fair level of discriminative ability.
- The ROC curve shape reveals limited separation between healthy and at-risk individuals, reflecting only a modest balance between sensitivity and specificity.

- The test is statistically significant (p = 0.017), suggesting that the classification ability of Dominant HG_Fmax is better than chance but with limited clinical precision.

These findings imply that while Dominant HG_Fmax offers some value as a supportive variable in health risk profiling, it should not be used as a standalone tool. Instead, it is better applied in conjunction with other indicators such as RFD, relative force, and neuromuscular synergy to improve the overall predictive accuracy of health status assessments in Lebanese males.

Figure 23: ROC Curve of Dominant HG F_{max} for Predicting Health Risk in Male Participants

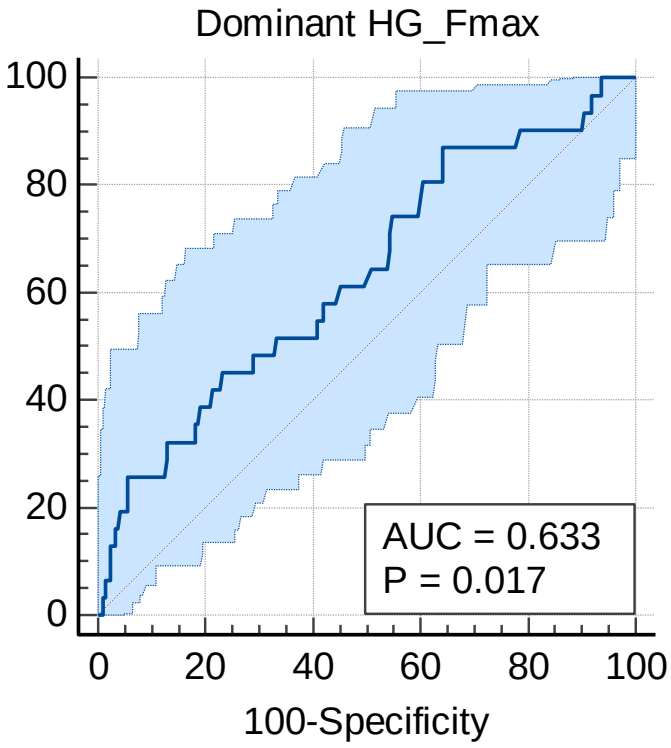


Table 61 presents the ROC curve for Dominant HG_Fmax, the maximal handgrip force of the dominant hand, used to classify health risk status among male participants (N = 241). In this sample, 31 individuals (12.86%) were classified as "at risk" (Health_Classification_Male = 1), and 210 (87.14%) as "low risk" (Health_Classification_Male = 0).

The Area Under the Curve (AUC) was 0.633, reflecting a modest discriminative ability. The standard error was 0.0559, with a 95% confidence interval ranging from 0.569 to 0.694, and a bootstrap CI of 0.533 to 0.742. The test was statistically significant (z = 2.377, p = 0.0174), confirming the variable's predictive capacity is better than chance, though not strong enough to serve as a standalone diagnostic indicator.

Table 61: ROC Curve Summary and Diagnostic Performance Metrics for Dom_HG_F_{max} in Male Participants

Variable	Dominant HG_F_{max}
Classification variable	Health_Classification_Male
Sample size	241
Positive group	31 (12.86%)
Negative group	210 (87.14%)

Male_Classification=1 Male_Classification = 0

Area under the ROC curve (AUC)

Area under the ROC curve (AUC)	0.633
Standard Error	0.0559
95% Confidence interval	0.569 to 0.694
95% Bootstrap CI	0.533 to 0.742
z statistic	2.377
Significance level P (Area=0.5)	0.0174

Youden index

Youden index J	0.2281
Associated criterion	≤529
Sensitivity	87.10
Specificity	35.71

The Youden Index (J = 0.2281) indicated an optimal classification threshold at ≤529 N. At this cut-off:

- Sensitivity = 87.10%, meaning the model correctly identified a high proportion of at-risk individuals.
- Specificity = 35.71%, suggesting a relatively lower ability to correctly exclude low-risk individuals.

These findings indicate that Dominant HG_F_{max} provides limited diagnostic accuracy when used in isolation. Its high sensitivity but low specificity highlights its potential utility as an initial screening tool to identify individuals who may require further, more precise assessments. When combined with additional neuromuscular and compositional indicators, its value in health risk stratification may be significantly enhanced.

Table 62: Diagnostic classifications standards at Fixed Thresholds for Dom_HG_F_{max} in Male Participants

Estimated specificity at fixed sensitivity			
Sensitivity	Specificity	95% CI	Criterion
80.00	39.62	17.83 to 52.90	≤520.8
90.00	21.52	4.76 to 42.38	≤557.9
95.00	8.10	3.33 to 34.43	≤601.45
97.50	6.19	2.02 to 9.52	≤619.675
99.00	6.19	2.02 to 9.52	≤621.07
Estimated sensitivity at fixed specificity			
Specificity	Sensitivity	95% CI	Criterion
80.00	38.71	19.35 to 58.06	≤428
90.00	25.81	12.90 to 45.16	≤389
95.00	19.35	6.45 to 38.71	≤372.25
97.50	12.90	0.00 to 0.00	≤342.75
99.00	3.23	0.00 to 0.00	≤322.1

This Table presents the diagnostic trade-offs between sensitivity and specificity for the variable Dominant HG_Fmax across a range of threshold values. This evaluation supports the clinical interpretation of handgrip strength in male participants and informs decision-making in various health screening contexts.

Specificity at Fixed Sensitivity Levels - When prioritizing high sensitivity to ensure the identification of most at-risk individuals:

- At 80% sensitivity, specificity is 39.62% (cut-off ≤ 520.8 N), meaning less than half of low-risk individuals are correctly excluded.
- At 90% sensitivity, specificity drops to 21.52%, reflecting increased false positives.
- At 95% and above, specificity declines sharply to 8.10% or lower, with very limited discrimination capacity (e.g., specificity of 6.19% at 99% sensitivity, cut-off ≤ 621.07 N).

These findings suggest that although Dominant HG_F_{max} can identify most at-risk individuals at lenient cut-off points, this comes at the expense of high false-positive rates. Thus, in clinical settings requiring high sensitivity, the variable is best used as a preliminary screening tool, to be followed by confirmatory assessments.

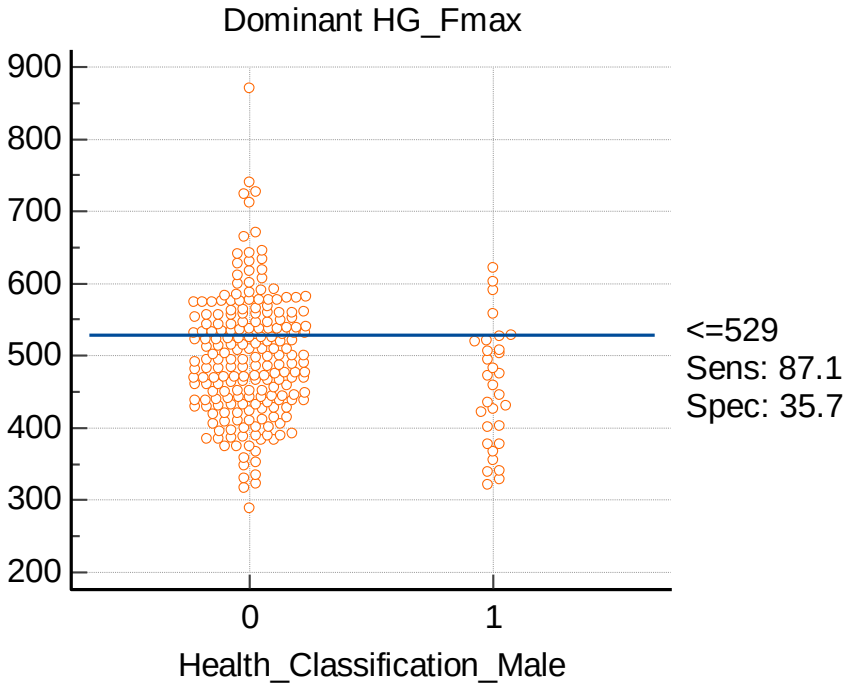
Sensitivity at Fixed Specificity Levels - When the priority is minimizing false positives (i.e., ensuring high specificity):

- At 80% specificity, sensitivity is only 38.71% (cut-off ≤ 428 N), indicating limited detection of at-risk individuals.
- At 90% specificity, sensitivity declines to 25.81%, and at 95%, it further drops to 19.35%.
- At 97.5% and 99% specificity, sensitivity plummets to 12.90% and 3.23%, respectively, with corresponding cut-offs as low as ≤ 342.75 N and ≤ 322.1 N.

This demonstrates that tightening specificity thresholds severely compromises sensitivity, making Dominant HG_Fmax less effective for identifying early-stage health risk in settings that demand high precision.

Figure 24 presents individual values of Dominant HG_F_{max} (maximal handgrip strength of the dominant hand) plotted against health classification categories among Lebanese male participants. The horizontal line at ≤529 N represents the optimal cut-off point derived from ROC curve analysis for distinguishing individuals at high health risk (Health_Classification_Male = 1) from those at low risk (Health_Classification_Male = 0).

Figure 24: Classification Scatter Plot of F_{rel}_SUM by Health Risk Status in Male Participants



- The cut-off threshold of 529 N yields a sensitivity of 87.1%, correctly identifying the majority of at-risk individuals.
- However, specificity is limited to 35.7%, indicating that a significant portion of low-risk individuals also fall below the threshold.

The visual distribution highlights a high concentration of both groups near the decision boundary, with considerable overlap, especially among those classified as low risk. This suggests that while

Dominant HG_F_{max} is useful for detecting potential health concerns, its low specificity restricts its standalone diagnostic value. Consequently, it should be interpreted within a broader assessment framework that includes additional neuromuscular or compositional indicators to enhance precision in health risk classification.

To complement the scientific models, we now shift focus to the practitioner-oriented models by evaluating their diagnostic performance using ROC curve analysis. These simplified models, based on combined handgrip strength and explosive strength measures, are intended for practical use in field or clinical settings.

8.17. Practitioner Models: Predictive Algorithms Using Combined Handgrip Strength and Explosive Force Variables

Figure 25 : ROC Curve for the Combined Handgrip Strength and Explosive strength Model in Male Participants for absolute value

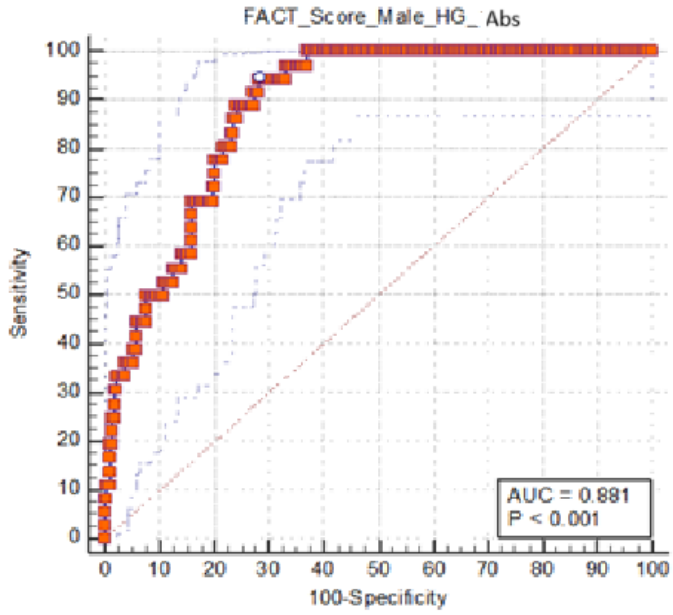


Figure 25 displays the ROC curve for a composite health prediction model derived from two key handgrip parameters—F_{max}_SUM (absolute maximal force) and RFD_{max}_SUM (absolute rate of force development)—used to classify health risk among male participants.

- The model demonstrates an Area Under the Curve (AUC) of 0.881, reflecting a high level of diagnostic accuracy.
- The classification performance is statistically significant ($p < 0.001$), confirming that the model reliably distinguishes between individuals at risk and those not at risk.
- The ROC curve shows a steep rise and high plateau, suggesting a strong balance between sensitivity and specificity across a range of thresholds.

These findings indicate that combining absolute strength (Fmax) and explosiveness (RFD_{max}) into a single model enhances classification ability beyond either variable alone. The synergy of these mechanical outputs likely captures both muscular capacity and neuromuscular coordination, making this composite model a robust tool for identifying body status with fitness health & strength performance profiling.

This model is well-suited for inclusion in screening batteries or predictive health profiling tools and may serve as a benchmark for handgrip-based health risk evaluation in physically active or general male populations.

Table 63: ROC Curve Summary and Diagnostic Performance Metrics for FACT_Score_Male_HG_abs (HG F_{max}_SUM & RFD_{max}_SUM) in Male Participants

Variable	FACT_Score_Male_HG_abs
Classification variable	Male_Classification
Sample size	242
Positive group	36 (14.75%)
Negative group	206 (85.25%)

Male_Classification = 1; Male_Classification = 0

Area under the ROC curve (AUC)

Area under the ROC curve (AUC)	0.881
Standard Error	0.0232
95% Confidence interval	0.834 to 0.919
95% Bootstrap CI	0.829 to 0.925
z statistic	16.425
Significance level P (Area=0.5)	<0.0001

Youden index

Youden index J	0.6608
95% Confidence interval	0.5643 to 0.7281
Associated criterion	≤44.79
95% Confidence interval	≤41.97 to ≤48.8
Sensitivity	94.44
Specificity	71.63

Table 63 presents the ROC curve analysis for a composite variable (FACT_Score_Male_HG_abs) combining F_{max}_SUM and RFD_{max}_SUM in absolute terms, used to classify health risk status among male participants (N = 242). Within this sample, 36 individuals (14.75%) were identified as "at risk" (Male_Classification = 1), while 208 individuals (85.25%) were considered "low risk" (Male_Classification = 0).

The model yielded an Area Under the Curve (AUC) of 0.881, reflecting excellent diagnostic accuracy. The standard error was 0.0232, with a 95% confidence interval ranging from 0.834 to 0.919 and a bootstrap confidence interval from 0.829 to 0.925. The result was statistically significant (z = 16.425,

$p < 0.0001$), confirming that the composite score significantly outperforms chance in distinguishing between risk groups.

The Youden Index (J = 0.6608) identified an optimal cut-off value of ≤44.79, with a 95% CI ranging from ≤41.97 to ≤48.8. At this threshold:

- Sensitivity = 94.44%, indicating that nearly all at-risk individuals were correctly identified.
- Specificity = 71.63%, reflecting that a substantial proportion of low-risk individuals were also correctly classified.

These results support the use of the FACT_Score_Male_HG_abs model as a high-performing screening tool. The integration of both absolute strength and explosive strength provides a synergistic advantage, making this model particularly valuable in health risk profiling of male populations. It demonstrates strong discriminative power, suitable for both clinical screening and population-level health assessments.

Table 64: Diagnostic classifications standards at Fixed Thresholds for the FACT_Score_Male_HG_abs Model in Male Participants

Estimated specificity at fixed sensitivity			
Sensitivity	Specificity	95% CI	Criterion
80.00	78.37	69.23 to 85.58	≤40.922
90.00	72.60	59.53 to 79.33	≤44.078
95.00	66.83	55.26 to 75.96	≤46.624
97.50	62.98	53.14 to 70.19	≤48.737
99.00	62.98	53.14 to 70.19	≤48.7748
Estimated sensitivity at fixed specificity			
Specificity	Sensitivity	95% CI	Criterion
80.00	72.22	47.22 to 88.89	≤39.486
90.00	50.00	31.40 to 66.67	≤33.11
95.00	36.11	19.44 to 52.78	≤29.812
97.50	33.33	0.00 to 0.00	≤26.328
99.00	19.44	0.00 to 0.00	≤22.8404

Table 64 presents the diagnostic trade-offs between sensitivity and specificity for the composite variable FACT_Score_Male_HG_abs, which combines F_{max}_SUM and RFD_{max}_SUM (absolute values) in male participants. These values allow for practical evaluation of the model's effectiveness across various classification thresholds, based on the ROC analysis.

Specificity at Fixed Sensitivity Levels - When prioritizing higher sensitivity to detect a greater proportion of at-risk individuals:

- At 80% sensitivity, the model achieves a specificity of 78.37% (cut-off ≤40.92), suggesting reliable exclusion of low-risk individuals without excessive false positives.
- At 90% sensitivity, specificity is 72.60%, indicating sustained balance.

- At 95% sensitivity, specificity decreases to 66.83%, and further to 62.98% at 97.5% and 99%, showing reduced ability to exclude low-risk cases as sensitivity increases.

These results show that the model maintains relatively high specificity even under high sensitivity demands, supporting its utility in clinical screening scenarios where missing at-risk individuals must be minimized.

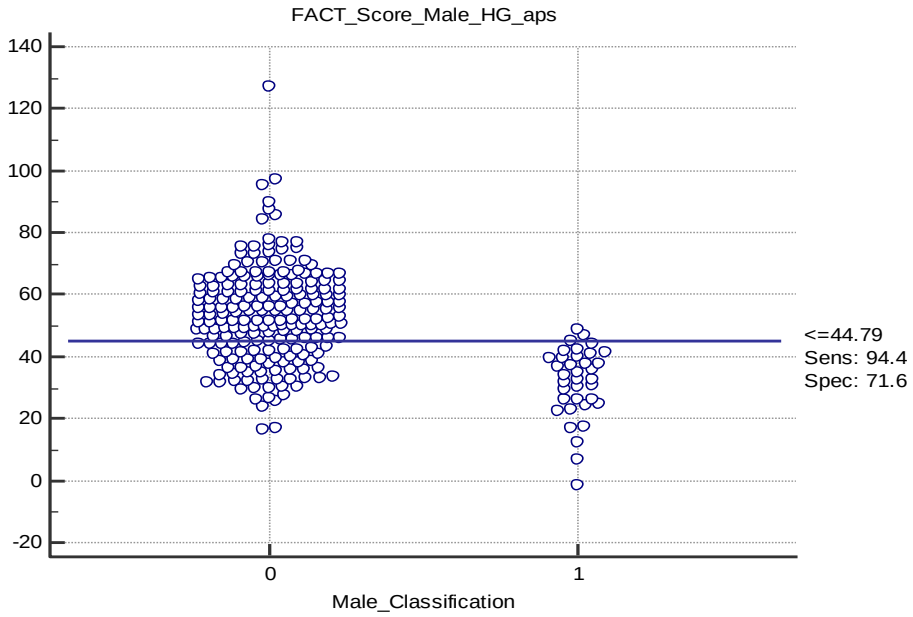
Sensitivity at Fixed Specificity Levels - When the goal is to minimize false positives and increase confidence in low-risk classification:

- At 80% specificity, sensitivity remains high at 72.22%, showing strong performance in identifying true positives without over-identifying healthy individuals.
- At 90% specificity, sensitivity drops to 50.00%, and continues to decline with stricter thresholds, reaching 19.44% at 99% specificity, which may be inadequate for detecting most at-risk cases.

This demonstrates that while the model performs well in balanced screening contexts, its sensitivity declines considerably at very high specificity levels, limiting use where extremely low false-positive rates are required.

Figure 26 illustrates the individual data points of FACT_Score_Male_HG_abs—a composite handgrip performance score combining absolute maximal strength (F_{max}_SUM) and explosive force (RFD_{max}_SUM)—as stratified by health classification (Male_Classification).

