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**A LATENT CLASS ANALYSIS PREDICTIVE MODELING APPROACH
TO PROFILE DIVISION I COLLEGIATE ATHLETES FOR NUTRITION
AND RELATIVE ENERGY DEFICIENCY IN SPORT (RED-S)
CONCERN**

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A LATENT CLASS ANALYSIS PREDICTIVE MODELING APPROACH TO PROFILE
DIVISION I COLLEGIATE ATHLETES FOR NUTRITION AND RELATIVE ENERGY
DEFICIENCY IN SPORT (RED-S) CONCERN

A Dissertation

presented in partial fulfillment of requirements

for the degree of Doctor of Philosophy

in the Department of Nutrition and Hospitality Management

The University of Mississippi

MORGAN L. DELVENTHAL

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ABSTRACT

Screening collegiate athletes for nutrition-related concerns and low energy syndromes such as Relative Energy Deficiency in Sport (RED-S) provides insight for nutrition care and can lead to necessary referrals in the sports medicine team. Screening may be a part of an athletic department's protocol, but there is a lack of consensus on a validated tool for this population. The goal of this cross-sectional research was to use a Latent Class Analysis (LCA) predictive modeling approach to determine classes of collegiate athletes who present with nutrition and RED-S concern. LCA is a person-centered approach, intending to uncover subgroups of a population with common characteristics. A total of 216 athletes (144 female, 72 male) at a Division I university competing in various team sports completed a pre-participation nutrition screening survey prior to participation in athletic sports. Measures such as menstrual function, bone health, disordered eating, restrictive diets, food insecurity, body image, and nutrition knowledge were collected. For female athletes, the LCA model provided some clinical relevance that female athletes can be profiled into a two-class solution, providing practitioners and sports dietitians insight into profiling athletes who may be at risk for low energy syndromes. For male athletes, there was not enough evidence that a two-class solution was superior to a one-class solution, highlighting the need for high-quality low energy syndrome tools to be developed in the male collegiate athlete population. Future research should consider large sample sizes of athletes to conduct predictive modeling techniques along with high quality, validated measurement tools.

DEDICATION

To my dad, thank you for giving me the greatest gift I could ask for- believing in me. For teaching me to work hard, to lead with kindness, to cherish what I have, and to choose faith over fear. Your life was a testament to true success. You are forever in my heart. I love you.

“I think of my father’s passing and I think of how narrowly we define success. The culture sets the bar unnaturally, imagining success is linear, objective, externalized terms. You are a success if you make a fortune, or become famous, or win awards. No, no, success is actually something else, something more subtle and incremental, something internally true and privately held. I think of my father’s traumatic life and recognize what a profound success it was for him to simply stay alive, to shift his lens toward positivity, to smooth the rough edges forged in life’s fires. That alone was extraordinary. Success is finding a way to grow in the heart of a hopeless landscape.

To that I bow.” -Jeff Brown

LIST OF ABBREVIATIONS AND SYMBOLS

AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
BMR	Basal Metabolic Rate
CSSD	Board Certified Specialist in Sports Dietetics
DE	Disordered Eating
EA	Energy Availability
ED	Eating Disorder
EI	Energy Intake
EEE	Estimated Energy Expenditure
FFM	Fat Free Mass
IOC	International Olympic Committee
IBS	Irritable Bowel Syndrome
LESS	Low Energy Syndrome in Sport
OTS	Overtraining Syndrome
NCAA	National Collegiate Athletic Association
RD	Registered Dietitian
RED-S	Relative Energy Deficiency in Sport

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CHAPTER I

INTRODUCTION

Energy deficiency in sports is due to overexercising or underfueling which can occur with or without intention. Low energy availability (low EA) is the result of the imbalance of energy availability which disrupts a eucaloric state. This can have detrimental short- and long-term health and performance-related consequences in athletes. The term “RED-S” or Relative Energy Deficiency in Sport was devised by the International Olympic Committee (IOC) in 2014 to expand the “female athlete triad” model. In contrast to the female athlete triad, RED-S includes male athletes and additional health and performance consequences other than bone health and menstrual dysfunction. The IOC published a 2018 update to the original Consensus Statement expanding on the pathophysiology of the possible health and performance-related consequences. Other recent publications have called for the need for an increased focus to be on RED-S at the Olympic Sports Federations level and for drastic paradigm changes to be made for the health of female athletes (Ackerman et al., 2020; M. L. Mountjoy, Burke, Stellingwerff, & Sundgot-Borgen, 2018). There are calls for increasing awareness of RED-S, emphasizing the importance to athletes’ health and prevention of long-term health consequences (Ackerman et al., 2020). Furthermore, awareness and education is key for athletes, support staff, and coaches to

create a culture of positive beliefs about nutrition and food, the importance of energy for health, positive body image, and menstrual dysfunction awareness.