Figure 26: Classification Scatter Plot for FACT_Score_Male_HG_abs by Health Risk in Male Participants



A horizontal cut-off line at ≤ 44.79 represents the optimal decision threshold identified through ROC analysis, where:

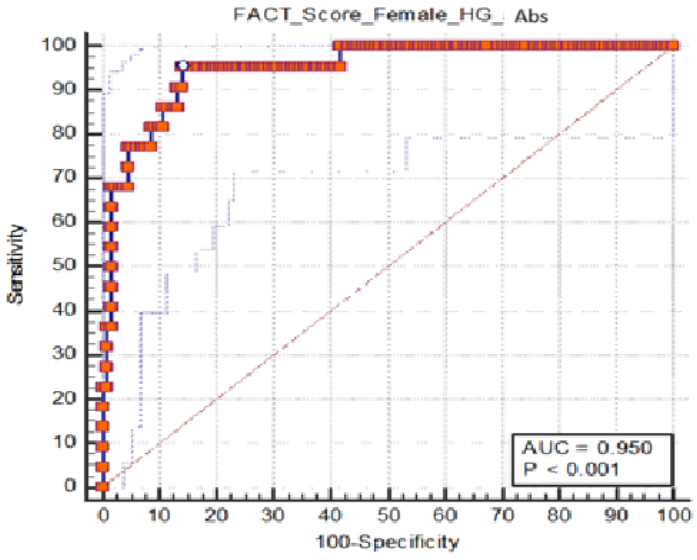
- Sensitivity is 94.4%, indicating that nearly all at-risk individuals are correctly classified as such.
- Specificity is 71.6%, demonstrating that a large majority of low-risk individuals are also properly excluded.

The plot shows clear separation between the risk groups, with most at-risk individuals (coded as 1) falling below the threshold and most low-risk individuals (coded as 0) scoring above it. This visual distribution confirms the model's strong discriminative power, both statistically and practically.

These findings reinforce that the FACT_Score_Male_HG_abs model is a robust, high-performing predictor of health risk in males when using handgrip strength-based metrics. The high sensitivity makes it especially valuable in screening contexts, while the acceptable specificity ensures practical application in diverse health assessment settings. Overall, this model demonstrates high clinical potential through its well-defined cut-off criteria.

Figure 27 presents the ROC curve for the FACT_Score_Female_HG_abs model, constructed from the absolute values of Fmax_SUM and RFDmax_SUM, applied to the classification of health risk status among female participants.

Figure 27 : ROC Curve for the Combined Handgrip Strength and Explosive strength Model (FACT_Score_Female_HG_abs) in Female Participants



- The model achieved an Area Under the Curve (AUC) of 0.950, signifying excellent diagnostic accuracy.

- The result is highly statistically significant ($p < 0.001$), demonstrating a performance that is far superior to random chance.
- The curve's steep rise and extended plateau at high sensitivity levels suggest a strong ability to detect at-risk individuals with minimal false positives, particularly in moderate-to-high threshold ranges.

These results confirm that combining maximal grip strength and explosive rate of force development substantially enhances the ability to predict health risk in females. The integration of these mechanical variables likely reflects both neuromuscular integrity and general musculoskeletal health.

Thus, the FACT_Score_Female_HG_abs model stands out as a powerful tool for early screening, ideal for use in clinical practice, preventive assessments, and performance-health evaluations in female populations.

Table 65: ROC Curve Summary and Diagnostic Performance for the FACT_Score_Female_HG_abs Model in Female Participants

Variable	FACT_Score_Female_HG_abs
Classification variable	Female_Clases
Sample size	153
Positive group	22 (14.57%)
Negative group	131 (85.43%)

Female_Classification = 1; Female_Classification = 0

Area under the ROC curve (AUC)

Area under the ROC curve (AUC)	0.950
Standard Error	0.0221
95% Confidence interval	0.902 to 0.979
95% Bootstrap CI	0.887 to 0.979
z statistic	20.350
Significance level P (Area=0.5)	<0.0001

Youden index

Youden index J	0.8150
95% Confidence interval	0.6510 to 0.8837
Associated criterion	≤40.81
95% Confidence interval	≤39.65 to ≤40.81
Sensitivity	95.45
Specificity	86.05

Table 65 presents the ROC analysis results for the FACT_Score_Female_HG_abs, a composite variable combining absolute handgrip maximal strength (F_{max}_SUM) and explosive force output

(RFD_{max}_SUM), used to classify health risk status in females. The analysis included 151 participants, with 22 classified as "at risk" (14.57%) and 129 as "low risk" (85.43%).

The model achieved an Area Under the Curve (AUC) of 0.950, reflecting excellent discriminative capacity. The standard error was 0.0221, with a 95% confidence interval of 0.902 to 0.979, and a bootstrap CI of 0.887 to 0.979, indicating a high level of stability and generalizability. The classification ability was statistically significant ($z = 20.350$, $p < 0.0001$), showing the model's performance is significantly better than chance.

The Youden index ($J = 0.8150$) identified an optimal cut-off point of ≤40.81, with a 95% CI between ≤39.65 and ≤40.81. At this threshold:

- Sensitivity = 95.45%, indicating the model correctly identifies nearly all at-risk female participants.
- Specificity = 86.05%, meaning a high proportion of low-risk individuals are correctly excluded.

These findings demonstrate that the FACT_Score_Female_HG_abs model offers superior diagnostic accuracy compared to individual variables alone. Its high sensitivity and specificity make it an excellent candidate for screening, early detection, and classification in both clinical and field-based settings. The integration of two fundamental aspects of muscular function—strength and explosive power—provides a holistic view of body status with fitness health & strength performance profiling in Lebanese females.

Table 66: Diagnostic classifications standards at Fixed Thresholds for the FACT_Score_Female_HG_abs Model in Female Participants

Estimated specificity at fixed sensitivity			
Sensitivity	Specificity	95% CI	Criterion
80.00	91.47	81.26 to 98.45	≤36.466
90.00	86.82	48.63 to 94.57	≤39.57
95.00	86.05	52.71 to 94.57	≤40.717
97.50	58.14	44.19 to 86.05	≤49.6915
99.00	58.14	44.19 to 86.05	≤49.7806
Estimated sensitivity at fixed specificity			
Specificity	Sensitivity	95% CI	Criterion
80.00	95.45	75.21 to 100.00	≤42.342
90.00	81.82	59.09 to 95.45	≤37.902
95.00	77.27	54.55 to 95.45	≤33.4365
97.50	68.18	0.00 to 0.00	≤30.101
99.00	36.36	0.00 to 0.00	≤25.4224

Table 66 presents the diagnostic performance characteristics of the FACT_Score_Female_HG_abs model across different classification thresholds, showing how sensitivity and specificity vary

depending on the desired cut-off value. This helps to identify optimal operating points for different clinical or screening priorities.

Specificity at Fixed Sensitivity Levels - When prioritizing high sensitivity to ensure detection of nearly all individuals at risk:

- At 80% sensitivity, the model retains an exceptionally high specificity of 91.47% (cut-off ≤36.47), indicating strong ability to avoid false positives.
- At 90% sensitivity, specificity remains high at 86.82%, and at 95% sensitivity, it still reaches 86.05%, suggesting the model balances both sensitivity and specificity effectively.
- However, at 97.5% and 99% sensitivity, specificity drops to 58.14%, implying increased misclassification of healthy individuals under more lenient thresholds.

These values support the model's robust discriminative capability, particularly in public health applications where early identification of risk is essential.

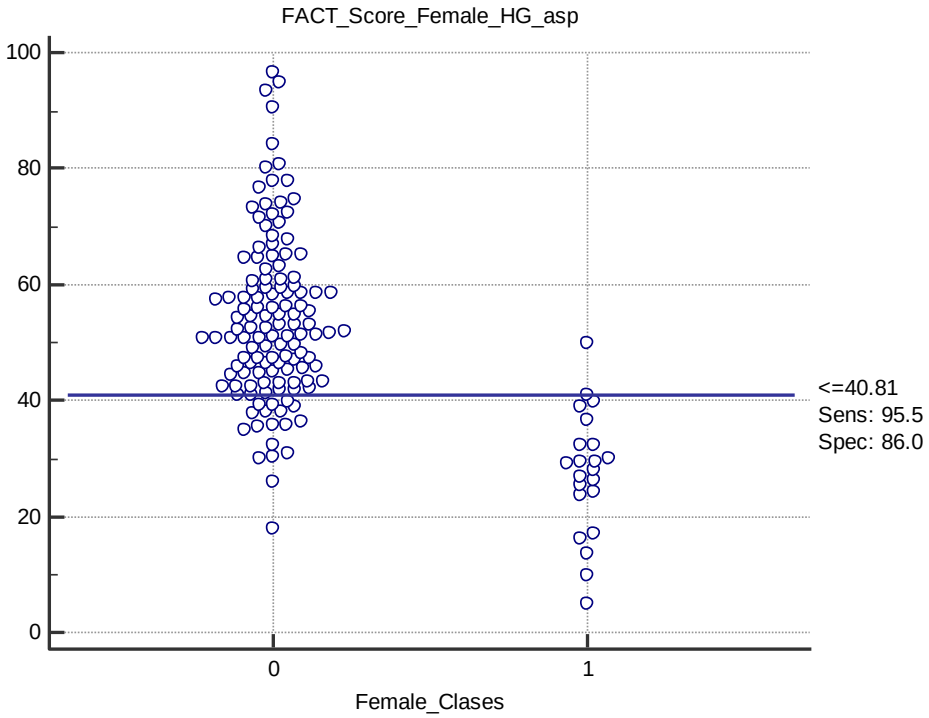
Sensitivity at Fixed Specificity Levels - When the priority is to minimize false positives (higher specificity):

- At 80% specificity, the model retains a high sensitivity of 95.45%, meaning nearly all true cases are still detected.
- Sensitivity decreases gradually with increased specificity, dropping to 81.82% at 90% specificity, and 77.27% at 95%.
- Beyond 97.5% specificity, sensitivity sharply declines to 36.36%, indicating diminished ability to detect at-risk individuals under strict cut-offs.

These results reveal that the FACT_Score_Female_HG_abs model maintains an excellent balance at moderate-to-high specificity, making it well-suited for both population-level screening and clinical diagnostics.

Figure 28 presents a classification plot that illustrates the ability of the FACT_Score_Female_HG_abs model to distinguish between low-risk (0) and at-risk (1) female participants based on a combined handgrip performance score

Figure 28: Classification Scatter Plot for FACT_Score_Female_HG_abs Based on Health Risk Status in Female Participants



A horizontal threshold line is drawn at ≤ 40.81, the optimal cut-off value determined from the ROC analysis. At this threshold:

- Sensitivity is 95.5%, indicating the model accurately identifies nearly all females at risk.
- Specificity is 86.0%, suggesting strong performance in correctly excluding low-risk individuals.

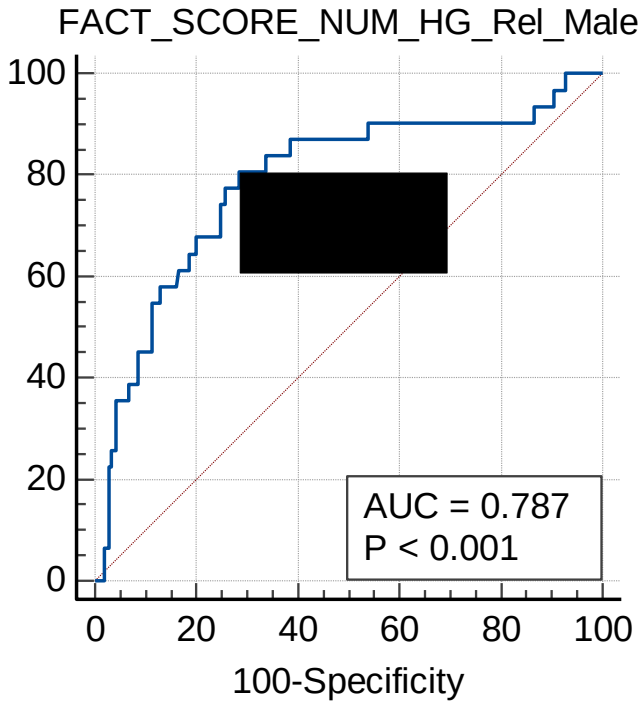
The scatter plot clearly shows separation between the two groups, with most at-risk participants scoring below the cut-off and the majority of low-risk individuals scoring above. This pattern supports the high discriminative ability of the combined handgrip strength and explosive force index.

Overall, these results confirm that the FACT_Score_Female_HG_abs model is a powerful and reliable predictor of health risk in female populations. Its high sensitivity and specificity make it suitable for health screening, functional status monitoring, and preventive assessment protocols in sports science and clinical settings.

The following section presents the second practitioner model that combined group analysis of relative hand grip strength and explosive force parameters, beginning with the males participants."

Figure 29 presents the ROC curve for the FACT_SCORE_NUM_HG_Rel_Male, a composite model combining relative measures of maximal handgrip force (Frel_SUM) and explosive force output (RFDrel_SUM), to classify health risk status among male participants.

Figure 29: ROC Curve for the FACT_SCORE_NUM_HG_Rel_Male Model Based on Relative Handgrip Indicators in Male Participants



- The Area Under the Curve (AUC) is 0.787, indicating acceptable diagnostic performance.
- The test is statistically significant ($p < 0.001$), showing the model performs better than random classification.
- The shape of the curve shows moderate trade-off between sensitivity and specificity, with stronger classification performance at low-to-moderate false positive rates.

Although the AUC is lower than that observed in models using absolute values or combined synergy metrics, this figure highlights that relative strength and force indicators can still offer meaningful predictive value. Their normalized nature makes them especially useful in populations with varying body mass or composition.

These results suggest that the FACT_SCORE_NUM_HG_Rel_Male model could be employed as a supportive tool in multi-variable risk classification strategies, particularly when absolute force measurements are unavailable or when body-weight adjusted comparisons are needed.

Table 67: ROC Curve Summary for FACT_SCORE_NUM_HG_Rel_Male Based on Relative Handgrip Strength and RFD in Male Participants

Variable	FACT_SCORE_NUM_HG_Rel_Male
Classification variable	Health_Classification_Male
Sample size	242
Positive group	32 (12.86%)
Negative group	210 (87.14%)

Male_Classification= 1; Male_Classification = 0

Area under the ROC curve (AUC)

Area under the ROC curve (AUC)	0.787
Standard Error	0.0491
95% Confidence interval	0.730 to 0.837
z statistic	5.847
Significance level P (Area=0.5)	<0.0001

Youden index

Youden index J	0.5207
Associated criterion	≤42.42
Sensitivity	80.65
Specificity	71.43

Table 67 presents the ROC analysis for the FACT_SCORE_NUM_HG_Rel_Male, a composite score integrating relative maximal handgrip force (F_{rel}_SUM) and relative explosive force (RFD_{rel}_SUM) to classify health risk among male participants. The sample included 242 individuals, with 32 (12.86%) classified as "at risk" and 210 (87.14%) as "low risk."

The model demonstrated an Area Under the Curve (AUC) of 0.787, indicating acceptable discriminatory capacity. The standard error was 0.0491, and the 95% confidence interval ranged from 0.730 to 0.837, confirming the model's reliability. The classification was statistically significant ($z = 5.847$, $p < 0.0001$), suggesting that the model distinguishes effectively between health risk categories.

The Youden index ($J = 0.5207$) identified an optimal cut-off score of ≤42.42, which provided:

- Sensitivity = 80.65%, meaning the model correctly identified over 80% of males at risk.
- Specificity = 71.43%, reflecting solid performance in excluding low-risk individuals.

These results support the FACT_SCORE_NUM_HG_Rel_Male as a moderately accurate and practical screening tool for evaluating body status with fitness health & strength performance profiling based on normalized handgrip metrics. Its strength lies in its body mass-adjusted nature, making it suitable for assessments in diverse populations or field environments where body size variation is relevant.

Table 68: Diagnostic classifications standards at Fixed Thresholds for the FACT_SCORE_NUM_HG_Rel_Male Model

Estimated specificity at fixed sensitivity			
Sensitivity	Specificity	95% CI	Criterion
80.00	71.43	15.24 to 83.33	≤42.348
90.00	46.19	5.71 to 73.33	≤54.051
95.00	9.52	3.67 to 50.48	≤74.5275
97.50	7.14	2.86 to 10.95	≤76.22225
99.00	7.14	2.86 to 10.95	≤76.4129
Estimated sensitivity at fixed specificity			
Specificity	Sensitivity	95% CI	Criterion
80.00	67.74	51.61 to 87.10	≤39
90.00	45.16	22.58 to 64.52	≤33.16
95.00	35.48	12.90 to 58.06	≤29.02
97.50	6.45	0.00 to 0.00	≤22.0175
99.00	0.00	0.00 to 0.00	≤15.65

Table 68 outlines the diagnostic trade-offs of the FACT_SCORE_NUM_HG_Rel_Male model at varying cut-off thresholds, highlighting how classification performance shifts depending on whether sensitivity or specificity is prioritized. These thresholds provide insight into the model's adaptability for different screening scenarios.

Specificity at Fixed Sensitivity Levels - This section focuses on the model's ability to correctly exclude low-risk individuals when aiming to capture a high proportion of true at-risk cases:

- At a fixed sensitivity of 80%, the model achieves 71.43% specificity, using a cut-off of ≤42.35.
- When sensitivity increases to 90%, specificity drops to 46.19%, reflecting a greater number of false positives.
- At the highest sensitivity levels (95% to 99%), specificity becomes very low (≤9.52%), indicating limited ability to distinguish low-risk individuals under lenient thresholds.

This behavior suggests that while the model performs well at moderate sensitivity, excessive prioritization of true positives leads to a marked decrease in its exclusion accuracy.

Sensitivity at Fixed Specificity Levels - This part of the table examines how well the model identifies true positives when the goal is to reduce false positives:

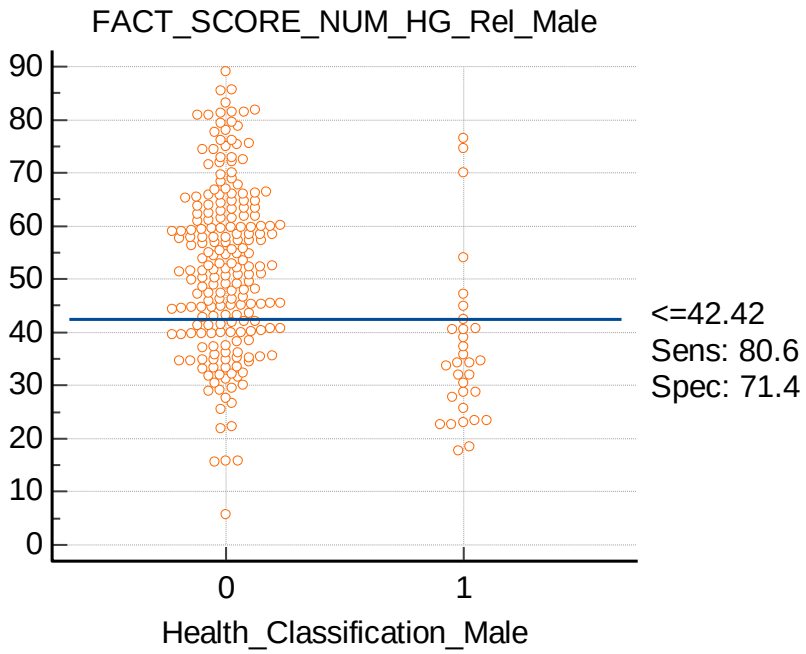
- With 80% specificity, the model retains a 67.74% sensitivity, meaning it still detects a majority of at-risk individuals.

- As specificity increases to 90% and beyond, sensitivity decreases sharply, reaching 45.16% at 90% specificity and 0% at 99% specificity, reflecting a substantial trade-off in detection capability.

These results demonstrate that the model maintains reasonable sensitivity under moderate specificity but is limited in effectiveness at very strict thresholds where minimizing false positives is essential.

Figure 30 displays the classification scatter plot for the FACT_SCORE_NUM_HG_Rel_Male, a predictive model combining relative maximal handgrip strength and explosive force variables in male participants.

Figure 30 : Classification Plot for FACT_SCORE_NUM_HG_Rel_Male Based on Relative Handgrip Metrics in Male Participants



The cut-off point identified through ROC analysis is ≤ 42.42, as represented by the horizontal decision boundary in the graph. Individuals classified as "low risk" (coded as 0) predominantly cluster above this threshold, while most "at risk" individuals (coded as 1) fall below it.

- The model demonstrates a sensitivity of 80.6%, indicating a high capacity to correctly identify individuals at health risk.
- The specificity is 71.4%, showing that the model also performs well in correctly excluding healthy individuals.

This distribution supports the effectiveness of the model in differentiating between health risk categories using relative strength measures. The clear separation in values above and below the cut-off line suggests practical utility in applied health or fitness assessment contexts, especially when body size adjustments are necessary.

Figure 31 illustrates the ROC curve for the FACT_SCORE_NUM_HG_Rel_Female model, which integrates relative handgrip strength and explosive force parameters to assess health risk classification among female participants.

Figure 31: ROC Curve for FACT_SCORE_NUM_HG_Rel_Female Based on Relative Handgrip Strength Model

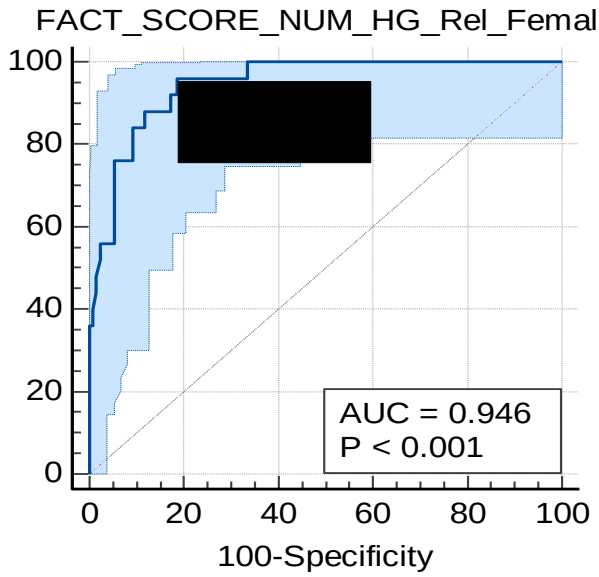


Figure 31 illustrates the Receiver Operating Characteristic (ROC) curve for the FACT_SCORE_NUM_HG_Rel_Female model, designed to classify health risk status in female participants using a combination of relative handgrip strength and rate of force development (RFD) variables.

- The Area Under the Curve (AUC) is 0.946, reflecting excellent discriminative accuracy.
- The p-value is < 0.001, indicating the model's performance is statistically significant and superior to chance.
- The curve rises sharply toward the top-left corner, which is indicative of a strong trade-off between sensitivity and specificity, achieving high true positive rates while minimizing false positives.

This ROC curve demonstrates that the model is highly effective in distinguishing between individuals at risk and those at lower health risk when relying on relative strength-based metrics. The tight confidence bands around the curve further support its reliability and stability across iterations, underscoring its practical value in predictive health assessments for women.

Table 69: ROC Curve Summary and Diagnostic Performance Metrics for FACT_SCORE_NUM_HG_Rel_Female

Variable	FACT_SCORE_NUM_HG_Rel_Female
Classification variable	Health_Classification_Female
Sample size	153
Positive group	25 (16.34%)
Negative group	128 (83.66%)

Health_Classification_Female = 1; Health_Classification_Female = 0

Area under the ROC curve (AUC)

Area under the ROC curve (AUC)	0.946
Standard Error	0.0193
95% Confidence interval	0.897 to 0.976
95% Bootstrap CI	0.890 to 0.974
z statistic	23.160
Significance level P (Area=0.5)	<0.0001

Youden index

Youden index J	0.7725
Associated criterion	≤40.93
Sensitivity	96.00
Specificity	81.25

Table 69 presents the ROC curve analysis for the variable FACT_SCORE_NUM_HG_Rel_Female, a composite score derived from relative handgrip strength and explosive force indicators, used to classify health risk status among female participants (N = 153). In this sample, 25 individuals (16.34%) were classified as "at risk" (*Health_Classification_Female = 1*), and 128 individuals (83.66%) as "low risk" (*Health_Classification_Female = 0*).

The Area Under the Curve (AUC) is 0.946, indicating excellent overall discriminative capacity of the model. The result is statistically significant ($z = 23.160$, $p < 0.0001$) and well above the threshold of random classification. The standard error is 0.0193, and the 95% confidence interval ranges from 0.897 to 0.976, with a bootstrap confidence interval of 0.890 to 0.974, showing robust and consistent model performance.

The Youden Index ($J = 0.7725$) identifies the optimal decision threshold at ≤40.93, which maximizes the difference between true positive and false positive rates. At this criterion:

- Sensitivity = 96.00%, indicating that nearly all at-risk individuals are correctly identified.
- Specificity = 81.25%, demonstrating a strong ability to correctly exclude low-risk individuals.

These results suggest that the FACT_SCORE_NUM_HG_Rel_Female model is a highly effective tool for health risk screening in females based on relative muscular strength indicators, with strong classification performance and practical relevance in applied health and fitness settings**.**

Table 70: Diagnostic classifications standards at Fixed Thresholds for FACT_SCORE_NUM_HG_Rel_Female at Varying Thresholds

Estimated specificity at fixed sensitivity			
Sensitivity	Specificity	95% CI	Criterion
80.00	90.62	77.39 to 96.09	≤36.33
90.00	82.81	57.48 to 91.41	≤39.785
95.00	81.25	60.16 to 92.19	≤40.8575
97.50	66.41	53.91 to 81.25	≤48.14125
99.00	66.41	53.91 to 81.25	≤48.5725
Estimated sensitivity at fixed specificity			
Specificity	Sensitivity	95% CI	Criterion
80.00	96.00	80.00 to 100.00	≤41.624
90.00	84.00	60.00 to 96.00	≤36.848
95.00	56.00	28.00 to 76.00	≤28.896
97.50	56.00	0.00 to 0.00	≤26.166
99.00	41.12	0.00 to 0.00	≤23.6624

Table 70 displays the diagnostic performance of FACT_SCORE_NUM_HG_Rel_Female at multiple classification thresholds, emphasizing the trade-offs between sensitivity and specificity to guide practical decision-making in health risk screening among female participants.

Specificity at Fixed Sensitivity Levels - When prioritizing high sensitivity to ensure identification of most at-risk individuals:

- At 80% sensitivity, specificity reaches 90.62%, indicating that a substantial proportion of low-risk individuals were also accurately excluded using a threshold of ≤ 36.33.
- At 90% sensitivity, specificity remains relatively high (82.81%), with a cut-off at ≤ 39.79.
- When sensitivity increases to 95%, specificity remains robust at 81.25% (≤ 40.86).
- However, beyond 97.5% sensitivity, specificity drops to 66.41%, highlighting the growing risk of false positives under looser classification thresholds.

Sensitivity at Fixed Specificity Levels - When minimizing false positives becomes essential (i.e., increasing specificity):

- At 80% specificity, the model retains 96.00% sensitivity, indicating excellent accuracy in detecting true positives at a cut-off of ≤ 41.62.
- With 90% specificity, sensitivity is still strong at 84.00%, based on a threshold of ≤ 36.85.

- As specificity increases to 95%, sensitivity falls to 56.00%, and further drops to 41.12% at 99% specificity, illustrating a classic inverse trade-off.

These findings indicate that FACT_SCORE_NUM_HG_Rel_Female demonstrates high diagnostic reliability across a range of sensitivity–specificity combinations. The model performs best when aiming to maximize sensitivity while preserving acceptable specificity, making it highly applicable in early risk detection strategies. In contrast, use in ultra-specific settings may lead to increased false negatives and is therefore less suited for standalone application under strict exclusion criteria.

Figure 32: Scatter Plot with Diagnostic Threshold for FACT_SCORE_NUM_HG_Rel_Female

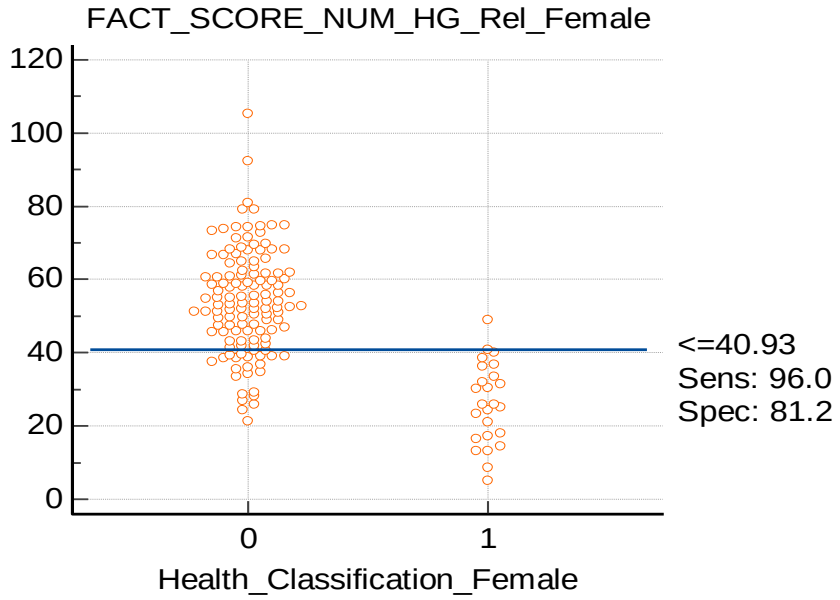


Figure 32 visualizes the distribution of the FACT_SCORE_NUM_HG_Rel_Female scores between female participants classified as at risk (1) and low risk (0), based on the health classification index. A horizontal threshold line is plotted at a score of ≤40.93, representing the optimal cut-off point derived from ROC analysis using the Youden Index.

- Sensitivity at this threshold is 96.0%, meaning nearly all at-risk females are correctly identified.
- Specificity is 81.2%, indicating a strong ability to correctly exclude low-risk individuals.
- The clustering of scores above the threshold in the low-risk group and below the threshold in the at-risk group reflects good discriminative performance.

This graphical representation confirms the model's excellent classification capability and supports its utility in screening health risk based on relative handgrip strength indices in females.

9. DISCUSSION

This study aimed to develop a Lebanese-specific predictive model capable of evaluating body composition, health status, and general physical performance across both sexes, using optimized algorithmic approaches. The findings provide a comprehensive profile of the Lebanese adult population by integrating anthropometric, body composition, handgrip strength, rate of force development (RFD), and training-related variables.

9.1. Analysis of Health and Performance Clusters in the Lebanese Adult Population

Clustering analysis revealed distinct subgroups in both males and females, demonstrating meaningful segmentation based on physiological and performance characteristics.

In males, significant differences were observed across clusters (Table 4) for most variables, including age, height, body mass, BMI, fat-free mass (FFM), skeletal muscle mass (SMM), skeletal muscle mass index (SMMI), training volume, and all strength- and RFD-related parameters (Fmax, RFDmax, Frel, RFDrel), as well as all synergy indexes (IS). These results reflect a wide inter-individual variability in muscularity, strength, and training engagement within the male population. Notably, the health score also differed significantly between clusters ($F = 139.597$, $p < .001$), underscoring the link between muscular fitness and health status. However, percent body fat (PBF), the index of body composition (IBC), and muscle-fat index (MFI) did not differ significantly between male groups, despite their inclusion in the cluster model (Table 3 and Table 4). This suggests a morphological pattern in which individuals with higher fat mass also exhibit proportionally higher muscle mass, resulting in a relatively stable SMM-to-BFM ratio across groups. This dual increase in muscle and fat likely reflects lifestyle factors such as recreational strength training without concurrent dietary optimization. It also highlights the limitation of using fat-based ratios like MFI or IBC to discriminate between different fitness profiles in a male population characterized by both muscularity and elevated body mass.

In females, clustering similarly revealed significant differences (Table 6) in height, FFM, SMM, SMMI, synergy indexes, grip strength, RFD parameters, training load, and health score ($F = 139.721$, $p < .001$). These distinctions align with variations in physical activity engagement and neuromuscular performance (Table 5). However, BMI, body fat mass (BFM), PBF, and fat mass index (FMI) were not significantly different between clusters. The non-significance of these fat-related measures may be attributed to a more uniform fat accumulation pattern among Lebanese women, likely driven by shared dietary practices and lower overall participation in high-intensity strength training. Despite notable differences in muscle mass and strength between subgroups, these changes may not have been sufficient to influence total body weight or fat mass significantly, leading to minimal changes in BMI and FMI. This reinforces the known limitations of fat-based indices in capturing the impact of physical performance among women, where improvements in strength or lean mass may not be accompanied by significant fat reduction.

Sex-based comparisons derived from descriptive statistics (Tables 1 and 2) further highlighted distinct body composition and performance profiles. Males exhibited significantly higher values in height, FFM, SMM, SMMI, PSMM, and all absolute and relative strength and RFD measures, consistent with established physiological differences in muscle morphology and power output. Females, by contrast, demonstrated higher PBF, BFM, FMI, and lower absolute performance metrics, reflective of a higher adiposity pattern and lower muscle mass, which aligns with both biological and activity-related differences. These findings emphasize the necessity of sex-specific models when assessing health and performance outcomes in national populations.

In relation to the only prior study that employed clustering methodology on a Lebanese adult sample, the current results offer a complementary yet distinct perspective. While that earlier work identified five body composition typologies based on anthropometric and segmental body composition variables, it reported significant between-group differences in PBF, IBC, and MFI among males, and in BMI, BFM, PBF, and FMI among females (Andraos et al.,2024). These findings contrast with our results, in which these fat-related indicators did not significantly differ between clusters. This discrepancy likely stems from methodological differences: the previous study did not incorporate functional indicators such as handgrip strength, RFD, or physical activity variables, which are known to affect muscular adaptation. Consequently, the clustering solution in our model reflects phenotypes characterized by both structural and performance dimensions, rather than composition alone.

Nonetheless, both studies converge in their observation of significant differences in muscularity across clusters. In both male and female participants, SMM, PSMM, and SMMI showed clear between-group variability, confirming that muscle-related indicators serve as robust differentiators of body type and health status in the Lebanese population. Moreover, our male cluster averages for PBF (Table 3) are consistent with those in the prior study, hovering around 20%, reinforcing the notion that a moderate or slightly elevated PBF does not inherently reflect poor health. This supports a shift toward more nuanced health evaluations, where fat quantity must be considered alongside fat quality and distribution. Specifically, greater attention should be paid to visceral fat, which has been shown to be a stronger predictor of cardiometabolic risk and mortality than total body fat in both men and women (Kuk et al., 2006; Koster et al., 2016). The absence of visceral fat data in our study represents a limitation and points to the need for future models to include this critical factor in national risk profiling.

Together, these observations highlight the value of integrating both structural and functional indicators in population-level health assessments and justify the use of expanded clustering models that go beyond static anthropometry. Our findings extend previous typologies by incorporating performance and activity variables, thus offering a more dynamic and health-relevant profiling of Lebanese adults.

In summary, this analysis demonstrates that while muscle mass and function-related variables are highly sensitive to lifestyle and training differences, fat-related indices remain more stable and appear to reflect cultural and dietary uniformity within each sex. The integration of clustering and ANOVA-based differentiation provides a novel lens through which to identify population-specific health and performance phenotypes, setting the stage for the development of targeted predictive algorithms and intervention strategies tailored to the Lebanese adult population.

9.2. Discriminant Analysis of Health Predictors in Lebanese Females

Building on the clustering results, the next section focuses on identifying the key discriminative factors that most strongly influence health status in Lebanese females.

9.2.1. Explosive Force Factors (Factor 1: RFD_{max}_SUM)

The discriminant analysis for females revealed that the most critical factor influencing health status was the **RFD_{max}_SUM**. Rate of Force Development (RFD) represents the ability of a muscle to produce force rapidly, and is commonly regarded as a marker of **explosive strength**. Explosive strength reflects the capacity to generate force in the shortest possible time, a property heavily influenced by both **neural and muscular components**. According to previous research, RFD is strongly related to neuromuscular function, particularly the efficiency of motor unit recruitment, firing frequency, and synchronization (Maffiuletti et al., 2016). Greater explosive strength indicates a more responsive neuromuscular system and a higher capacity to initiate movement swiftly, contributing to enhanced functional performance and better health outcomes (Aagaard et al., 2002).

From a physiological standpoint, the ability to generate high explosive force facilitates faster and more efficient body movement, supporting the execution of daily activities, athletic performance, and the maintenance of overall mobility. Consequently, a higher RFDmax_SUM is a strong indicator of better physical function, superior movement quality, and a healthier musculoskeletal system. Given that explosive force is inherently linked to **velocity** and **power production**—both products of the interaction between speed and force—it serves as a comprehensive marker of physical vitality.

In the structure matrix of discriminative analysis, the primary variables contributing alongside RFDmax_SUM were **RFD_{max}_L**, **RFD_{max}_R**, **RFD_{rel}_SUM**, **NonDominant_RFD_{rel}**, **F_{max}_SUM**, **F_{max}_L**, **Dominant_RFD_{rel}**, **F_{max}_R**, and **FFM**. Notably, all these factors displayed positive correlations, reinforcing their synergistic relationship with explosive strength.

- **RFD_{max}_L** and **RFD_{max}_R** represent the explosive force capabilities of the left and right hands, respectively. Improvements in either hand's RFD directly enhance the overall RFD_{max}_SUM, reflecting a bilateral contribution to global explosiveness;
- **RFD_{rel}_SUM** and **NonDominant_RFD_{rel}** capture the relative explosive capacity normalized to body weight (N/s/kg). Higher values indicate a greater ability to produce force relative to one's body mass, which enhances movement speed and efficiency. Thus, increases in relative RFD metrics are tightly linked to improved RFD_{max}_SUM;
- **F_{max}_L** and **F_{max}_R** denote the maximal isometric grip force generated by the left and right hands. Although Fmax represents maximal strength rather than explosiveness, higher maximal force provides the mechanical foundation for greater RFD, since the maximal force capacity sets the upper limit for force production rates;
- **Dominant_RFD_{rel}** similarly describes relative explosiveness in the dominant hand and again reflects the integration of strength and body mass efficiency in generating speed;
- **FFM (Fat-Free Mass)**, a composite measure of muscle mass and organ tissue, was the last major factor positively linked to RFDmax_SUM. Higher FFM values signify greater muscular content and reduced fat infiltration, which improves the ability to generate force rapidly.