Best practices regarding RED-S screening have yet to be developed for athletes in varying developmental stages from adolescence to masters level athletes. The body of literature for RED-S has primarily focused on assessment and diagnosis strategies such as the RED-S Clinical Assessment Tool (CAT) rather than detection and screening (M. Mountjoy et al., 2015). Early detection of athletes at risk for RED-S through RED-S specific screening may improve athlete health, and prevent irreversible damages if the syndrome goes undetected.

The prevalence of RED-S in college athletes is currently unknown at this time. There is an overall lack of consensus regarding nutrition screening, specifically low EA and RED-S screening for this population. College athletes may be at a heightened risk for low EA due to varying levels of nutrition education when entering college, lack of education about fueling for increased training loads in college, possible toxic training environments, and participation in sports considered “high-risk” for RED-S and team sports. Additionally, college athletes must balance school work and sports training and competitions often results in busy schedules. Athletes may benefit from consultations with registered dietitians (RD) and board-certified specialists in sports dietetics (CSSD) to determine fueling needs, strategies to meet energy demands, and careful planning of meals and snacks around schedules.

Athletes who participate in high-risk sports such as aesthetic sports, endurance sports, or weight category sports are known to be at an increased risk of developing low EA or RED-S, but the prevalence is understudied and unknown for team sports (M. Mountjoy et al., 2014). College

athletics is comprised of various team sports with different sports offered depending on the college or university. The National Collegiate Athletic Association (NCAA) identifies the following sports into categories by season include: fall sports that include men's and women's cross country, field hockey, football, men's and women's soccer, women's volleyball, men's water polo; winter sports that include men's and women's basketball, bowling, fencing, men's and women's gymnastics, men's and women's ice hockey, rifle, skiing, men's and women's swimming & diving, men's and women's indoor track & field, wrestling; and spring sports that include baseball, beach volleyball, men's and women's golf, men's and women's lacrosse, rowing, softball, men's and women's tennis, men's and women's outdoor track & field, men's volleyball, and women's water polo.

Current research conducted on female athletes and high-risk sports on the topics of low EA and low energy syndromes such as RED-S and the Female and Male Athlete Triad has driven the bulk of research efforts behind RED-S, and has contributed to the defining principles of the syndrome. With the majority of research on high-risk sports, excluding team sports, the question that is yet to be answered is how will future findings in team sports contribute and shape the future of low energy syndromes. Will additional sports not previously considered be classified as high-risk? Will awareness for the syndrome appear in male sports? How will universities and colleges screen, assess and treat athletes that present with RED-S? Future research on this topic should be inclusive of athletes from team sports, of racially diverse backgrounds, and for both males and females in order to gain additional understanding on this complex syndrome. The aim of this research is to profile athletes at risk for nutrition-related concern and RED-S in the collegiate setting, including racially diverse athletes, males and females, and team sport athletes.

This research seeks to explore predictive modeling in collegiate athletics, an emerging method in sport science, with hopes of understanding how athletes may be profiled through cross-sectional data. The traditional RED-S framework along with additional possible contributing factors such as nutrition knowledge and food insecurity will be used as indicators, suggesting how new considerations may impact low energy syndromes. The goal of this study is to detect student-athletes who may be of nutrition-specific health concern related to Relative Energy Deficiency in Sport (RED-S) at the time of pre-participation health evaluations through a latent class analysis predictive model. This study seeks to explore and answer two questions:

1. What conceptual groups exist that distinctly categorize female student-athletes that are of nutrition-specific health concern related to Relative Energy Deficiency in Sport (RED-S)?
2. What conceptual groups exist that distinctly categorize male student-athletes that are of nutrition-specific health concern related to Relative Energy Deficiency in Sport (RED-S)?

The first question will be answered through a latent class analysis model that identifies levels of a latent categorical variable through the analysis of observed continuous and categorical variables. The observed variables include measures consistent with the traditional framework of RED-S for female athletes such as disordered eating, restrictive diets/dieting, menstruation, bone health, will be included in this model. Along with the traditional indicators, three additional measures will be considered. Food insecurity, nutrition knowledge, and body image will be

included in the model to explore how the RED-S framework can evolve in the future with additional research efforts.

The second question will be answered through a latent class analysis model that identifies levels of a latent categorical variable through the analysis of observed continuous and categorical variables. The observed variables include measures consistent with the traditional framework of RED-S for male athletes such as disordered eating, restrictive diets/dieting, and bone health, will be included in this model. Along with the traditional indicators, three additional measures will be considered. Food insecurity, nutrition knowledge, and body image will be included in the model to explore how the RED-S framework can evolve in the future with additional research efforts.

CHAPTER II

REVIEW OF LITERATURE

Background on RED-S

RED-S was introduced by the IOC as a “broader, more comprehensive term” in 2014 to describe the previously known low energy condition of the Female Athlete Triad (M. Mountjoy et al., 2014). The IOC expert working group developed the 2014 RED-S Consensus Statement to update the 2005 Female Athlete Triad Consensus Statement in light of new and continued research on this topic that has evolved in recent years. The Consensus Statement includes current literature to update and replace the previous documents, risk assessment guidelines, and return-to-play guidelines to assist in the decision-making process (M. Mountjoy et al., 2014).

RED-S is defined as “impaired physiological function including, but not limited to, metabolic rate, menstrual function, bone health, immunity, protein synthesis, cardiovascular health caused by relative energy deficiency” with consideration to both male athletes and female athletes (M. Mountjoy et al., 2014).. The Triad syndrome was expanded to account for the multiple physiological effects of low energy beyond the three entities of energy availability, menstrual function, and bone health.

The underlying etiological cause of RED-S is low EA due to the imbalance of energy due to inadequate energy intake or excess energy expended. EA is calculated using the below formula (Anne B. Loucks, 2004; Anne B Loucks, Kiens, & Wright, 2011):

$$\text{Energy Availability (EA)} = \frac{\text{Energy Intake (EI) (kcal)} - \text{Exercise Energy Expenditure (EEE) (kcal)}}{\text{Fat Free Mass (FFM) (kg)}}$$

Low EA may be influenced by eating disorders (ED) or disordered eating (DE) but is situational and may occur without any influence from ED/DE (M. Mountjoy et al., 2014).

The ten health consequences of RED-S were initially introduced in the 2014 Consensus Statement from Mountjoy et. al include menstrual function, bone health, endocrine, metabolic, hematological, growth and development, psychological, cardiovascular, and gastrointestinal (2014). Ten potential performance effects of RED-S outlined in the same Consensus Statement include increased injury risk, decreased training response, impaired judgment, decreased coordination, irritability, depression, decreased glycogen stores, decreased muscle strength, and decreased endurance performance (2014). The authors in a 2015 publication include consideration that the visual representation of a complex syndrome can be difficult, and the intention of the web figures is mainly to educate athletes and coaches through a simple tool (Margo Mountjoy et al., 2015). However, it is difficult to visualize the complex interactions of physiological and psychological and their mechanisms in the figures.

Low Energy Availability

The optimal state of EA is 45kcal/kg fat-free mass per day is recommended for proper physiological functions, the range of 30-45kcal/kg fat-free mass per day is considered sub-

optimal, and less than 30kcal/kg fat-free mass per day is considered low EA and may result in the impaired processes (D. Logue et al., 2018). The body responds to low EA by downregulating fundamental body processes and enters “energy-saving mode” to conserve energy with a decreased basal metabolic rate (BMR) (Keay & Rankin, 2019). The effects of low EA will be explained in detail through the pathophysiology of RED-S below. Collecting information regarding LEA in free-living subjects cannot be without error and it has been speculated that the current methods to determine LEA through the published formula and ranges can lead to inaccuracies. The pitfalls of collecting LEA information include that a standard protocol does not exist, the equipment and resources needed to calculate each part, and the errors that may arise due to the estimations (Burke, Lundy, Fahrenholtz, & Melin, 2018).