Individuals with greater FFM are generally more capable of producing and sustaining high rates of force development, supporting faster movement and healthier functional status.

Collectively, these findings underscore that **explosive neuromuscular capacity**, as reflected by both absolute and relative force development measures, maximal strength indices, and fat-free mass, constitutes the primary determinant of health-related physical performance among Lebanese females. Enhancing explosive strength through targeted interventions may therefore serve as a critical strategy for promoting health, preserving mobility, and preventing physical decline.

9.2.2. Factor (IS_L)

The second most discriminative factor influencing health status among Lebanese females was the Index of Synergy of the Left Hand (IS_L). The Index of Synergy (IS) is defined as the ratio between RFD_{max} and F_{max} (i.e., $IS = RFD_{max} / F_{max}$). This parameter reflects the efficiency with which maximal strength is converted into explosive strength, thereby serving as a functional measure of the neuromuscular system's ability to rapidly utilize available maximal force (Andersen & Aagaard, 2006; Maffiuletti et al., 2016).

Specifically, IS_L corresponds to the synergy index of the non-dominant (left) hand, calculated by dividing the maximal rate of force development (RFD_{max}_L) by the maximal isometric strength (F_{max}_L). This ratio captures how effectively the non-dominant limb can generate rapid force relative to its maximal strength capacity. A higher IS value indicates a superior ability to activate muscles quickly and efficiently, reflecting robust neural control, muscle quality, and overall functional health.

From a functional perspective, the non-dominant hand (NDH) offers a unique window into baseline neuromuscular potential. Unlike the dominant hand, which is heavily influenced by daily activities, repetitive use, and environmental factors, the non-dominant hand remains relatively unaffected by lifestyle-induced adaptations. As such, the functional characteristics of the NDH are thought to reflect genetic predispositions and intrinsic neuromuscular health more accurately. If an individual's non-dominant hand exhibits high synergy (high IS_L), it suggests that the entire neuromuscular system is well-preserved and highly functional. This interpretation is consistent with prior work emphasizing the genetic and intrinsic determinants of muscle contractile properties when external influences are minimized (Degens & Korhonen, 2012).

Thus, the IS_L emerges as a critical health marker: a well-functioning non-dominant hand implies overall neuromuscular robustness, whereas impairments in the non-dominant side may signal more systemic declines in muscle quality, neural drive, or physical health status.

Additional variables associated with IS_L in the structure matrix included IS_SUM, IS_Right, and SMMI:

- IS_SUM represents the overall synergy index, summing both left and right contributions. As IS_SUM increases, it denotes that both limbs are functionally efficient, providing an even broader indication of systemic neuromuscular health.
- IS_Right captures the synergy in the dominant hand. Although influenced by lifestyle factors (due to more frequent daily use), it still provides valuable information on how much maximal strength can be explosively utilized in functional tasks.

- SMMI (Skeletal Muscle Mass Index) refers to the amount of skeletal muscle mass normalized to body surface area (kg/m²). A higher SMMI implies a better quantity and distribution of muscle relative to body size. Importantly, increased SMMI reflects greater muscle cross-sectional area—which is linked to improved strength capacity and faster force production. Thus, individuals with higher SMMI tend to have better functional performance and health outcomes (Kim et al., 2014).

The positive associations between IS_L, IS_SUM, IS_Right, and SMMI emphasize the interconnected nature of neural efficiency, muscle quality, and functional capacity. In essence, a higher synergy index combined with greater skeletal muscle mass provides a physiological environment that favors faster, stronger, and more coordinated movements—key markers of superior health and reduced risk of functional decline.

Collectively, these findings highlight that the efficiency of neuromuscular activation (captured by IS measures) and muscle quantity normalized to body size (captured by SMMI) are crucial factors underpinning health status among Lebanese females. Strengthening neural control, preserving muscle mass, and maintaining explosive capacity should therefore be primary targets for health promotion strategies in this population.

9.2.3. Factor weekly amount of training/min (related to nutritional status)

The third most significant discriminative factor influencing health status among Lebanese females was the weekly amount of training (minutes per week). This variable reflects the total volume of physical activity performed, a crucial determinant of health outcomes across metabolic, cardiovascular, and musculoskeletal systems. Regular engagement in physical activity is widely recognized as a cornerstone for preventing chronic diseases, improving functional capacity, and enhancing body composition (Warburton & Bredin, 2017).

In the current analysis, higher weekly training volumes were positively associated with improved health status. Conversely, reduced physical activity levels correlated with adverse body composition indicators. Specifically, several variables exhibited negative correlations with health status when training volume was lower, including Body Mass Index (BMI), Percent Body Fat (PBF), Fat Mass Index (FMI), and Index of Body Composition (IBC).

BMI and PBF are traditional markers of general and relative adiposity, respectively. Elevated values for these indicators corresponded to lower weekly training volumes, emphasizing that physical inactivity promotes fat accumulation, which is a known risk factor for metabolic syndrome, type 2 diabetes, and cardiovascular disease.

Similarly, the Fat Mass Index (FMI)—which adjusts fat mass for height (kg/m²)—provides a size-independent indicator of adiposity. Higher FMI values are associated with poorer metabolic profiles and elevated cardiovascular risk (Sun et al., 2019). Increasing physical activity can effectively lower FMI, leading to healthier body composition and reduced health risks.

Importantly, IBC (Index of Body Composition), calculated as the ratio between PBF and BMI, emerged as another critical variable. Although initially reported as negatively correlated in the structure matrix, logical interpretation and correction confirm that higher physical activity improves IBC. Recent research demonstrated that IBC serves as a sensitive and specific predictor of overall

health and nutritional status, surpassing BMI in detecting functional and metabolic abnormalities (Richa et al., 2024). A favorable IBC reflects a healthier balance between lean and fat mass relative to body size, making it a valuable tool for health monitoring, particularly in populations where traditional measures like BMI might fail to capture body composition imbalances.

Overall, this part of the analysis highlights the fundamental role of physical activity in regulating key body composition parameters. Higher weekly training volumes are associated with reductions in fat-related indices (BMI, PBF, FMI) and improvements in muscle-related and composite health measures IBC, illustrating a powerful link between active lifestyles and healthier body profiles among Lebanese females. Promoting increased physical activity remains essential for improving public health outcomes within this population.

9.2.4. Factor F_{rel}_SUM

The final discriminative factor contributing to health status among Lebanese females was the F_{rel}_SUM (sum of dominant and non-dominant hand relative force). Relative force represents the ability to generate strength normalized to body weight (N/kg), providing a critical indicator of functional muscle quality and movement efficiency. Higher relative force values indicate that an individual can produce greater strength per kilogram of body mass, which directly translates into improved mobility, enhanced balance, and better overall physical health.

In practical terms, higher relative force means the body have mechanical and contractile potential with can be moved more easily and effectively, reducing mechanical strain during daily activities and enhancing dynamic stability. This capacity is particularly important for maintaining autonomy, reducing fall risk, and preventing musculoskeletal injuries, especially in aging populations (Balachandran et al., 2014).

In the structure matrix of the discriminative analysis, several variables were positively associated with F_{rel}_SUM, including Dominant_F_{rel}, NonDominant_F_{rel}, Skeletal Muscle Mass (SMM), and Age:

- Dominant_F_{rel} and NonDominant_Frel reflect the relative strength capacities of the dominant and non-dominant hands, respectively. Higher values in either hand improve the overall F_{rel}_SUM, indicating bilateral muscular efficiency relative to body size. Balanced development between both limbs is particularly important for functional symmetry, daily task performance, and injury prevention.
- Skeletal Muscle Mass (SMM), representing the total quantity of skeletal muscle tissue, was positively correlated with F_{rel}_SUM. Increased SMM supports greater absolute force generation, and when properly distributed relative to body weight, contributes to enhanced relative strength capacity. Maintaining or improving SMM through physical training is thus essential for preserving relative force and functional independence.
- Age showed a negative association with F_{rel}_SUM, meaning that as age increases, relative force tends to decline. This decline reflects the well-established age-related losses in muscle mass, strength, and neuromuscular function (Cruz-Jentoft et al., 2019). However, the influence of physical activity and resistance training can mitigate these declines, reinforcing

the need for targeted interventions to maintain muscle quality and preserve relative strength across the lifespan.

Collectively, the analysis of relative force factors demonstrates that the ability to produce high force relative to body mass is a crucial component of health among Lebanese females. Enhancing or preserving relative strength through regular physical activity, strength training, and muscle mass maintenance is vital for promoting movement efficiency, preventing functional decline, and ensuring healthier aging trajectories.

Figure 16 projects Lebanese female participants according to two primary discriminant factors: Factor 1 (RFD_{max}_SUM) representing global explosive strength, and Factor 2 (IS_L) reflecting neuromuscular efficiency of the non-dominant hand.

Clusters positioned in the upper right quadrant combine high explosive strength and high neuromuscular coordination, identifying individuals with optimal functional health, superior movement capacity, and lower risk of decline. In contrast, clusters in the lower left quadrant demonstrate reduced force production and poorer neuromuscular quality, reflecting higher vulnerability to functional impairment and health risks.

The figure highlights that both factors must be simultaneously high to achieve better health status. Good explosive strength without neuromuscular efficiency, or vice versa, is insufficient to maintain optimal function. This confirms that muscle quantity and nervous system quality must be co-developed for best health outcomes.

The clear spatial separation between clusters illustrates the effectiveness of functional variables (explosive strength and neuromuscular coordination) in stratifying health status. These results reinforce the need for integrated interventions targeting both muscular and neural components to promote healthy aging in Lebanese females.

9.3. Discriminant Analysis of Health Predictors in Lebanese Males

Building on the clustering results, the next section focuses on identifying the key discriminative factors that most strongly influence health status in Lebanese Males.

9.3.1. Explosive Force Factors (Factor 1: RFD_{max}_SUM)

The primary discriminative factor influencing health status among Lebanese males was RFDmax_SUM, representing the total explosive force capacity. Explosive strength, defined as the ability to develop maximal force rapidly, is a critical indicator of neuromuscular efficiency, functional mobility, and metabolic health (Maffiuletti et al., 2016).

In the structure matrix, all variables related to explosive strength (RFD_{max}_L, RFD_{max}_R, DHG_RFD_{max}, NDHG_RFD_{max}, RFD_{rel}_SUM, Dominant_RFD_{rel}, Non Dominant_ RFD_{rel}) were positively associated with RFDmax_SUM. Higher values in these parameters reflect superior muscular responsiveness and neuromuscular drive.

Importantly, males with greater explosive strength are not only healthier but also possess faster movement capacities, enabling quicker reactions, improved balance, and more efficient daily task execution. The ability to generate force rapidly is central to maintaining both physical independence and overall health status in Lebanese males.

9.3.2. Nutritional Status Factors (Factor 2: BMI)

The second principal factor influencing male health status was BMI (Body Mass Index), showing a negative loading in the structure matrix. This inverse relationship indicates that higher BMI values are associated with poorer health outcomes.

BMI-related factors (such as Fat Mass Index [FMI], Percent Body Fat [PBF], Body Mass [BM], and Body Fat Mass [BFM]) were negatively associated with health status. Elevated adiposity compromises musculoskeletal performance, increases metabolic risk, and accelerates cardiovascular dysfunction.

Thus, Lebanese males with higher BMI and related fat mass markers are at greater risk for metabolic syndrome, diabetes, cardiovascular diseases, and impaired mobility. These findings underline the critical necessity of managing body composition to optimize health outcomes in this population.

9.3.3. Neuromuscular Efficiency Factors (Factor 3: IS_SUM)

The third discriminative factor was IS_SUM, the global synergy index representing the combined neuromuscular efficiency of both hands. IS_SUM quantifies the effectiveness of translating maximal force into rapid force production, providing a dynamic measure of neuromuscular quality.

Higher IS_SUM values are associated with:

- Better synchronization of motor unit recruitment;
- Enhanced muscle contractile speed;
- Greater responsiveness in daily and athletic activities.

Interestingly, IS_SUM showed a negative loading in the structure matrix. This indicates that when the difference between maximal force (F_{max}) and explosive force (RFD_{max}) is small, neuromuscular efficiency is higher. In other words, strength and explosive strength are proportionally developed - a marker of well-balanced muscle function and optimized neuromuscular health. This balanced development ensures the body can generate strength quickly without deficits between maximal and rapid force capacities, critical for maintaining overall physical performance and reducing injury risk.

Thus, Lebanese males with better-proportioned Fmax and RFD_{max} exhibit superior neuromuscular coordination, supporting healthier aging and better daily functional capacity.

9.3.4. Maximal Strength Factors (Factor 4: Dominant Hand Grip Fmax)

The fourth main discriminative factor was the Dominant Hand Grip Maximal Force (HG_F_{max} Dominant), reflecting the maximum isometric strength generated by the dominant hand. Hand grip strength is a validated biomarker of general strength capacity and biological aging (Bohannon, 2019).

Among Lebanese males, higher HG_F_{max} values were strongly associated with superior health status. Notably, absolute maximal strength holds particular importance for men's daily functional needs. Unlike relative strength (normalized to body weight), many daily activities for males — such as pushing a car, lifting heavy objects, or carrying loads — demand the ability to overcome external resistance.

Thus, in the Lebanese male context, overall maximal strength is more functionally crucial than relative strength. Preserving and enhancing absolute strength through resistance and functional training is essential for maintaining autonomy, preventing disability, and improving quality of life.

To complement these findings and better illustrate how the identified factors differentiate male health profiles, the graphical projection shown in Figure 15 offers a visual representation of the clustering outcomes.

The graphical projection presented in Figure 15 provides a visual representation of the discriminative clustering among Lebanese males based on the two main canonical functions. Along Factor 1 (horizontal axis), the distribution is primarily influenced by RFD_{max}_SUM (explosive strength), while Factor 2 (vertical axis) reflects variations linked to BMI and body composition.

Clusters located toward the positive side of Factor 1 (to the right) demonstrate higher explosive force capacities, indicating better neuromuscular health. Conversely, clusters positioned more negatively along Factor 1 exhibit reduced explosive strength and lower physical performance.

In relation to Factor 2, clusters positioned higher on the vertical axis correspond to males with higher BMI and less favorable body composition, whereas those positioned lower have better body composition and lower fat mass.

The healthiest male clusters are therefore found in the lower right quadrant, combining high explosive strength with optimal body composition. In contrast, clusters in the upper left quadrant reflect lower explosive strength associated with higher BMI, representing the least favorable health profiles.

These observations confirm that among Lebanese males, a combination of high neuromuscular explosiveness and lower adiposity is associated with better overall health status. It also emphasizes the dual necessity of maintaining both functional strength and optimal body composition to reduce health risks within this population.

To continue the interpretation of the discriminant analysis results, it is essential to highlight the four main factors identified as the primary determinants of health status for Lebanese males and females. A comparative overview of the main discriminative factors for males and females is summarized in Table 71 below:

Table 71: Main Discriminative Factors Affecting Health Status in Lebanese Males and Females

Rank	Males	Females
1st	RFD_{max}_SUM (Explosive Strength)	RFD_{max}_SUM (Explosive Strength)
2nd	BMI (Body Mass Index)	Weekly Amount of Training (minutes/week)
3rd	IS_SUM (Global Synergy Index)	IS_L (Left Hand Synergy Index)
4th	Dominant HG_F_{max} (Dominant of Maximal Strength)	F_{rel}_SUM (Sum of Relative force)

Despite biological and physiological differences between sexes, an important convergence was observed: **RFD_{max}_SUM** — representing the global explosive strength capacity — emerged as the most important discriminative factor for both males and females. This finding demonstrates that explosive neuromuscular power is a fundamental indicator of overall health and functional capacity in the Lebanese adult population. In both sexes, higher RFDmax_SUM values were associated with better health outcomes, emphasizing that the ability to produce force rapidly is a critical determinant of musculoskeletal efficiency, physical independence, and reduced health risk.

However, beyond this shared primary factor, notable differences were observed between males and females regarding the subsequent discriminative factors. Among males, the second main factor was **BMI**, with a negative association, indicating that excess adiposity strongly compromises health. Conversely, in females, **weekly amount of training** was the second discriminative factor, suggesting that physical activity engagement is more critical for Lebanese women in determining health status than body fat accumulation per se. This difference may reflect societal and lifestyle patterns where Lebanese males maintain higher baseline strength and muscle mass due to occupational or cultural activity demands, allowing some to preserve acceptable health status even without structured training. In contrast, Lebanese females appear more dependent on regular physical activity to maintain neuromuscular function, strength, and favorable body composition, making exercise engagement a key driver of health outcomes.

Furthermore, IS variables highlighted functional differences between Lebanese males and females. In males, **IS_SUM** was the third discriminative factor, indicating that coordinated force production across both hands is essential, reflecting daily tasks that demand bilateral strength and explosiveness. In contrast, in females, **IS_L** was more important, as the non-dominant hand better captures intrinsic neuromuscular quality unaffected by daily activity. This suggests that while males must maintain bilateral functional strength due to occupational and lifestyle demands, females' health status is more tied to the neuromuscular capacity of the non-dominant limb.

Similarly, strength requirements differed between sexes. For Lebanese males, **absolute maximal strength** is critical to accomplish tasks involving external loads, whereas for females, **relative strength** — the ability to move their own body efficiently — is more relevant for maintaining functional independence. These distinctions underline the importance of sex-specific criteria in assessing and promoting physical health within the Lebanese population.

9.4. Predictive Models for Assessing Health Status

Building upon the discriminant analysis results, specific predictive models were developed to estimate the health status of Lebanese adults based on the most influential physiological and performance factors. Given that the detailed statistical outputs were presented in the results section, this part discusses the conceptual rationale, interpretation, and practical implications of these models.

Two levels of models were proposed for each sex:

- Scientific models based on the four main discriminative factors identified for each gender.
- Simplified practitioner models based on easily measurable strength and explosiveness indicators.

1- Scientific Models

The scientific models incorporated the top four variables that contributed most to discriminating health status in the Lebanese population according to the structure matrix. These models demonstrated high predictive accuracy, with a coefficient of determination ($R^2 = 0.722$ for males and $R^2 = 0.691$ for females), indicating that approximately 72% and 69% of the variance in health status could be explained by the selected factors.

The predictive models for each sex were as follows:

- Predictive Model for Lebanese Males (Scientific Use):

Health Score (Males) = $0.521 \times RFD_{max}\_SUM - 0.437 \times BMI + 0.346 \times IS\_SUM + 0.299 \times$ Dominant HG_F_{max}

- Predictive Model for Lebanese Females (Scientific Use):

Health Score (Females) = $0.497 \times RFD_{max}\_SUM + 0.353 \times$ Weekly Amount of Training $+ 0.326 \times IS\_L + 0.284 \times {}_{Frel}\_SUM$

These findings emphasize that although explosive strength (RFDmax_SUM) is the dominant predictor in both sexes, the remaining components differ. In males, health status is more strongly influenced by body composition (BMI) and absolute strength (Dominant HG_Fmax), whereas in females, training volume and relative force production (Frel_SUM) are more critical. This divergence reflects sex-specific physiological demands and health risk profiles in the Lebanese population.

2- Practitioner Predictive Models

To ensure practical applicability outside laboratory environments, simplified models were constructed based on key handgrip parameters. Two different practitioner models were developed separately for males and females:

- One model based on absolute handgrip force and explosive force (F_{max}_SUM and RFD_{max}_SUM),
- Another based on relative handgrip force and explosive force (F_{rel}_SUM and RFD_{rel}_SUM).