Pathophysiology of RED-S

The pathophysiology of RED-S seeks to explain impaired processes associated with the syndrome (Horn, 2014). Each of the components of RED-S have unique physiological impairments that affect different bodily processes and systems. The central contributing factor of these impairments is low EA. While the 2014 IOC Consensus Statement introduced the possible health consequences of RED-S, the 2018 update to the original Consensus Statement expands on each of the processes. Although more information is provided, at this time the current literature on each of the health consequences remains limited to some systems proposed in the original Consensus Statement. This highlights the need for studies to study the effects of metabolic, hematological, growth and development, cardiovascular, gastrointestinal, immunological, and psychological in athletes suspected of RED-S. Menstrual function, endocrine, and bone health

have been examined in closer detail due to the parallels with the Triad. While the proposed health consequences provide information beyond the Triad, practitioners should continue to examine all of the possible effects of RED-S in the future to determine if other unknown aspects of health are impacted by RED-S and to confirm that the original proposed health systems are affected by various athletes from different sports, races, and ages.

Parallels between overtraining Syndrome (OTS) and Relative Energy Deficiency in Sport (RED-S) are starting to be drawn. In a recent publication, authors explain the pathways, symptoms and complexities of the syndromes and how researchers may consider the similarities between the two (Stellingwerff et al., 2021). Both OTS and RED-S identification are based on a diagnosis of exclusion but share the quality that both conditions affect health and performance outcomes in athletes. A validated diagnosis method or tool does not currently exist for overtraining syndrome or RED-S, but both have an overlap of symptoms. Decreased energy availability and carbohydrate availability may be a confounding factor in overtraining syndrome. Misdiagnosis of OTS may occur due to lack of awareness of RED-S. If LEA, under-fueling, or low carbohydrate availability drive under-recovery in those suspected of over-training syndrome or RED-S, adequate nutrition support is of high importance to prevent detrimental health and performance outcomes

The pathophysiology of the currently known body systems affected by RED-S will be outlined in detail below, describing how low EA leads to the disruption of the body system or process. RED-S remains in its early stages; many physiological mechanisms derive from athletes suspected of low EA or athletes in energy-deficient states such as eating disorders or disordered

eating. This highlights the need for original research to be conducted on athletes suspected of RED-S to further aid in the understanding of this complex syndrome.

Endocrine and Menstrual Function

In respect to low EA, specific endocrine markers of interest have been studied. These include hypothalamic releasing factors that include corticotrophin releasing hormone (CRH), gonadotrophic releasing hormone (GnRH), thyrotropin releasing hormone (TRH). Pituitary trophic hormones include thyroid stimulating hormone (TSH), adrenocorticotrophic hormone (ACTH), follicle stimulating hormone (FSH), luteinizing hormone (LH), and growth hormone (GH). Hormones produced by target organs include estradiol from the ovaries and testes, as well as thyroid hormones, T3 and T4 (Keay, Francis, & Hind, 2018; Keay & Rankin, 2019). T3 has been studied as a biomarker of EA, but results have been inconclusive. Female athletes may have lower levels of T3 if menstrual irregularities are present with low EA, but males may not be influenced in the same way (D. Logue et al., 2018).

In a state of energy deficiency there is a decrease in insulin and an increase in glucagon, increases in glycerol and free fatty acids and lower fasting glucose levels (D. Logue et al., 2018). This is due to the body relying on stored energy requiring processes such as gluconeogenesis and glycogenolysis to occur for the body to have readily available glucose from non-carbohydrate sources in a fasted state (Rui, 2014). These physiological metabolic impairments lead to the outcomes of RED-S, so there is a great need for sex-specific tools to measure and identify biomarkers that provide insight into the extent of low EA in both male and female athletes (D. Logue et al., 2018).