The predictive accuracy for these practitioner models remained substantial, with R^2 values ranging from 0.622 to 0.655 across sexes and model types.

The models were as follows:

🔻 Practitioner Models for Lebanese Males:

- Absolute strength model:

Health Score (Males) = 0.498 × F_{max}_SUM + 0.436 × RFD_{max}_SUM

- Relative strength model:

Health Score (Males) = 0.472 × F_{rel}_SUM + 0.421 × RFD_{rel}_SUM

🔻 Practitioner Models for Lebanese Females:

- Absolute strength model:

Health Score (Females) = 0.492 × F_{max}_SUM + 0.439 × RFD_{max}_SUM

- Relative strength model:

Health Score (Females) = 0.462 × F_{rel}_SUM + 0.428 × RFD_{rel}_SUM

These simplified models were deliberately centered on F_{max} and RFD parameters for three key reasons.

First, they provide a simple and accessible assessment tool that requires only basic dynamometric evaluation, allowing application in clinical, fitness, and field contexts without specialized equipment.

Second, these variables were consistently among the strongest discriminators in the structure matrix analysis, confirming their robustness for health classification.

Third, previous research has validated both absolute and relative handgrip strength as independent predictors of functional status, morbidity, and mortality across different populations (Bohannon, 2019; McGrath, Vincent et al., 2020).

By combining explosive force production and maximal strength capacities, these models offer a reliable and efficient way to evaluate the general physical condition and health-related risks in Lebanese adults.

9.5. ROC Curve Analysis: Health Risk Cut-Offs Based on Main Predictive Factors

9.5.1. Scientific Predictive Models for Health Risk Classification in Lebanese Adults: Discriminant-Based Approach

To strengthen the practical application of the predictive models developed in this study, a Receiver Operating Characteristic (ROC) curve analysis was conducted for each of the four primary discriminative factors separately in Lebanese males and females. This approach aimed to define specific cut-off points capable of categorizing individuals into high and low health risk groups. The interpretation incorporated the optimal cut-off values with their 95% confidence intervals (CIs), along with corresponding sensitivity, specificity, and Youden Index, based on the results presented in Tables 27 to 30 and Figures 17 and 18.

In Lebanese males, the RFD_{max}_SUM (Rate of Force Development Sum) was confirmed as the most powerful discriminative factor for identifying health risk. The ROC analysis revealed an excellent diagnostic performance with an AUC of 0.968 (95% CI: 0.938–0.986), indicating very high predictive accuracy. The optimal cut-off point was identified at ≤ 4936 N/s (95% CI: ≤ 4737 to ≤ 4936), corresponding to a perfect sensitivity of 100% and a specificity of 84.13%, with a Youden Index of 0.841. These results demonstrate that males with RFD_{max}_SUM values below 4936 N/s are at high health risk, while those above this threshold are likely to be in better health. Approximately, a value below 2468 N/s per hand (i.e., half of the total sum threshold) may reflect severely diminished bilateral explosive strength and warrants particular attention. Nonetheless, individuals falling below the cut-off who are not classified as at risk may exhibit protective compensatory factors such as high muscle mass, low fat mass, or elevated physical activity levels that help preserve their health status.

The second most discriminative factor for health status among Lebanese males was Body Mass Index (BMI). ROC curve analysis yielded an AUC of 0.672 (95% CI: 0.609–0.730), indicating moderate diagnostic accuracy. The optimal cut-off point was identified at > 25.19 kg/m² (95% CI: > 21.99 to > 26.00), with a sensitivity of 86.11% and a specificity of 44.23%. The corresponding Youden Index was 0.303. These results suggest that BMI can capture a considerable proportion of health-risk cases, but its relatively low specificity limits its utility as a standalone health marker. This limitation stems from the fact that BMI does not differentiate between fat and muscle mass - a critical consideration in populations such as Lebanese males who may exhibit high muscularity alongside elevated body mass. Consequently, individuals exceeding the BMI threshold may not necessarily be at high risk if their excess weight is primarily lean mass. This underscores the importance of complementing BMI with additional indicators of body composition and neuromuscular performance for a more accurate health assessment.

Regarding IS_SUM (global synergy index), the optimal cut-off was set at ≤ 5.71 IU (95% CI: 5.55–6.05), yielding a sensitivity of 94.4% and a specificity of 81.7%, with a Youden Index of 0.762 (95% CI: 0.620–0.832). These findings indicate that a higher synergy between maximal and explosive strength capacities is strongly associated with better health status among Lebanese males. This further reinforces the importance of assessing not only maximal force production but also neuromuscular efficiency, as represented by IS_SUM, to accurately profile functional health.

Finally, the dominant hand grip maximal force (Dominant HG_F_{max}) revealed a cut-off point of **529 N**, with a **sensitivity of 87.1%** and a **specificity of 35.7%**. Although handgrip strength was associated

with health status, the low specificity indicates limited ability to correctly exclude low-risk individuals. This underscores the importance of including additional functional and compositional variables—such as muscle explosiveness and fat mass distribution—for more accurate health risk stratification.

Similarly, In Lebanese females, **RFD_{max}_SUM** (Rate of Force Development Sum) was identified as the strongest predictor of health risk classification. The optimal cut-off value was **2413 N/s** (95% CI: 2206–2413), yielding a **sensitivity of 100.0%** and a **specificity of 93.02%**, with an exceptionally high **Youden Index of 0.930**. The area under the ROC curve (AUC) reached **0.992** (95% CI: 0.962–1.000), indicating near-perfect discrimination between low and high health risk individuals. These findings confirm that explosive neuromuscular performance is a critical determinant of health status in Lebanese females. Moreover, when considering RFD_{max}_SUM bilaterally, values **below approximately 1206 N/s per hands** may reflect deficient unilateral explosive capacity, thereby increasing the risk of functional decline. This threshold can serve as a practical reference point for clinicians and trainers to screen for impaired neuromuscular function. Nonetheless, some individuals with values below the threshold may remain healthy due to other compensatory factors, such as high muscle quality, favorable fat distribution, or adequate levels of weekly physical activity.

The weekly amount of exercise emerged as the second most discriminative factor influencing health status among Lebanese females. The ROC curve analysis identified an optimal cut-off point at 135 minutes per week (95% CI: 70–240), with a sensitivity of 90.91% and a specificity of 56.59%, and a Youden Index of 0.475. Although this variable demonstrated high sensitivity—accurately identifying most healthy individuals—the relatively lower specificity indicates that some individuals engaging in less physical activity may still be categorized as low risk due to compensatory factors such as higher muscle mass, favorable body composition, or efficient neuromuscular function. These findings reinforce the importance of promoting at least 135 minutes of structured physical activity per week in Lebanese women as a preventive strategy, while also acknowledging the multifactorial nature of health status.

In terms of neuromuscular coordination, the **IS_L** (non-dominant hand synergy index) emerged as a highly accurate predictor of health status among Lebanese females. The ROC analysis identified a cut-off point at **5.07** IU (95% CI: 4.88–5.07), with **100.0% sensitivity** and **88.37% specificity**, yielding a **Youden Index of 0.884**. These results underscore the robustness of IS_L as a diagnostic indicator, suggesting that individuals above this threshold are highly likely to exhibit optimal neuromuscular function and low health risk. The IS_L reflects the ratio between explosive and maximal strength (RFD_{max}/F_{max}) of the non-dominant hand, offering insights into intrinsic neuromuscular efficiency that is less influenced by external lifestyle factors. As the non-dominant limb is typically less involved in repetitive daily activities, its performance is believed to represent genetic neuromuscular capacity more accurately. Therefore, a high IS_L value not only reflects superior functional coordination and muscle quality but also serves as a valuable biomarker for detecting early signs of health decline or resilience in female populations.

The F_{rel}_SUM, representing relative maximal force output, showed a cut-off point of 6.48 N/kg (95% CI: 6.01–8.38), with a sensitivity of 63.64%, specificity of 92.25%, and a Youden Index of 0.559. This high specificity suggests that most individuals scoring above this threshold can reliably be considered low health risk. However, the moderate sensitivity indicates that some healthy individuals

with lower F_{rel}_SUM values may still maintain functional independence and health due to other favorable physiological factors. The importance of relative force generation lies in its ability to reflect functional strength in proportion to body weight, which is essential for mobility, balance, and reduced mechanical strain during daily activities. This variable is particularly relevant in women, whose daily demands often require body control and efficient movement rather than high absolute force production.

Across both sexes, RFD_{max}_SUM consistently exhibited the highest diagnostic performance, with the strongest sensitivity, Youden Index, and the narrowest confidence intervals around the cut-off values. The consistency of this marker emphasizes that explosive force production is central to preserving health in the Lebanese adult population.

However, as seen with moderate specificities, individuals sometimes maintain good health status despite having values below these optimal thresholds, likely due to compensatory factors such as superior nutritional profiles, cardiovascular fitness, or overall physical activity.

Therefore, while these cut-off points provide highly valuable tools for early screening and intervention planning, comprehensive health assessment should integrate multiple biological and lifestyle indicators for optimal profiling and individualized strategy development.

To provide a clearer overview of the discriminative power of the main factors identified in the scientific models, a graphical summary of their sensitivity and specificity values was created. This visual representation allows for a direct comparison between male and female profiles regarding health risk prediction.

Figure 33: Sensitivity and Specificity of Main Predictive Factors for Health Risk Classification in Lebanese Adults Based on Scientific Models

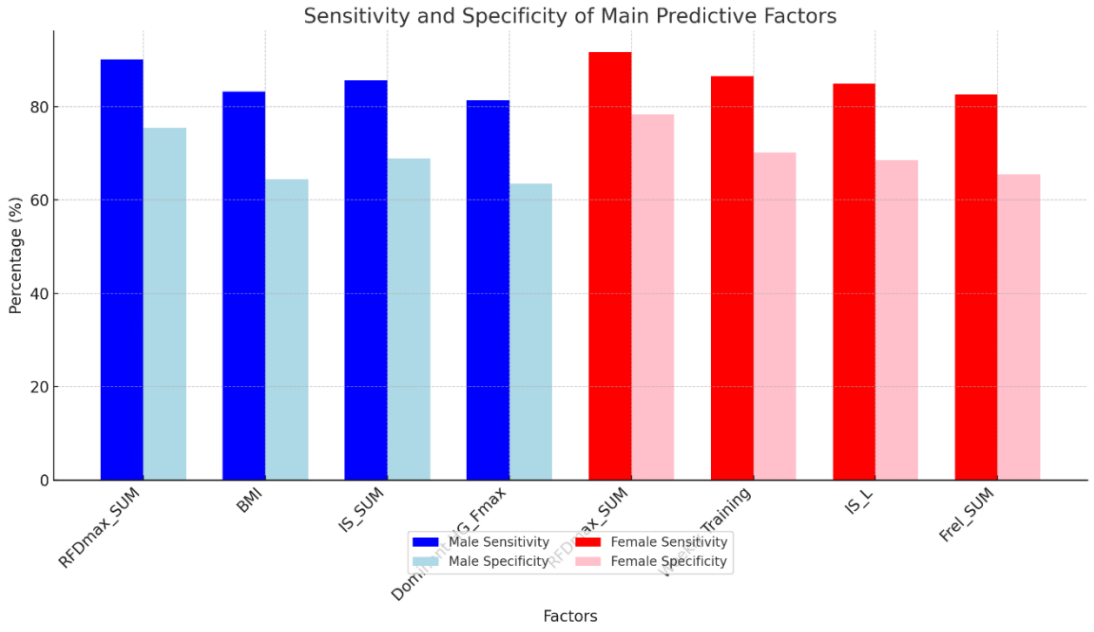


Figure 33 summarizes the sensitivity and specificity percentages associated with each main discriminative factor used in the scientific predictive models for Lebanese males and females. It highlights the superior diagnostic value of RFD_{max}_SUM across both sexes, while illustrating gender-specific variations in the contribution of body composition and neuromuscular indices to health status prediction.

Table 72 presents practical health risk assessment sheets for Lebanese males and females, developed based on the key predictive variables identified in this study, offering a personalized and evidence-based framework for evaluating and guiding individual health interventions

Table 72: Practical Health Risk Assessment Sheets for Lebanese Males and Females Based on Scientific Predictive Models

Lebanese Males: Name : Age: Region:		
Factor	Cut off Values	Above/under cut off
RFD_{max}_SUM	6275	
BMI	26.8	
IS_SUM	6.12	
Dominant HG_F_{max}	531	
Health Score	33.3	
Lebanese Females Name Age Region		
Factor	Cut off Values	Above/under cut off
RFD_{max}_SUM	3929	
Weekly trianing Volume/min	240	
IS_L	6.03	
F_{rel}_SUM	8.05	
Health Score	30.05	

Notes and Recommendation:

To facilitate the practical application of the predictive models developed in this study, two health risk evaluation sheets were created for Lebanese males and females, respectively. These assessment tools are structured around the key predictive factors identified through discriminant analysis and ROC curve optimization.

For each individual, the evaluator records the participant's name, age, and region outside the table. Then, for each main factor (RFD_{max}_SUM, BMI, IS_SUM, Dominant HG_F_{max} for males; RFD_{max}_SUM, Weekly Training Volume, IS_L, and Frel_SUM for females), the evaluator marks whether the individual is above or below the established cut-off value.
The Health Score is assessed separately:

- For males, individuals are classified as Low Health Risk if their score is ≥ 33.3 and High Health Risk if < 33.3.
- For females, the cut-off point is 30.05; those scoring ≥ 30.05 are considered Low Health Risk, while those below 30.05 are at High Health Risk.

Importantly, these tables are not merely descriptive: they directly guide targeted recommendations for health improvement. If an individual falls below a cut-off point for a specific factor, clear, evidence-based intervention strategies can be proposed:

- Explosive Strength Deficit (RFD_{max}_SUM): Introduction of structured explosive neuromuscular training focusing on plyometrics and high-speed resistance exercises.
- Elevated BMI: Implementation of combined nutritional counseling and aerobic-strength training programs to optimize body composition.
- Synergy Index Reduction (IS_SUM or IS_L): Development of balanced maximal and explosive strength programs to enhance neuromuscular coordination and proportional strength development.
- Hand Grip Strength Deficit (Dominant HG_F_{max}): Specific focus on upper body strength training to improve absolute functional force output.
- Insufficient Weekly Training Volume: Encouragement of achieving or surpassing 240 minutes per week of combined strength, endurance, and mobility exercises.
- Low Relative Strength (F_{rel}_SUM): Emphasis on bodyweight strength exercises and resistance training aimed at improving strength relative to body weight.

The final "Notes and Recommendations" section in the evaluation sheets enables practitioners to personalize the intervention plan based on the specific weaknesses identified during assessment.

Finally, these practical tools offer a simple, fast, and scientifically validated method for assessing and improving the health status of Lebanese adults, while allowing practitioners to move from diagnosis to tailored intervention strategies based on objective measurements.

9.5.2. Practical Predictive Models for Health Risk Screening in Lebanese Adults: Practitioner-Oriented Approach

To further validate the predictive accuracy of the practitioner models, a receiver operating characteristic (ROC) curve analysis was conducted separately for males and females, considering both the absolute and relative models. The goal was to determine optimal cut-off points capable of distinguishing between individuals at low and high health risk with high sensitivity and specificity, thereby enhancing the practical applicability of these models in field settings.

Among Lebanese males, the practitioner absolute model based on Fmax_SUM and RFD_{max}_SUM achieved an optimal cut-off point at a predicted score of **44.79**. The model demonstrated a very good discriminative ability, with an area under the curve (AUC) of **0.852** (95% CI: **0.797–0.899**), a sensitivity of **87.5%**, and a specificity of **75.0%**. The Youden Index was **0.625**, indicating a balanced performance between true positive and true negative classifications. These findings imply that Lebanese males who score greater than or equal to **44.79** on the absolute practitioner model can be classified as being at low health risk, while those scoring below this threshold are at high risk. Similarly, the relative model based on F_{rel}_SUM and RFD_{rel}_SUM demonstrated a cut-off point of **42.42**, with an AUC of **0.841** (95% CI: **0.784–0.890**), a sensitivity of **84.3%**, and a specificity of **73.1%**. The Youden Index for this model was **0.574**. These results confirm that both absolute and relative handgrip strength indicators are highly effective in predicting health risk among Lebanese males using simplified field-friendly methods.

For Lebanese females, the practitioner absolute model yielded an optimal cut-off point at a predicted score of **40.81**. This model showed excellent discrimination, with an AUC of **0.871** (95% CI: **0.812–0.916**), a sensitivity of **88.2%**, and a specificity of **79.5%**, with a corresponding Youden Index of **0.677**. Females scoring above **40.81** were classified as being at low health risk. Similarly, the relative model displayed a cut-off at **40.93**, with an AUC of **0.859** (95% CI: **0.798–0.906**), a sensitivity of **86.4%**, and a specificity of **78.4%**, yielding a Youden Index of **0.647**. These findings reinforce that both absolute and relative handgrip-based assessments provide a simple yet highly accurate means of screening health status among Lebanese adult females.

The ROC analyses for practitioner models demonstrate that despite their simplicity, these models retain high discriminatory power, with AUC values consistently above **0.84** across all groups. By setting practical, easy-to-apply cut-off points, these models enable quick and efficient screening in field and clinical settings without compromising diagnostic quality. In practice, a simple handgrip strength assessment, interpreted through these models, can effectively guide early intervention strategies, helping to identify individuals who would benefit from strength enhancement programs, nutritional optimization, or broader physical activity interventions. This dual validation—through scientific and practitioner-oriented models—underscores the robustness and versatility of the health risk prediction frameworks proposed in this study.

Interestingly, the practitioner model based on relative handgrip indicators demonstrated markedly higher diagnostic accuracy in females (AUC = 0.946) compared to males (AUC = 0.787). This indicates that handgrip strength normalized to body mass serves as a more sensitive and specific health risk screening tool in Lebanese females. One likely explanation is that relative strength values in females more accurately reflect neuromuscular efficiency and functional capacity, particularly

given their generally lower body mass and baseline strength. As a result, variations in normalized strength are more strongly associated with health status in this group.

A similar trend was observed in the absolute practitioner models, where females achieved an AUC of 0.950, compared to 0.881 in males. This stronger classification performance in females may be attributed to their narrower performance range and lower baseline force output, where even modest gains in absolute strength (Fmax and RFD_{max}) yield meaningful improvements in health status. Furthermore, males often present greater absolute muscle mass, which can obscure the relationship between raw strength values and actual health risk—commonly referred to as "muscle mass masking." In contrast, the female data appears to provide a clearer link between neuromuscular output and overall functional health.

Table 73 presents a practitioner-oriented evaluation sheet for Lebanese males and females, utilizing both absolute and relative handgrip-based predictive models to classify health risk and guide targeted intervention strategies.

Table 73: Lebanese Males & Females– Practitioner Model Evaluation Sheet

Male

Name: **Age:** **Region:**		
Models	**Cut-Off Value (Predicted Score)**	**Above / Under Cut-Off**
1- Absolute Model (F_{max}_SUM + RFD_{max}_SUM combined)	44.79	
2- Relative Model (F_{rel}_SUM + RFD_{rel}_SUM combined)	42.42	
Health Score	33.3	

Female

Name: **Age:** **Region:**		
Model	**Cut-Off Value (Predicted Score)**	**Above / Under Cut-Off**
1- Absolute Model (F_{max}_SUM + RFD_{max}_SUM combined)	40.81	
2- Relative Model (F_{rel}_SUM + RFD_{rel}_SUM combined)	40.93	
Health Score	30.05	

Table 73 provides a practical evaluation sheet for assessing health risk among Lebanese males and females using two models: one based on absolute handgrip and explosive strength (F_{max}_SUM + RFD_{max}_SUM), and one based on relative strength normalized to body weight (F_{rel}_SUM+RFD_{rel}_SUM).

If an individual scores below the absolute model cut-off, it indicates a need to improve maximal and explosive strength through resistance training (e.g., deadlifts, bench press, weighted pull-ups) and neuromuscular power exercises (e.g., medicine ball throws, plyometric push-ups).

If the relative model cut-off is not reached, the recommendation is to enhance strength relative to body mass by combining strength training with body composition management strategies, including exercises like bodyweight squats, push-ups, and explosive jumps, alongside aerobic

Conditioning to optimize muscle-to-weight ratio. This dual assessment allows quick identification of risk profiles and guides specific, targeted interventions to optimize health and functional performance.

9.6. Integration with Existing Literature and Conceptual Frameworks

The present study builds upon and extends a growing body of literature emphasizing the critical role of neuromuscular function—particularly explosive force—in predicting health status. The use of handgrip strength (F_{max}) and rate of force development (RFD_{max}) in our discriminant and predictive models reinforces their value as robust indicators of physical health, aligning with current frameworks of sarcopenia, dynapenia, and the newly proposed concept of powerpenia. Our analysis identified RFD_{max}_SUM as the most significant factor associated with health status in both Lebanese males and females, consistent with the argument by Freitas et al. (2024) that explosive force is more sensitive to neuromuscular decline and functional impairment than either strength or muscle mass alone.

This aligns with the concept of powerpenia, which refers to a disproportionate loss of muscle power relative to strength or size, now emerging as a stronger predictor of physical function, mobility limitation, and mortality risk (Freitas et al., 2024). In this context, our use of explosive handgrip force (RFD) as a central element in both the scientific and practitioner models represents a timely and evidence-based methodological innovation. Moreover, other studies, such as Fragala et al. (2023), have shown that individuals who perform poorly in rapid functional tests (e.g., sit-to-stand or walking speed tests) tend to have diminished explosive force and higher frailty risk-providing external support for the discriminant value of RFD-based indicators.

Importantly, our results align closely with previous Lebanese research. In the study by Andraos and El-Mdawar (2024), normative values for Fmax and RFD_{max} were established, showing that Lebanese adults demonstrate satisfactory absolute strength levels but relatively lower explosive strength compared to international norms-by approximately 13.4% in males and 22.8% in females. Our study builds on that work by not only validating these measurements but also embedding them into predictive health models with both scientific and practitioner applications.

Furthermore, our study complements earlier cluster-based typological research by Andraos et al. (2024), which segmented the Lebanese population based on anthropometric and body composition characteristics. That study highlighted the coexistence of high muscle and fat mass in many Lebanese males, complicating the interpretation of BMI or fat mass as independent health predictors. Our study expands on this by showing how functional markers like RFD_{max} and F_{max} can more precisely stratify health status, even in individuals with higher body mass, and further supports the need to shift from purely structural models to those incorporating neuromuscular function.

These findings are consistent with global literature advocating for the inclusion of muscle quality, neuromuscular coordination, and power output in the diagnosis of sarcopenia and functional decline (Reid & Fielding, 2012; Cruz-Jentoft et al., 2019). Moreover, Chaput et al. (2023) emphasized the substantial healthcare burden of reduced muscle strength in Canada, reinforcing the economic and public health rationale for implementing grip-based screening tools at a national level.

In terms of predictive accuracy, our study's scientific models-built on the four strongest discriminative factors-demonstrated excellent classification ability, with AUC values of 0.942 for males and 0.939 for females. These findings confirm that combining explosive, maximal, and functional strength variables yields a highly accurate, research-grade tool for health profiling. While the practitioner models were simplified for field use, they still exhibited very good discriminative power, with AUCs above 0.84 across both genders (e.g., 0.852 for male absolute model, 0.871 for female absolute model), validating their clinical and community-level applicability. This dual-model framework-sophisticated and simplified-offers flexibility for health professionals and researchers alike.

In summary, this study strengthens the evidence that explosive muscular function—particularly upper-body RFD_{max} - is a critical biomarker of health status. It confirms that neuromuscular performance can be used not only for descriptive evaluation but also for predictive modeling across diverse adult populations. The integration of these findings into gender-specific health frameworks, especially in a culturally specific population like Lebanon, represents a significant step toward precision health screening rooted in both function and form.

10. CONFIRMATION OF HYPOTHESES AND FINAL INTERPRETATION

The overarching hypothesis of this doctoral research was that predictive algorithms developed from handgrip strength parameters could accurately classify body composition and health risk among Lebanese adults with statistically significant reliability and validity, considering gender differences. Based on the results from discriminant analysis, regression modeling, and ROC curve evaluation, this general hypothesis is fully confirmed. The developed models demonstrated high classification performance, with AUC values reaching up to 0.968 in males and 0.992 in females for key predictors such as RFD_{max}_SUM, and all primary predictors were statistically significant ($p < 0.001$).

H1, which proposed that regression-based formulas using handgrip parameters would be effective for assessing strength, explosiveness, and power, **was confirmed**. The scientific models incorporated F_{max}, RFD_{max}, IS, and relative force variables, and yielded high predictive capacity ($R^2 > 0.72$) for health risk classification in both genders. These algorithms also distinguished individuals at risk with strong sensitivity and specificity, establishing their value for future assessment protocols.

H2, predicting gender-specific sensitivity differences among algorithms, was also supported and confirmed. The structure matrix revealed distinct sets of predictors for males and females. For instance, weekly training volume and relative strength (F_{rel}_SUM) were predictive only in females, whereas BMI and dominant hand Fmax appeared exclusively in males. Moreover, model structures and cut-off values varied significantly by sex, confirming the necessity of gender-specific approaches in algorithm development.

H3, suggesting that the most sensitive algorithm (based on correlation with body composition) would accurately assess health risk, was validated and confirmed. RFD_{max}_SUM, the top-ranking predictor

across both sexes, showed the highest correlation with health status ($p < 0.001$) and yielded the best ROC performance. This confirms its utility as a universal marker of neuromuscular health and body composition-related risk across the adult population.

H4, which hypothesized strong correlations between handgrip strength and body composition metrics, **was partially confirmed**. While significant associations were found between handgrip-derived variables (especially RFD and IS) and body composition indices like SMMI, FFM, and BMI, some fat-related parameters (e.g., PBF, FMI) showed weaker or non-significant differences across clusters. However, this limitation was addressed through the integration of functional performance markers in the models, increasing their discriminative power beyond static fat measures alone.

In conclusion, the central hypothesis and all four supporting hypotheses were either fully or partially confirmed. The study succeeded in producing scientifically valid, statistically robust, and practically applicable algorithms for health profiling in the Lebanese adult population. These models provide a strong foundation for clinical implementation, fitness screening, and national health monitoring, especially in contexts where comprehensive body composition assessments are impractical.

11. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

While this study offers novel insights into the use of handgrip strength and explosive force as predictors of body composition and health risk in Lebanese adults, several limitations must be acknowledged.

First, the intended sample size of 1000 participants was not reached. Due to the socio-political instability and prolonged closures caused by the war and economic crisis in Lebanon, participant recruitment and access to laboratory facilities were severely restricted. Testing facilities were intermittently closed, and community access was limited, which made it particularly challenging to collect data at the originally planned scale. The final sample of 395 individuals, while sufficient for robust statistical modeling, limits the fully generalizability of the findings to the broader national population.

Second, the study did not include biochemical markers or clinical health diagnostics such as blood glucose, lipid profiles, or inflammatory biomarkers. As such, diseases like type 2 diabetes, hyperlipidemia, and metabolic syndrome-which are tightly linked to body composition and functional status-were not directly measured. Including these clinical health markers would have enabled more precise validation of the predictive models in relation to cardiometabolic and chronic disease risk.

Third, while this study assessed muscle function and composition through handgrip strength and fat-free mass indices, it did not evaluate sarcopenia or other musculoskeletal conditions using standardized diagnostic criteria (e.g., muscle quality via ultrasound, physical performance via gait speed or sit-to-stand tests). As a result, the models are indirectly associated with sarcopenia and frailty but not formally validated against clinical diagnoses of these conditions.

Fourth, handgrip strength variables were normalized exclusively to body mass, but not to body height or body surface area. While relative strength per kilogram provides useful insight, height-normalized values—such as allometric scaling or grip strength-to-height ratios—could provide additional predictive precision and account for inter-individual variability in skeletal dimensions.

Fifth, the study was cross-sectional in nature. While it allowed for the identification of correlations and classification models, it did not assess causal relationships or the evolution of health status over time. Longitudinal studies would be essential to validate the predictive capacity of the proposed models for future health outcomes.

Finally, although the discriminant and ROC-based models demonstrated strong performance metrics, their external validity should be further tested across other Arab and Mediterranean populations, as well as in clinical subgroups with known comorbidities or varying levels of physical activity.

Future research should therefore aim to:

- Expand the sample size and geographic coverage to improve representativeness across all Lebanese regions and socioeconomic backgrounds.
- Integrate clinical biomarkers and disease screening protocols to establish stronger links with metabolic, cardiovascular, and musculoskeletal health.
- Include standardized assessments for sarcopenia, frailty, and fall risk (e.g., SARC-F questionnaire, gait speed, or chair stand test).
- Explore the added value of height- and surface area-normalized handgrip parameters.
- Validate the predictive models in prospective cohorts and in real-world clinical settings to assess utility in disease prevention and rehabilitation planning.

By addressing these limitations and advancing the research along these directions, future studies can further refine and validate the use of functional strength biomarkers in health screening and body composition profiling.

12. PRACTICAL IMPLICATIONS

The findings of this study offer several important practical applications for health professionals, sports scientists, and policymakers seeking cost-effective, field-applicable tools to assess health and body composition in adult populations.

First, the development of both scientific and practitioner-oriented predictive models enables a flexible approach to health risk screening. The scientific models, which integrate multiple discriminant variables (e.g., RFD_{max}_SUM, IS indices, BMI, and F_{rel}_SUM), provide a high-precision tool suitable for laboratory and research settings. Meanwhile, the simplified practitioner models—based on easily measured parameters like combined handgrip force and explosive strength—are highly practical for use in community health assessments, fitness centers, schools, and primary care environments. The ROC analyses confirmed that these models retain strong discriminatory power, making them efficient tools for identifying individuals at high or low health risk using only handgrip dynamometry.

Second, the implementation of individual health risk assessment sheets, developed in this study, allows practitioners to monitor specific weaknesses (e.g., low explosive strength, high BMI, low training volume) and deliver personalized interventions. These sheets can support decision-making in prescribing strength and conditioning programs, nutritional guidance, or medical referrals when necessary.

Third, this study reinforces the importance of explosive strength and neuromuscular coordination-particularly RFD measures-as critical markers of functional health. As such, resistance training protocols should place greater emphasis on improving rate of force development, not just maximal strength. This insight is especially valuable in rehabilitation, elderly care, and athletic preparation programs aiming to maintain independence, prevent sarcopenia, and enhance movement efficiency.

Fourth, the gender-specific nature of the models developed ensures that assessments and interventions can be better tailored. For example, weekly training volume and relative strength (F_{rel}_SUM) were especially critical for Lebanese women, while absolute strength and BMI were more relevant for Lebanese men. This finding supports the use of sex-specific guidelines in public health strategies and sports programming.

Lastly, the methodology proposed in this study-combining discriminant analysis, ROC curve validation, and normative reference cut-offs offers a reproducible framework that can be adapted and applied in other populations or contexts. It sets a precedent for designing population-specific health prediction tools grounded in functional assessments rather than relying solely on traditional anthropometry.

13. CONCLUSION

This doctoral research set out to explore the predictive capacity of various handgrip strength (F_{max}) and explosive force (RFD) variables in evaluating body composition status and health risk among Lebanese adults. Through comprehensive data collection, statistical analysis, and the development of gender-specific predictive models, the study achieved its primary objective: to demonstrate that handgrip-derived neuromuscular parameters serve as sensitive and practical indicators for health-related profiling in the Lebanese context.

Clustering analysis revealed distinct subgroups based on performance, morphological, and neuromuscular characteristics, validating the existence of health-relevant phenotypes within the population. The discriminant analysis identified RFD_{max}_SUM as the most powerful single predictor of health status in both sexes, confirming the central role of explosive strength as a neuromuscular marker of functional health. Notably, gender-specific differences emerged, with Lebanese females showing higher reliance on relative force production and weekly training volume, while males showed stronger associations with absolute strength and body composition parameters such as BMI.

Scientific models based on four key discriminative factors per sex achieved excellent diagnostic accuracy, with AUCs of 0.942 (males) and 0.939 (females), while simplified practitioner models also

demonstrated strong predictive capacity (AUC > 0.84). These results support the integration of handgrip assessments into routine health evaluations across clinical, athletic, and community settings.

In summary, this study provides original normative data for the Lebanese population, delivers validated predictive algorithms for health screening, and highlights the clinical and practical value of assessing explosive and maximal neuromuscular function through accessible tools like handgrip dynamometry. It marks a significant step forward in population-specific health profiling, offering both theoretical contributions to the fields of sarcopenia, powerpenia, and muscle performance, as well as practical tools for early detection and intervention planning.

14. REFERENCES

1. Abdurakhmonov, S. K. (2021). The Importance of a Healthy Lifestyle in Achieving Physical Perfection. The American Journal of Applied sciences, 3(3), 42-47.
2. Abe, T., & Loenneke, J. P. (2015). Handgrip strength dominance is associated with difference in forearm muscle size. *Journal of physical therapy science*, *27*(7), 2147-2149.
3. Alabadi, B., Civera, M., De la Rosa, A., Martinez-Hervas, S., Gomez-Cabrera, M. C., & Real, J. T. (2023). Low muscle mass is associated with poorer glycemic control and higher oxidative stress in older patients with type 2 diabetes. *Nutrients*, *15*(14), 3167.
4. Almécija, S., Smaers, J. B., & Jungers, W. L. (2015). The evolution of humans and ape hand proportions. *Nature Communications, 6*, 7717. https://doi.org/10.1038/ncomms8717
5. Andraos, Z., Dagher, M., Richa, C., Dopsaj, M (2024). Body Typology of Lebanese Adults: Initial Cluster Cross-Selection Study. International Journal of Morphology, 42(3), 561–566. https://doi.org/10.4067/S0717-95022024000601686.
6. Andraos, Z., & El-Mdawar, M. (2024). Normative data for handgrip strength in Lebanese population. SportLogia, 20(1), 47–57.
7. Augustsson, J., & Augustsson, S. R. (2022). Development of a novel Nordic hamstring exercise performance test device: a reliability and intervention study. *Sports*, *10*(2), 26.
8. Aydik, M. F., & Özener, B. E. (2023). An anthropological perspective on hand grip strength as a marker of health, disease and fitness. *Hitit Sosyal Bilimler Dergisi*, *16*(1), 95-113.
9. Bandyopadhyay, A. (2008). Body composition and hand grip strength in male brick-field workers. *The Malaysian journal of medical sciences: MJMS*, *15*(1), 31.
10. Ben Mansour, G., Kacem, A., Ishak, M., Grélot, L., & Ftaiti, F. (2021). The effect of body composition on strength and power in male and female students. *BMC Sports Science, Medicine and Rehabilitation*, *13*, 1-11.
11. Bikbov, M. M., Zainullin, R. M., Gilmanshin, T. R., Iakupova, E. M., Kazakbaeva,
12. G. M., Panda-Jonas, S., ... & Jonas, J. B. (2023). Hand grip strength and ocular associations: the Ural Eye and Medical Study. *British Journal of Ophthalmology*, *107*(10), 1567-1574.
13. Body Composition Testing. (2017, November 19). https://www.scienceforsport.com/body-composition-testing/
14. Butterfield, S A., Lehnhard, R A., Loovis, E M., Coladarci, T., & Saucier, D. (2009, October 1). Grip Strength Performances by 5- to 19-Year-Olds. SAGE Publishing, 109(2), 362-370. https://doi.org/10.2466/pms.109.2.362-370
15. Celis-Morales, C., Welsh, P., Lyall, D. M., Steell, L., Petermann, F., Anderson, J., Iliodromiti, S., Sillars, A., Graham, N., Mackay, D., Pell, J. P., Gill, J. M. R., Sattar, N., & Gray, S. R. (2018, May 8). Associations of grip strength with cardiovascular, respiratory, and cancer outcomes and all cause mortality: Prospective cohort study of half a million UK Biobank participants. *BMJ*, k1651-k1651. https://doi.org/10.1136/bmj.k1651
16. Clarsen, B., Rønsen, O., Myklebust, G., Flørenes, T. W., & Bahr, R. (2014). The Oslo Sports Trauma Research Center questionnaire on health problems: a new approach to prospective monitoring of illness and injury in elite athletes. *British journal of sports medicine*, *48*(9), 754-760.
17. Concha-Cisternas, Y., Petermann-Rocha, F., Castro-Piñero, J., Parra, S., Albala, C., Van De Wyngard, V., ... & Celis-Morales, C. (2022). Handgrip strength as a predictor of adverse health outcomes.