In a recent 2018 review article focusing on the topic of reproductive hormones and dietary intake regulating hormones, the authors review studies that include male and female athletes that present with low EA and low energy states such as anorexia nervosa (K. Elliott-Sale, A. Tenforde, A. Parziale, B. Holtzman, & K. Ackerman, 2018). The review covers literature related to metabolic, endocrine, menstrual function, and bone health with are health consequences in the RED-S model resulting from low EA on reproductive and interrelated hormonal pathways in the body (M. Mountjoy et al., 2014). Hormones that have been examined and may be affected by RED-S include adipokines, ghrelin and peptide YY (PYY), oxytocin, insulin, amyline, incretins, growth hormone, insulin-like growth factor-1 (IGF-1), thyroid hormones, and cortisol (K. Elliott-Sale et al., 2018). More complex systems like the hypothalamic-pituitary-gonadal axis and bone health processes such as bone mineral density, microarchitecture, and turnover makers have also been studied in low EA and RED-S. The endocrine and metabolic effects relating to RED-S were described by McCall and Ackerman with an emphasis on specific markers that should be examined using direct measurements (2019). Ackerman et al also expanded on to other processes such as the hypothalamic-pituitary-adrenal axis (HPA axis) and the hypothalamic-pituitary-thyroid axis. Hence, the measurement of hormonal functions including hunger and satiety hormones in athletes suspected of RED-S may be helpful (McCall & Ackerman, 2019).

Past research on the hormonal effects of low EA in males is minimal (Burke, Close, et al., 2018; De Souza, Koltun, & Williams, 2019; A. S. Tenforde, Barrack, Nattiv, & Fredericson, 2016) compared to the vast number of past literature in female athletes (Ackerman et al., 2019; K. J. Elliott-Sale, A. S. Tenforde, A. L. Parziale, B. Holtzman, & K. E. Ackerman, 2018;

Falsetti, Gambera, Barbetti, & Specchia, 2002; Heikura et al., 2018; Keay et al., 2018; Maimoun, Georgopoulos, & Sultan, 2014; Nose-Ogura et al., 2019).

It is well established that practitioners look at the menstrual function in female athletes to assess endocrine function. The age of onset menstrual cycle, the state of being eumenorrheic, amenorrhoeic or oligomenorrheic, and frequency of missed cycles are often analyzed when assessing menstruation in female athletes. Functional hypothalamic amenorrhea (FHA) is described by the IOC as “disruption of gonadotropin releasing hormone (GnRH) pulsatility at the hypothalamus, followed by alterations of LH and follicle stimulating hormone release from the pituitary and decreased estradiol and progesterone levels” and is considered the most severe of menstrual dysfunction requiring intervention (M. Mountjoy et al., 2018). Menstrual disorders such as FHA must be diagnosed by a healthcare professional through a clinical evaluation. The 2014 Female Athlete Triad Coalition Consensus Statement outlines an amenorrhea algorithm to follow if an individual is suspected for primary or secondary amenorrhea, and prolonged oligomenorrhoea with the expertise of a physician or endocrinologist if necessary (De Souza et al., 2014). This algorithm may be useful for practitioners to use when examining athletes who may be suspected of menstrual dysfunction.

Related to menstrual function, a study found that higher levels of cortisol have been observed in females with menstrual dysfunction, and can indicate physiological stress during intensive training (D. Logue et al., 2018). In junior elite female swimmers, ovarian suppression impaired athletic performance. Ovarian suppression mainly occurs when the training is carried out with the body was in a state of energy conservation and this leads to poor performance (VanHeest, Rodgers, Mahoney, & De Souza, 2014).

While some short-term effects of RED-S have been studied, the long-term health effects are lesser known. In the context of the endocrine system, long-term reproductive health is currently understudied and remains unknown (M. Mountjoy et al., 2014). Reproduction is closely related to EA in relation to survival, so the repercussions of long-term reproductive athlete health such as longitudinal studies related to fertility may be of interest to future researchers (K. J. Elliott-Sale et al., 2018).

Bone Health

Similarly to endocrine function, bone health is often studied relating to the Triad and low EA (Barrack, Fredericson, Tenforde, & Nattiv, 2017; Beals & Hill, 2006; A. F. Doyle-Lucas, J. D. Akers, & B. M. Davy, 2010; Ashley F. Doyle-Lucas, Jeremy D. Akers, & Brenda M. Davy, 2010; K. J. Elliott-Sale et al., 2018; Heikura et al., 2018; Keay et al., 2018; Maimoun et al., 2014; Nose-Ogura et al., 2019). Physiologically, lower levels of insulin-like growth factor-1 (IGF-1), T3 and T4, and estradiol, contributing to osteoporotic bones (Keay et al., 2018; Keay & Rankin, 2019). Bone mineral density can be measured using Dual-energy X-ray absorptiometry (DXA). Practitioners can assess the risk levels of athletes using Z-scores from the DXA and number of stress fractures (E. Joy et al., 2014). Typically, two or greater stress fractures, one or greater stress fracture in trabecular bone sites, and a Z-score greater than or equal to two is indicative of high risk (E. Joy et al., 2014). Unfortunately, many athletes may not notice the repercussions of low EA and RED-S until an injury such as a stress fracture occurs. Past history of vitamin D deficiency should also be considered to determine on an individual basis if an athlete may present with vitamin D deficiency.

Metabolic Function

The impairment of metabolic function seen in RED-S is due to the reduction of glucose utilization, mobilization of fat stores, reduced metabolic rate and lowered production of growth hormone (A. B. Loucks & Thuma, 2003). The 2018 IOC Consensus Statement update provided additional information for the metabolic component of RED-S by including possible reductions in resting metabolic rate (RMR), leptin, T₃, IGF-1, and an increase in ghrelin (M. Mountjoy et al., 2018). Overall, information regarding metabolic alterations due to RED-S at this time is not well established. Resting metabolic rate may provide some insight into how the body may be reach an energy deficient state similar to starvation and energy conservation, but direct relationships have not been established. It is important to note that published guidelines for testing for markers or metabolic testing in athletes suspected of RED-S is currently unknown and unavailable for assessment and treatment. A study on male and female ballet dancers found that a reduced RMR ratio of predicted to measured rate (RMR<0.90) can be used as a surrogate marker for energy deficiency (Staal, Sjödín, Fahrenholtz, Bonnesen, & Melin, 2018).

Hematological Changes

The interconnected relationship between low EA and iron deficiency has been discussed in the IOC 2014 Consensus Statement with regards to various aspects of athlete health, but there are many gaps (M. Mountjoy et al., 2014). Female athletes may experience iron deficiency anemia at a higher frequency than males due to menstruation, but the direct or indirect contribution to energy deficiency is not clear. Furthermore, the frequency in which males have hematological repercussions related to RED-S is not documented at this time. A narrative review

on iron considerations for athletes outlines the possibility of impaired iron regulation in athletes due to RED-S. This could be resulting from a low EA state with possible inadequate dietary intake and/or iron absorption (M. Sim et al., 2019). Past history of iron deficiency may also be considered to determine on an individual basis if an athlete may present with iron deficiency or anemia.

Growth and Development

Athletes of all ages may participate in sporting events and team sports, so it is important to consider how RED-S may affect athletes of all ages. Youth and adolescent athletes with reported eating disorders such as anorexia may experience impaired growth and development through altered GH and IGF-1 levels and restricted linear growth, but it is unknown how adolescent athletes suspected of RED-S may suffer the health consequence of altered growth and development (M. Mountjoy et al., 2018).

Psychological Health

Psychological health consequences may precede or be a cause of low EA (M. Mountjoy et al., 2014). The incidence rates of individuals suspected of RED-S and those with a diagnosed eating disorders are currently unknown. Various aspects of psychological well-being, mental health, and diagnosed psychological disorders should be examined when exploring athletes suspected of RED-S. Athletes with various diagnosed eating disorders and disordered eating tendencies should be examined for the risk of RED-S and low EA.

Cardiovascular Health

Research on RED-S is lacking regarding the relationship between suspected RED-S and cardiovascular health consequences is lacking. From the current body of literature on athletes diagnosed with FHA and/or EDs such as anorexia nervosa that are in a severe state of low EA, it can be noted that endothelial dysfunction, unfavorable lipid profiles, bradycardia, hypotension, and arrhythmias may occur along with other possible significant cardiovascular changes (M. Mountjoy et al., 2018). Cardiovascular health consequences should be of high concern to the sports physician and sports medicine team due to the severity in nature.

Gastrointestinal Health

Athletes in a low EA state or with a diagnosed eating disorder such as anorexia nervosa may experience varying symptoms related to impaired functioning of the gastrointestinal tract, with possible symptoms such as delayed gastric emptying, constipation, and increased intestinal transit time (M. Mountjoy et al., 2018). Gastrointestinal health consequences may include a broad definition of issues related to impaired functions, so a large gap remains in how to effectively screen, assess, and treat individuals suspected of RED-S with such health consequences. Gastrointestinal issues such as irritable bowel syndrome (IBS), Celiac disease, and other gastrointestinal tract-related diseases may be worth considering when assessing low EA and RED-S. The relationship between low energy intake due to dietary restrictions and RED-S should be explored.