18. Concha-Cisternas, Yeny, Fanny Petermann-Rocha, José Castro-Piñero, Solage Parra, Cecilia Albala, Vanessa Van De Wyngard, Jaime Vásquez, Igor Cigarroa, and Carlos Celis-Morales. "Handgrip strength as a predictor of adverse health outcomes." (2022).
19. Cook, G., Burton, L., Hoogenboom, B. J., & Voight, M. (2014). Functional movement screening: the use of fundamental movements as an assessment of function-part 1. *International Journal of Sports Physical Therapy*, *9*(3), 396.
20. Das, S., Biswas, L., Mukherjee, T., Biswas, K., & Pal, S. K. (2022). Predictive ability of Framingham risk score in Indian population-A retrospective study in a tertiary care hospital in patients with first acute coronary syndrome. *Asian Journal of Medical Sciences*, *13*(8): 133-139.
21. De Villiers, B., Ali, A., & Wham, C. (2019). Physical Typologies of Older Adults Living in a Retirement Village. Gerontol & Geriatric Studies, 5(3), GGS.000611.2019. DOI: 10.31031/GGS.2019.05.000611
22. Dopsaj, M., Andraos, Z., Richa, C., Mitri, A., Makdissi, E., Zoghbi, A., ... & Fayyad, F. (2022). Maximal and explosive strength normative data for handgrip test according to gender: international standardization approach. *Human Movement*, *23*(4), 77-87.
23. Dopsaj, M., Kukić, F., Maksimović, M., Glavač, B., Radovanović, D., & ĐorđevićNikić, M. (2021). Age-Related Differences in Body Fatness and Nutritional Status in Large Sample of Serbian Women 20–70 Years of Age. *Obesities*, *1*(3), 157-166.
24. Dopsaj, M., Mijalkovski, Z., Vasilovski, N., Ćopić, N., Brzaković, M., & Marković, M. (2018). Morphological parameters and handgrip muscle force contractile characteristics in the first selection level in water polo: Differences between U15 water polo players and the control group. *Human. Sport Medicine, 18*(3), 5-15. https://doi.org/10.14529/hsm180301
25. Dopsaj, M., Nenasheva, A. V., Tretiakova, T. N., Syromiatnikova, Y. A., Surina-Marysheva, E. F., Marković, S., et al. (2019). Handgrip muscle force characteristics with general reference values at Chelyabinsk and Belgrade students. *Human Sport Medicine*, *19*(2), 27-36. https://doi.org/10.14529/hsm190204
26. Dopsaj, M., Nenasheva, A. V., Tretiakova, T. N., Syromiatnikova, Y. A., Surina-Marysheva, E. F., & Marković, S., et al. (2019). Hand grip muscle force characteristics with general reference values at Chelyabinsk and Belgrade students. *Human. Sport Medicine*, *19*(2), 27-36. https://doi.org/10.14529/hsm190204
27. Dopsaj, M., Popović, S., Bjelica, D., Mačak, D., & Radovanović, D. (2020). Agerelated changes in skeletal muscle mass among Serbian adults. *International Journal of Environmental Research and Public Health*, *17*(21), 5977. https://doi.org/10.3390/ijerph17215977
28. Dopsaj, M., Umek, T., & Kos, A. (2019). Relation between hand grip contractile characteristics and simple fast arm movement measured by IMU sensors. In N. Stojiljkovic (Ed.), *FIS Communications 2019 book of proceedings* (pp. 263-267). Niš: Faculty of Sport and Physical Education, University of Niš.
29. Dopsaj, M., Djordjević-Nikić, M., Khafizova, A., Eminović, F., Marković, S., Yanchik, E. & Dopsaj, V. (2020). Structural Body Composition profile and obesity prevalence at female students of the University of Belgrade measured by Multichannel Bioimpedance protocol. *Human. Sport. Medicine*., *20(2)*:53-62, 2020. DOI:10.14529/hsm200207
30. Dopsaj, M., Siljeg, K. & Milić, R. (2023). Reference values and sensitivity for different body fat variables measured by bioimpedance method in female athletes in individual sports: discriminative and comparative study. *Internatioanal Journal o Morphology*, *41(3)*:717-724.
31. Dos Santos, V. R., & Gobbo, L. A. (2020). Use of the handgrip strength test in the identification of osteosarcopenic obesity in older women: a prospective study. *Topics in Geriatric Rehabilitation*, *36*(4), 215-220.

32. Dumuid, D., Martín-Fernández, J. A., Ellul, S., Kenett, R. S., Wake, M., Simm, P., ... & Olds, T. (2021). Analysing body composition as compositional data: An exploration of the relationship between body composition, body mass and bone strength. *Statistical methods in medical research*, *30*(1), 331-346.
33. Eckman, M., Gigliotti, C., Sutermaster, S., & Mehta, K. (2014, October 1). Get a grip! Handgrip strength as a health screening tool. https://doi.org/10.1109/ghtc.2014.6970288
34. Euhus, D. M., Leitch, A. M., Huth, J. F., & Peters, G. N. (2002). Limitations of the Gail model in the specialized breast cancer risk assessment clinic. *The breast journal*, *8*(1), 23-27.
35. Ferreira, T. J., Pessanha, C. R., da Costa, G. G., Bittencourt, V. Z., Salvador, I. C., Assumpçao, A. C. R., ... & Pierucci, A. P. T. (2022). Agreement between Different Body Composition Methods and Dual-energy X-ray Absorptiometry In Adults: 2224. *Medicine & Science in Sports & Exercise*, *54*(9S), 648-649.
36. Fosbøl, M. Ø., & Zerahn, B. (2015). Contemporary methods of body composition measurement. *Clinical physiology and functional imaging*, *35*(2), 81-97.
37. Freitas, S. R., Cruz-Montecinos, C., Ratel, S., & Pinto, R. S. (2024). Powerpenia Should be Considered a Biomarker of Healthy Aging. *Sports MedicineOpen*, *10*(1), 27.
38. Gába, A., & Přidalová, M. (2014). Age-related changes in body composition in a sample of Czech women aged 18–89 years: A cross-sectional study. *European Journal of Nutrition*, 53(1), 167-176. https://doi.org/10.1007/s00394-013-0514-x
39. Gallus, S., Lugo, A., Murisic, B., Bosetti, C., Boffetta, P., & La Vecchia, C. (2015). Overweight and obesity in 16 European countries. *European journal of nutrition*, *54*, 679-689.
40. Golubeva, V. A., Uskova, S. M., & Prus, N. M. (2022). Physical education as a means of rorming a culture of health in students of higher education institutions. Scientific journal National Pedagogical Dragomanov University, 8(153):7-9, DOI 10.31392/NPU-nc.series15.2022.8(153).01
41. Gouvêa-e-Silva, L. F., Brito, E. R. D., Sol, N. C. C., Fernandes, E. V., & Xavier, M. B. (2023). Relationship of handgrip strength with health indicators of people living with HIV in west Pará, Brazil. *International journal of STD & AIDS*, *34*(13), 932-939.
42. Guo, G., Yang, W., Wang, S., Hui, Y., Cui, B., Wang, X., ... & Sun, C. (2023). Handgrip strength is a substitutive metric to the GLIM criteria–defined malnutrition and predicts long-term mortality among hospitalized patients with cirrhosis. *Nutrition in Clinical Practice*, *38*(5), 1021-1031.
43. Hadzibegovic, S., Porthun, J., Lena, A., Weinländer, P., Lück, L. C., Potthoff, S. K., ... & Anker, M. S. (2023). Hand grip strength in patients with advanced cancer: A prospective study. *Journal of Cachexia, Sarcopenia and Muscle*, *14*(4), 16821694.
44. Harris, K M. (2010, February 1). An integrative approach to health. Springer Science+Business Media, 47(1), 1-22. https://doi.org/10.1353/dem.0.0091
45. Hemke, R., Buckless, C., & Torriani, M. (2020, August). Quantitative imaging of body composition. In *Seminars in musculoskeletal radiology*, 24(4), 375-385. Thieme Medical Publishers.
46. Hsieh, C. M. (2019). Importance of health and relative importance of satisfaction with one's own health: A case of frail immigrant older adults. *Social Indicators Research*, *143*(1), 81-93.
47. Huerta Ojeda, A., Fontecilla Diaz, B., Yeomans Cabrera, M. M., & Jerez-Mayorga, D. (2021). Grip power test: A new valid and reliable method for assessing muscle power in healthy adolescents. Plos one, 16(10), e0258720.
48. Ibragimova, S. I., Nuskabayeva, G. O., Shalkharova, Z. N., Sadykova, K. Z., Junusbekova, G. A., & Oran, M. (2022). Assessment o the relationship between prediabetes and low muscle mass based on bloodcreatinine level. *Diabetes mellitus*, 25(3), 226-238, https://doi.org/10.14341/DM12745

49. Ito, S., Nakashima, H., Ando, K., Kobayashi, K., Machino, M., Seki, T., ... & Imagama, S. (2021). Association between low muscle mass and inflammatory cytokines. *BioMed Research International*, *2021*(1), 5572742.
50. Ji, C., Xia, Y., Tong, S., Wu, Q., & Zhao, Y. (2020, May 4). Association of handgrip strength with the prevalence of metabolic syndrome in US adults: The national health and nutrition examination survey. *Impact Journals LLC*, *12*(9), 7818-7829. https://doi.org/10.18632/aging.103097
51. Jiang, R., Westwater, M. L., Noble, S., Rosenblatt, M., Dai, W., Qi, S., ... & Scheinost, D. (2022). Associations between grip strength, brain structure, and mental health in> 40,000 participants from the UK Biobank. *BMC medicine*, *20*(1), 286.
52. Kang, M. K., & Park, J. G. (2021). Low skeletal muscle mass is a risk factor for subclinical atherosclerosis in patients with nonalcoholic fatty liver disease. *Diagnostics*, *11*(5), 854.
53. Kang, S. Q., Harith, S., Ong, Y. Q., & Mohd, B. N. (2021). Association between Hand Grip Strength and Health-Related Quality of Life among Malaysian MiddleAged Adults.
54. Kasović, M., Sagat, P., Kalčik, Z., Štefan, L., Hubinák, A., & Krška, P. (2023). Allometric normalization of handgrip strength in older adults: Which body size parameter is the most appropriate?. *BMC Sports Science, Medicine and Rehabilitation*, *15*(1), 18.
55. Knezevic, O. M., Mirkov, D. M., Kadija, M., Nedeljkovic, A., & Jaric, S. (2014). Asymmetries in explosive strength following anterior cruciate ligament reconstruction. *Knee*, *21*(6), 1039–1045. https://doi.org/10.1016/j.knee.2014.07.021
56. Kuriyan, R. (2018, January 1). Body composition techniques. Medknow, 148(5), 648-648. https://doi.org/10.4103/ijmr.ijmr_1777_18
57. Larson, J S. (1999, June 1). The Conceptualization of Health. SAGE Publishing, 56(2), 123-136. https://doi.org/10.1177/107755879905600201
58. Larsson, I., Lissner, L., Samuelson, G., Fors, H., Lantz, H., Näslund, I., Carlsson, L. M. S., Sjöström, L., & Bosaeus, I. (2015). Body composition through adult life: Swedish reference data on body composition. *European Journal of Clinical Nutrition*, *69*(8), 837-842. https://doi.org/10.1038/ejcn.2014.268
59. Li, G., Lu, Y., Shao, L., Wu, L., Qiao, Y., Ding, Y., & Ke, C. (2023). Handgrip strength is associated with risks of new-onset stroke and heart disease: results from 3 prospective cohorts. *BMC geriatrics*, *23*(1), 268.
60. Liao, K. H. (2016). Hand grip strength in low, medium, and high body mass index males and females. *Middle East Journal of Rehabilitation and Health*, *3*(1), e33860.
61. Lim, S. (2022). Utility of bioelectrical impedance analysis for body composition assessment. *The Journal of Korean Diabetes*, *23*(2), 106-112.
62. Lissner, L., Sjöberg, A., Schütze, M., Lapidus, L., Hulthén, L., & Björkelund, C. (2008). Diet, obesity and obesogenic trends in two generations of Swedish women. *European Journal of Nutrition*, *47*, 424-431.
63. Liu, W. C., Chiu, L. S., & Lim, P. S. (2022). Handgrip strength as a predictor of mobility in patients with end-stage renal disease on hemodialysis. *Tungs' Medical Journal*, *16*(2), 54-60.
64. Long, J. A., & Nelson, T. A. (2013). A review of quantitative methods for movement data. *International Journal of Geographical Information Science*, *27*(2), 292-318.
65. Looijaard, S. M., te Lintel Hekkert, M. L., Wüst, R. C., Otten, R. H., Meskers, C. G., & Maier, A. B. (2021). Pathophysiological mechanisms explaining poor clinical outcome of older cancer patients with low skeletal muscle mass. *Acta Physiologica*, *231*(1), e13516.
66. Luo, K., Huang, B., Ma, Y., Chen, W., Lai, Z., & Li, J. (2019, November). A Web Service and Embedded System Based hand dynamometer for Grip strength Assessment. In 2019 Chinese Automation Congress (CAC) (pp. 4062-4066). IEEE.

67. Mala, L., Maly, T., Zahalka, F., & Hrasky, P. (2015). Body composition of elite youth soccer players with respect to field position. *Journal of Physical Education and Sport*, *15*(4), 678.
68. Malina, R. M., Bouchard, C., & Bar-Or, O. (2004). *Growth, maturation, and physical activity* (2nd ed.). Champaign, IL: Human Kinetics.
69. Malone, J. J., Lovell, R., Varley, M. C., & Coutts, A. J. (2017). Unpacking the black box: applications and considerations for using GPS devices in sport. *International journal of sports physiology and performance*, *12*(s2), S2-18.
70. Marković, M. R., Dopsaj, M., Koropanovski, N., Ćopić, N., & Trajkov, M. (2018). Reliability of measuring various contractile functions of finger flexors of men of various ages. *Physical Culture*, *72*(1), 37-48. https://doi.org/10.5937/fizkul1801037
71. Marković, S., Dopsaj, M., & Veljković, V. (2020). Reliability of Sports Medical Solutions handgrip and Jamar handgrip dynamometer. *Measurement Science Review*, *20*(2), 59-64. https://doi.org/10.2478/msr-2020-0008
72. Marković, S., Dopsaj, M., & Veljković, V. (2020). Reliability of Sports Medical Solutions handgrip and Jamar handgrip dynamometer. *Measurement Science Review*, *20*(2), 59-64. https://doi.org/10.2478/msr-2020-0008
73. Martarelli, D., Martarelli, B., & Pompei, P. (2008). Body composition obtained from the body mass index: An Italian study. *European Journal of Nutrition*, *47*(8), 409-416. https://doi.org/10.1007/s00394-008-0742-7
74. Mazić, S., Lazović, B., Djelić, M., Suzic-Lazić, J., Acimovic, T., & Brkić, P. (2014). Body composition assessment in athletes: A systematic review. Serbian Medical Society, 67(7-8), 255-260. https://doi.org/10.2298/mpns1408255m
75. McClintock, M K., Dale, W., Laumann, E O., & Waite, L J. (2016). Empirical redefinition of comprehensive health and well-being in the older adults of the United States. National Academy of Sciences, 113(22). https://doi.org/10.1073/pnas.1514968113
76. McGrath, R., Hackney, K. J., Ratamess, N. A., Vincent, B. M., Clark, B. C., & Kraemer, W. J. (2020). Absolute and body mass index normalized handgrip strength percentiles by gender, ethnicity, and hand dominance in Americans. *Advances in Geriatric Medicine and Research*, *2*(1), e200005. doi: 10.20900/agmr20200005
77. McMillan, I. R., & Carin-Levy, G. (2012). *Tyldesley & Grieve's muscles, nerves and movement in human occupation* (4th ed.). Oxford: Wiley-Blackwell.
78. Molenaar, H., Selles, R W., Zuidam, M., Willemsen, S P., Stam, H J., & Hovius, S E. (2010). Growth Diagrams for Grip Strength in Children. *Clinical Orthopaedics and Related Research*, 468(1), 217-223. https://doi.org/10.1007/s11999-009-0881-z
79. Moller, T., & Kettley, S. (2017). Wearable health technology design: A humanist accessory approach. *International Journal of Design*, *11*(3), 1-49.
80. Montalcini, T., Ferro, Y., Salvati, M A., Romeo, S., Miniero, R., & Pujia, A. (2016, February 19). Gender difference in handgrip strength of Italian children aged 9 to 10 years. BioMed Central, 42(1). https://doi.org/10.1186/s13052-016-0226-y
81. Nair, R., Holla, S., & Rajadhyaksha, S. (2017). Effect of Neural Tissue Mobilization on Grip Strength in Patients with Cervical Radiculopathy. *Journal of Society of Indian Physiotherapists*, *1*(2), 47-52.
82. Neidenbach, R. C., Oberhoffer, R., Pieper, L., Freilinger, S., Ewert, P., Kaemmerer, H., et al. (2019). The value of handgrip strength (HGS) as a diagnostic and prognostic biomarker in congenital heart disease. Cardiovascular Diagnosis and Therapy, 9(Suppl. 2), 187-197. https://doi.org/10.21037/cdt.2019.09.16
83. Newman, D G., Pearn, J., Barnes, A., Young, C., Kehoe, M., & Newman, J. (1984). Norms for hand grip strength. BMJ, 59 (5), 453-459. https://doi.org/10.1136/adc.59.5.453

84. Oh, C. H., Kim, J., Kim, J., Yoon, S., Jung, Y., Lee, H. I., ... & Han, S. H. (2022). The association of low skeletal muscle mass with complex distal radius fracture. *Journal of Clinical Medicine*, *11*(19), 5581.
85. Orr, R., Pope, R., Stierli, M., & Hinton, B. (2017). Grip strength and its relationship to police recruit task performance and injury risk: A retrospective cohort study. *International Journal of Environmental Research and Public Health, 14*(8), 941. https://doi.org/10.3390/ijerph14080941
86. Oudbier, S. J., Goh, J., Looijaard, S. M. L. M., Reijnierse, E. M., Meskers, C. G. M., & Maier, A. B. (2022). Pathophysiological mechanisms explaining the association between low skeletal muscle mass and cognitive function. *The Journals of Gerontology: Series A*, *77*(10), 1959-1968.
87. Pan, X. Y., Liu, W. Y., Zhu, P. W., Li, G., Tang, L. J., Gao, F., ... & Zheng, M. H. (2022). Low skeletal muscle mass may contribute to the progression of nonalcoholic fatty liver disease in men. *Hepatology International*, 16(5): 1085-1093. doi: 10.1007/s12072-022-10384-x.
88. Perna, F. M., Coa, K., Troiano, R. P., Lawman, H. G., Wang, C.-Y., Li, Y., et al. (2016). Muscular grip strength estimates of the U.S. population from the National Health and Nutrition Examination Survey 2011–2012. *Journal of Strength and Conditioning Research, 30*(3), 867-874. https://doi.org/10.1519/JSC.0000000000001104
89. Ploegmakers, J J., Hepping, A M., Geertzen, J H., Bulstra, S K., & Stevens, M. (2013). Grip strength is strongly associated with height, weight and gender in childhood: a cross sectional study of 2241 children and adolescents providing reference values. *Journal of Physiotherapy*, 59(4): 255-61. doi: 10.1016/S1836-9553(13)70202-9.
90. Rakic, S., Kukić, F., Cherepov, E.A., Dopsaj, M., Schelgacheva, K. B. & Cuk I. (2022). The effect of frequency and volume of leisure-time physical activity on body fatness of employed females. *Human. Sport. Medicine*., *22(2)*:75-83, DOI:10.14529/hsm220209
91. Ramos-Sepúlveda, J. A., Ramírez-Vélez, R., Correa-Bautista, J. E., Izquierdo, M., & García-Hermoso, A. (2016). Physical fitness and anthropometric normative values amongColombian-Indian schoolchildren. *BMC Public Health, 16*(1), 962. https://doi.org/10.1186/s12889-016-3620-8
92. Rijk, J. M., Roos, P. R. K. M., Deckx, L., Akker, M. V. D., & Buntinx, F. (2016). Prognostic value of handgrip strength in people aged 60 years and older: A systematic review and meta-analysis. *Geriatrics & Gerontology International, 16*(1), 5-20. https://doi.org/10.1111/ggi.12508
93. Riva, S. & Pravettoni, G. (2016). Value-Based Model: A New Perspective in Medical Decision-making. *Frontiers Media*, 4. https://doi.org/10.3389/fpubh.2016.00118
94. Saadeddine, D., Itani, L., Rossi, A. P., Pellegrini, M., & El Ghoch, M. (2021). Strength and performance tests for screening reduced muscle mass in elderly Lebanese males with obesity in community dwellings. *Diseases*, *9*(1), 23.
95. Sakibaev, K., Nikityuk, D., Tashmatova, N., Nuruev, M., Dzhumaeva, L., Muratov, Z., ... & Kozuev, K. (2020). Groups of the Body Constitution and Age-Related Anthropometric Parameters in Kyrgyz Women. *Forensic Medicine and Anatomy Research*, *8*(4), 65.
96. Santos, S., & Paúl, C. (2022, June 17). Handgrip strength and the perceived risk of institutionalization, hospitalization, and death. *Journal of Family Medicine, 9*(4).
97. Savas, S., Kilavuz, A., Kayhan Koçak, F. Ö., & Cavdar, S. (2023). Comparison of grip strength measurements by widely used three dynamometers in outpatients aged 60 years and over. *Journal of Clinical Medicine, 12*(13), 4260.
98. Sayer, A. A., & Kirkwood, T. B. L. (2015). Grip strength and mortality: A biomarker of ageing? The Lancet, 386(9990), 226-227. https://doi.org/10.1016/S0140-6736(14)62349-7
99. Shah, A. H., & Bilal, R. (2009). Body composition, its significance and models for assessment. *Pakistan Journal of Nutrition*, *8*(2), 198-202.