Immunological Health

Research on the association between altered immune function and RED-S is limited. However, the 2018 IOC Consensus Statement mentions that there is a possible link between low EA and immune health consequences (M. Mountjoy et al., 2018). When examining the immune system related to RED-S, the likelihood of illnesses and infections may be difficult to assess due to the complex nature related to the immune system.

Performance Related Consequences of RED-S

Associations between various performance-related consequences and surrogates of low EA have been established, but few studies have directly looked at the impact of low EA on performance (M. Mountjoy et al., 2018). A variety of indirect mechanisms such as impaired recovery, acute impairment of key processes such as glycogen storage or protein synthesis, impairment of optimal muscle mass and function may be impacted by low EA.

Overlap Between Terminology in Low Energy Syndromes and the Athlete Triad

Recently, a new working model similar to the Female Athlete Triad but for male athletes called “The Male Athlete Triad” was proposed. This new working model looks at how energy availability, reproduction, and bone health are affected in male athletes, mirroring the Female Athlete Triad model (De Souza et al., 2019). Male athletes may be more resilient to the effects of low energy availability, requiring a higher level of severity before disturbances are observed. Although a key defining factor of RED-S is the inclusion of male athletes, many cited studies in the 2018 Consensus Statement update regarding the explanation of the ten health consequences

of RED-S rely on research conducted solely on female athletes. Further studies should examine the effects of RED-S on males as well as in females.

A recent narrative review on the Female Athlete Triad, RED-S, and the Male Athlete Triad explores each of the conditions and their components with brief defining criteria provided (Statuta, 2020). The term “low-energy syndrome” was used to describe and group the three syndromes into one for ease of understanding in the review. At this time, the controversy between what each syndrome is defined as and the inevitable crossover between signs and symptoms related to each of the syndromes exists. As research emerges in the field, screening, assessment and diagnosis of said syndromes should be updated and should evolve as best practices relating to athlete health emerge. The term “low-energy syndrome in sport” (LESS) may be worth considering for future research for ease of understanding. Due to the complexity of the interrelated syndromes, the numerous proposed health and performance consequences outlined in the RED-S infographics, the influence of low EA, and the Male and Female Athletes Triad models, it can be confusing to researchers studying these similar syndromes.

Nutrition Specific to College Students

The transition time for college students and the adjustment to a new environment can be a time of new independence (Pancer, Hunsberger, Pratt, & Alisat, 2000). For students living on campus, a new environment away from home may change eating habits and access to food. A study across multiple universities found that 19% of first-year students were food insecure and were at a higher odds of poor sleep quality, disordered eating behaviors, lower grade point averages (GPA) and higher levels of stress (El Zein et al., 2019). Another study at a large

university in the southeastern United States found that 14% of students experience food insecurity with an emphasis on financial factors such as financial freedom, family support, food assistance, and other financial and food management skills that played a role in food insecurity (Gaines, Robb, Knol, & Sickler, 2014). If students have access to food preparation facilities such as dorm kitchens or community spaces with cooking areas, dietary intake may be positively impacted. A study on young adults found that the biggest barrier to food preparation was time, but those who reported frequent food preparation were more likely to meet targets for fat, calcium, fruits and vegetables, and whole grains as well as less fast-food consumption (Larson, Perry, Story, & Neumark-Sztainer, 2006). Student-athletes transitioning to college and universities may also experience common nutrition-related issues as previously mentioned, but must also balance busy schedules due to sport and increased energy needs. Future studies may wish to explore if similar food preparation, food insecurity, and financial factors impact this population.