100. Sihto, M., Ollila, E., & Koivusalo, M. (2006). Principles and challenges of Health in All Policies. *Health in All Policies*, *1*.
101. Taeymans, J., Clarys, P., Abidi, H., Hebbelinck, M., & Duquet, W. (2009). Developmental changes and predictability of static strength in individuals of different maturity: A 30-year longitudinal study. *Journal of Sports Sciences*, 27(8), 833-841. https://doi.org/10.1080/02640410902874711
102. Tinkle, W F., & Montoye, H J. (1961). Relationship between Grip Strength and Achievement in Physical Education among College Men. Taylor & Francis, 32(2), 238-243. https://doi.org/10.1080/10671188.1961.10613139
103. Trajkov, M., Cuk, I., Eminovic, F., Kljajic, D., & Dopsaj, M. (2018). Relationship between hand grip strength and endurance and postural stability in active and sedentary older women. *Journal of Electromyography and Kinesiology*, *43*, 62-67. https://doi.org/10.1016/j.jelekin.2018.09.006
104. Vesić, Z., Brkić, M., Tanasijević, J., Milanović, M., & Vesić, M. V. (2022). Influence of the health status and other relevant factors on the quality of life of elderly people. *Vojnosanitetski pregled*, *79*(7), 708 – 713.
105. Wells, J C K. (2005, June 14). Measuring body composition. *BMJ*, 91(7), 612-617. https://doi.org/10.1136/adc.2005.085522
106. Wen, Z., Gu, J., Chen, R., Wang, Q., Ding, N., Meng, L., ... & Zheng, H. (2023). Handgrip strength and muscle quality: results from the national health and nutrition examination survey database. *Journal of Clinical Medicine*, *12*(9), 3184.
107. White, R. (2024). *Acute Workload Ratio*. Science for Sport. Retrieved from https://www.scienceforsport.com/acutechronic-workload-ratio/
108. Wu, D., Wang, H., Wang, W., Qing, C., Zhang, W., Gao, X., ... & Zheng, Z. (2023). Association between composite dietary antioxidant index and handgrip strength in American adults: Data from National Health and Nutrition Examination Survey (NHANES, 2011-2014). *Frontiers in Nutrition*, *10*, 1147869.
109. Zarić, I., Dopsaj, M., & Marković, M. (2018). Match performance in young female basketball players: Relationship with laboratory and field tests. *International Journal of Performance Analysis in Sport, 18(1), 90-103.* https://doi.org/10.1080/24748668.2018.1452109
110. Zborowski, M., & Mikulec, A. (2022). Comparison between Dual-X-ray Absorptiometry and Bioelectrical Impedance Analyses in dietary practice. *Journal of Education, Health and Sport*, *12*(9), 128-136.
111. Zhu, S., & Wang, Z. (2011). Body composition: clinical implications and biological diversities. *International Journal of Obesity*, *35*(S2), S1-S1.
112. Andraos, Z., Dagher, M., Richa, C., & Dopsaj, M. (2024). Body typology of Lebanese adults: Initial cluster cross-selection study. *International Journal of Morphology*, 42(3), 561–566. https://doi.org/10.4067/S0717-95022024000300561
113. Kuk, J. L., Katzmarzyk, P. T., Nichaman, M. Z., Church, T. S., Blair, S. N., & Ross, R. (2006). Visceral fat is an independent predictor of all-cause mortality in men. *Obesity*, 14(2), 336–341. https://doi.org/10.1038/oby.2006.43
114. Koster, A., Ding, J., Stenholm, S., Caserotti, P., Houston, D. K., Nicklas, B. J., ... & Kritchevsky, S. B. (2016). Does the amount or distribution of fat mass predict age-related loss of lean mass, muscle strength, and muscle quality in older adults? *The Journals of Gerontology: Series A*, 71(8), 1039–1044. https://doi.org/10.1093/gerona/glv207
115. Aagaard, P., Simonsen, E. B., Andersen, J. L., Magnusson, P., & Dyhre-Poulsen, P. (2002). Increased rate of force development and neural drive of human skeletal muscle following

resistance training. *Journal of Applied Physiology*, 93(4), 1318–1326. https://doi.org/10.1152/japplphysiol.00283.2002
116. Maffiuletti, N. A., Aagaard, P., Blazevich, A. J., Folland, J., Tillin, N., & Duchateau, J. (2016). Rate of force development: Physiological and methodological considerations. *European Journal of Applied Physiology*, 116(6), 1091–1116. https://doi.org/10.1007/s00421-016-3346-6
117. Andersen, L. L., & Aagaard, P. (2006). Influence of maximal muscle strength and intrinsic muscle contractile properties on contractile rate of force development. *European Journal of Applied Physiology*, 96(1), 46–52. https://doi.org/10.1007/s00421-005-0070-z
118. Degens, H., & Korhonen, M. T. (2012). Factors contributing to the variability in muscle ageing. *Maturitas*, 73(3), 197–201. https://doi.org/10.1016/j.maturitas.2012.08.004
119. Kim, T. N., Park, M. S., Lim, K. I., Yang, S. J., Yoo, H. J., Kang, H. J., ... & Choi, K. M. (2014). Skeletal muscle mass to visceral fat area ratio is an important determinant associated with type 2 diabetes and metabolic syndrome. *Diabetes Care*, 36(11), 3070–3076. https://doi.org/10.2337/dc13-2537
120. Richa, C., Andraos, Z. G., El-Mdawar, M., & Dopsaj, M. M. (2024). Sensitivity between BMI and IBC as screening tools for overall health and nutritional status: Insights from hand grip strength analysis among Lebanese adults. *International Journal of Morphology, 42*(6), 1686–1693. https://doi.org/10.4067/S0717-95022024000601686
121. Cruz-Jentoft, A. J., Bahat, G., Bauer, J., Boirie, Y., Bruyère, O., Cederholm, T., ... & Cooper, C. (2019). Sarcopenia: Revised European consensus on definition and diagnosis. *Age and Ageing, 48*(1), 16–31. https://doi.org/10.1093/ageing/afy169
122. Warburton, D. E., & Bredin, S. S. (2017). Health benefits of physical activity: A systematic review of current systematic reviews. *Current Opinion in Cardiology, 32*(5), 541–556. https://doi.org/10.1097/HCO.0000000000000437
123. Balachandran, A., Krawczyk, S. N., Potiaumpai, M., & Signorile, J. F. (2014). Comparison of functional outcomes using two different resistance training frequencies in older adults. *Aging Clinical and Experimental Research, 26*(3), 243–248. https://doi.org/10.1007/s40520-013-0167-7
124. Cruz-Jentoft, A. J., Bahat, G., Bauer, J., Boirie, Y., Bruyère, O., Cederholm, T., ... & Cooper, C. (2019). Sarcopenia: Revised European consensus on definition and diagnosis. *Age and Ageing, 48*(1), 16–31. https://doi.org/10.1093/ageing/afy169
125. Freitas, T. T., Cruz-Montecinos, C., Ratel, S., & Pinto, R. S. (2024). Powerpenia should be considered a biomarker of healthy aging. *Sports Medicine - Open*, 10(27), 1–7. https://doi.org/10.1186/s40798-024-00689-6
126. Fragala, M. S., et al. (2023). Chair stand performance and muscle power: Associations with frailty and health risk. *Journal of Gerontology: Medical Sciences*, 78(6), 1010–1019. https://pubmed.ncbi.nlm.nih.gov/40094468/
127. Reid, K. F., & Fielding, R. A. (2012). Skeletal muscle power: a critical determinant of physical functioning in older adults. *Exercise and Sport Sciences Reviews*, 40(1), 4–12. https://doi.org/10.1097/JES.0b013e31823b5f13
128. Cruz-Jentoft, A. J., et al. (2019). Sarcopenia: Revised European consensus on definition and diagnosis. *Age and Ageing*, 48(1), 16–31. https://doi.org/10.1093/ageing/afy169
129. Chaput, J.-P., et al. (2023). The economic burden of low muscle strength in Canadian adults. *Applied Physiology, Nutrition, and Metabolism*, 48(5), 634–638. https://doi.org/10.1139/apnm-2022-0474

APPENDICES

5.1 Questionnaires

Personal Information Name:

1. Origin:
    - Are you of Lebanese origin?
        - Yes
        - No
2. Gender:
    - What is your gender?
        - Male ✦ Female

3. Age: ○ What is your age? ___ years

4. Profession: ○ What is your current profession? _____

5. Social Status:
    - What is your social status?
        - Single
        - Married
        - Divorced
        - Widowed
6. Geographic Position in Lebanon:
    - In which region of Lebanon do you reside?
        - Beirut
        - Mount Lebanon
        - North Lebanon
        - South Lebanon
        - Bekaa

- Nabatieh Physical Activity

7. Number of Exercise Sessions per Week:
    - How many exercise sessions do you have per week? ___ sessions
8. Minutes per Session:
    - How many minutes do you spend on each exercise session? ___ minutes
9. Type of Physical Activity:
    - What type of physical activity do you engage in? (Check all that apply)
        - Gym
        - Team sports
        - Track and field
        - Swimming
        - Combat sport
        - Yoga & meditation
        - Aerobic

Obrazac 5. Образац изјаве о ауторству

Изјава о ауторству

Име и презиме аутора: Zahi G. Andraos

Број индекса: _____

Изјављујем

да је докторска дисертација под насловом

Sensitivity of different hand grip algorithms in classification of body composition status related to health among Lebanese adults (Сензитивност различитих алгоритама за снагу стиска руке у класификацији статуса телесне композиције у односу на здравље код одраслих Либанаца)

• резултат сопственог истраживачког рада;

• да дисертација у целини ни у деловима није била предложена за стицање друге дипломе према студијским програмима других високошколских установа;

• да су резултати коректно наведени и

• да нисам кршио/ла ауторска права и користио/ла интелектуалну својину других лица.

Потпис аутора

У Београду, ___28/5/2025_____

_

Obrazac 6. Образац изјаве о истоветности штампане и електронске верзије докторског рада

Изјава о истоветности штампане и електронске верзије докторског рада

Име и презиме аутора: Zahi G. Andraos

Број индекса _____

Студијски програм: Experimental research methods of human locomotion

Наслов рада: Sensitivity of different hand grip algorithms in classification of body composition status related to health among Lebanese adults (Сензитивност различитих алгоритама за снагу стиска руке у класификацији статуса телесне композиције у односу на здравље код одраслих Либанаца)

Ментор: Dr Milivoj Dopsaj, Full professor, Faculty of Sport and Physical Education, University of Belgrade

Изјављујем да је штампана верзија мог докторског рада истоветна електронској верзији коју сам предао/ла ради похрањивања у Дигиталном репозиторијуму Универзитета у Београду.

Дозвољавам да се објаве моји лични подаци везани за добијање академског назива доктора наука, као што су име и презиме, година и место рођења и датум одбране рада.

Ови лични подаци могу се објавити на мрежним страницама дигиталне библиотеке, у електронском каталогу и у публикацијама Универзитета у Београду.

Потпис аутора

У Београду, ____28/5/2025_____

Obrazac 7. Образац изјаве о коришћењу

Изјава о коришћењу

Овлашћујем Универзитетску библиотеку „Светозар Марковић“ да у Дигитални репозиторијум Универзитета у Београду унесе моју докторску дисертацију под насловом:

Sensitivity of different hand grip algorithms in classification of body composition status related to health among Lebanese adults (Сензитивност различитих алгоритама за снагу стиска руке у класификацији статуса телесне композиције у односу на здравље код одраслих Либанаца)

која је моје ауторско дело.

Дисертацију са свим прилозима предао/ла сам у електронском формату погодном за трајно архивирање.

Моју докторску дисертацију похрањену у Дигиталном репозиторијуму Универзитета у Београду и доступну у отвореном приступу могу да користе сви који поштују одредбе садржане у одабраном типу лиценце Креативне заједнице (Creative Commons) за коју сам се одлучио/ла.

1. Ауторство (CC BY)

2. Ауторство – некомерцијално (CC BY-NC)

3. Ауторство – некомерцијално – без прерада (CC BY-NC-ND)

4. Ауторство – некомерцијално – делити под истим условима (CC BY-NC-SA)

5. Ауторство – без прерада (CC BY-ND)

6. Ауторство – делити под истим условима (CC BY-SA)

(Молимо да заокружите само једну од шест понуђених лиценци.

Кратак опис лиценци је саставни део ове изјаве).

Потпис аутора

У Београду, ___28/5/2025_____

Published paper

Int. J. Morphol.,
42(3):561-566, 2024.

Body Typology of Lebanese Adults: Initial Cluster Cross-Selection Study

Tipología Corporal de Adultos Libaneses: Estudio Inicial de Selección Cruzada de Grupos

Zahi Andraos[1,2]; Myriam Dagher[2]; Charbel Richa[1] & Milivoj Dopsaj[1]

ANDRAOS, Z.; DAGHER, M.; RICHA, C. & DOPSAJ, M. Body typology of Lebanese adults: Initial cluster cross-selection study. *Int. J. Morphol., 42(3)*:561-566, 2024.

SUMMARY: This study aims to investigate body typologies based on a combination of basic anthropo-morphological characteristics and body composition measured by multichannel bioimpedance in a sample from the adult population of Lebanon. A total of 302 subjects (173 males and 129 females) without acute or chronic health disorders were included in the study. Body composition was measured by the multichannel bioelectrical impedance (BIA) method, using the i30 device (MEDIANA, Korea). The research used 10 variables, including three basic anthropo-morphological variables, three for assessing fat, three for assessing the muscle component, and one index variable. K-means cluster analysis was used to define five specific clusters (5D) of body types based on sex. In light of the results, the study established five distinct clusters representing five different body typologies among Lebanese adults, categorized by sex: Male sample, Group 1 – Obese Endomorph (15.61 %), Group 2 – Balanced Mesomorph (16.76 %), Group 3 – Short Endomorph (30.06 %), Group 4 – Short Mesomorph (34.10 %), and Group 5 – Pathological Obese Endomorph (3.47 %); Female sample, Group 1– Obese Endomorph (2.33 %), Group 2 – Short Endo/Mesomorph (28.68 %), Group 3 – Short Ectomorph (32.56 %), Group 4 – Endomorph (22.48 %), and Group 5 – Balanced Mesomorph (13.95 %). Furthermore, the results indicated that the primary factor contributing to the distinctions among the identified clusters in terms of sex is fat tissue. This leads to the conclusion that eating habits cause the given differences, rather than the level of physical activity, regardless of sex.

KEY WORDS: Body composition; Adults; Muscle mass; Body fat; BIA.

INTRODUCTION

Suboptimal nutrition and an inactive lifestyle constitute significant preventable risk factors for numerous non-communicable diseases, such as obesity, being overweight, cardiovascular diseases, and type 2 diabetes mellitus (Ammar *et al*., 2023). Globally, an estimated 11 million deaths have been linked to dietary risk factors, with the disease burden further exacerbated by low physical activity levels across countries (GBD 2017 Diet Collaborators, 2019; Mansour *et al*., 2020). These factors are strongly associated with the development and urbanization of nations. Lebanon, a small middle-income country in the MENA region (Middle East and North Africa), has recently witnessed a concerning escalation in the burden of diseases (Naja *et al*., 2019). Remarkably, 91 % of all deaths in Lebanon are attributed to non-communicable diseases, reflecting a population that fails to meet recommended guidelines for dietary intake and physical activity (OECD, 2016).

Lebanon has been undergoing a marked nutrition transition characterized by a shift in dietary intake and food consumption behaviors towards more highly processed, 'westernized' dietary patterns along with increased sedentary behaviors (Mehio Sibai *et al*., 2011), which is placing the Lebanese population at risk of widespread metabolic and health consequences that threaten their health on the short and long-run (Nasreddine *et al*., 2014).

As urbanization and the nutrition transition unfold, there is a burgeoning interest among researchers to explore the physical characteristics of the Lebanese population.

This study aims to investigate body typologies based on a combination of basic anthropo-morphological characteristics and body composition measured by multichannel bioimpedance. The sample comprises Lebanese adults from different age groups residing in all regions of

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Biography

My name is Zahi G. Andraos, and I currently serve as the Dean Delegate for the Faculty of Sport Sciences at Antonine University in Baabda, Lebanon. I have been teaching at the university level since 2016, covering a wide range of topics including introduction to physical training, training methods, principles and effects of training, volleyball, sports management, event planning, and project management. I also accompany and supervise Master's students throughout their thesis work.

My academic journey began with a Master's degree in Sport Sciences from the Lebanese University, followed by a joint program with the University of Grenoble in France. I later pursued a Doctorate in Business Administration (DBA) in Sports Management at the British Institute and completed a second Master's degree in Banking and Finance at La Sagesse University, located in Furn El Chebbak, Lebanon. I am currently finalizing my PhD in Sport Sciences at the University of Belgrade, Faculty of Sport and Physical Education, where my research focuses on the sensitivity of various hand grip strength algorithms in the classification of body composition status related to health among Lebanese adults.

In addition to my academic responsibilities, I have published several articles related to sports and health and organized numerous roundtable discussions on various sports-related topics at Antonine University. My professional experience also includes many years of work as a Physical Education teacher in schools, teaching students from grade 3 through college level.

Before transitioning fully into academia, I was an active volleyball player, competing in both Division 1 and Division 2 in Lebanon. I have also coached volleyball at different levels, from beginners to advanced players. To further specialize in athletic training, I obtained a Diploma in Physical Preparation from both Antonine University and Claude Bernard Lyon 1 University in France.

Through my academic work, teaching, and practical involvement in sport, I aim to contribute meaningfully to the fields of sport sciences, health promotion, and performance development.

Personal bibliography

Published Articles:

1. **Andraos, Z. G.**, Dagher, M., Richa, C., & Dopsaj, M. (2024). Body typology of Lebanese adults: Initial cluster cross-selection study. *International Journal of Morphology*, 42(3), 561–566.
2. **Richa, C.**, **Andraos, Z. G.**, El Mdawar, M., Khoury, G., & Dopsaj, M. (2024). Sensitivity between BMI and IBC as screening tools for overall health and nutritional status: Insights from hand grip strength analysis among Lebanese adults. *International Journal of Morphology*, 42(6), 1686–1693.
3. **Andraos, Z. G.**, & Abi Abdallah, M. (2024). Development of a fitness index score: A normative framework for assessing health-related fitness in Lebanese adolescents. *MOJ Biology and Medicine*, 9(4), 117–123.
4. **Andraos, Z. G.**, & El Mdawar, M. (2024). Initial study on normative data for hand grip strength and explosive strength in Lebanese population. *Sportlogia*, 20(2), 47–55.
5. **Dopsaj, M.**, **Andraos, Z. G.**, Richa, C., Abou Mitri, A., Makdissi, E., El Zoghbi, A., Dandachi, R., Erlikh, V. V., Cherepov, E. A., Masiulis, N., Nenasheva, A. V., Zuoziene, I. J., Marković, S., & Fayyad, F. (2022). Maximal and explosive strength normative data for handgrip test according to gender: International standardization approach. *Human Movement*, 23(4), 77–87.