Nutrition Specific to College Athletes

The National Collegiate Athletic Association (NCAA) is comprised of 1,098 colleges and universities, 102 athletics conferences, nearly 500,000 college athletes on 19,886 teams in 24 sports across 3 divisions (NCAA, 2021). Student-athletes participating in NCAA athletics in the United States receive academic support, medical care, access to coaching, facilities, and equipment at their respective university. Annually, NCAA schools award nearly \$3.5 billion dollars in athletic scholarships with some Division I schools offering additional funds to cover costs not covered by a scholarship. NCAA Division I and II schools can provide unlimited meals

to support the nutritional needs of student-athletes, but only some schools have registered dietitians (RD), nutritionists, and other health professionals designated to work with athletes. A study found that nutrition education from a registered dietitian improved energy intake, macronutrient intake, and nutrition knowledge in 11 NCAA Division I female volleyball athletes (Valliant, Pittman Emplaincourt, Kieckhaefer Wenzel, & Garner, 2012).

Athletes attending universities and colleges are often 18 to 24 years old, living on their own away from family for the first time, and are required to balance school work and sport obligations. Nutritionally this can be a critical time as growth and development of adolescence is ending, peak bone mass is reached (females age 18, males age 20), and fueling demands for college levels sports may increase. These factors relate to energy availability and the importance of meeting nutritional needs for health and performance.

A unique aspect of collegiate athletics is the focus on team sports and the subcultures within different institutions and individual teams. Body image has been linked to disordered eating and eating disorder behaviors but is not currently included in the RED-S framework. Body image was considered with eating disorder behaviors in elite Icelandic athletes, with 17.9% of the athletes having severe or moderate body image dissatisfaction, and 18.2% of athletes above the clinical cutoff for body image concern, with more women's scores being higher than the men's overall (Kristjansdottir, Sigurethardottir, Jonsdottir, Thornorsteinsdottir, & Saavedra, 2019). Social media may also play into one's body image and appearance-related comparisons, which has been looked at in college females (Hendrickse, Arpan, Clayton, & Ridgway, 2017). In college athletes body image may be of concern due to weight pressures from peers, teammates,

coaches, fans and other individuals. The WPS tool was developed for male collegiate athletes and the sample included athletes from aesthetic sports such as diving and weight class sports such as wrestling in which body appearance and weight are a focus. Body image is an important component to assess because of the relation to dieting behavior and the psychological component of RED-S that can precede or be a result of RED-S.

It has been speculated that RED-S may occur at an increased rate in high-risk sports, but if all sports including team sports are not included in the body of literature and work, then the prevalence may be unknown. To date, there have been further research is needed to investigate the incidence of RED-S in team sports (M. L. Mountjoy et al., 2018).

Literature on the Method

Nutrition screening and assessments are typically conducted in the clinical healthcare setting for conditions such as malnutrition, sarcopenia, and critically ill patients. Screening implies the process of indicating risk factors for a deprived nutrition condition and nutrition assessment providing the nutrition diagnosis for conditions such as undernutrition in the hospital setting (Correia, 2018). A review by Charney explains in detail the distinction between screening and assessment in healthcare, and notes how nutrition screening can facilitate the development of nutrition assessment programs for best nutrition intervention outcomes (Charney, 2008).

A recent review on questionnaires as measures for low energy availability (LEA) and relative energy deficiency in sport (RED-S) in athletes found thirteen questionnaires to identify LEA/RED-S risk (A. Sim & Burns, 2021). The most widely used validated questionnaires were

the LEAF-Q and the EDE-Q. The LEAF-Q determines LEA risk but nearly half of the questions are related to menstrual function so it cannot be used in males. The BEDA-Q was also mentioned, noting that is only validated in female elite adolescent athletes, the items are not female-specific and the possibility exists for utilizing the tool in male athletes. The BEDA-Q measure was also recently used to assess LEA in female athletes (Ackerman et al., 2019). The current available questionnaires may be effective in identifying intentional energy restriction but there is a current need for questionnaires that identify unintentional imbalances between energy intake and estimated energy expenditure

Latent Class Analysis

Latent Class Analysis (LCA) was introduced as a technique to explore latent classes of individuals in an exploratory manner utilizing a unrestricted model (McCutcheon, 1987). LCA is an explanatory modeling technique that allows for the grouping of individuals with similar characteristics (Mori, Krumholz, & Allore, 2020). The aim of this model is to estimate the probability of each athlete being a member of each latent class. LCA can be a helpful modeling technique that focuses on individuals rather than indicators. Personal behaviors and characteristics are used to determine latent profiles based on similar responses to the indicators and variables of interest (Spurk, Hirschi, Wang, Valero, & Kauffeld, 2020). The goal is to uncover underlying patterns of shared behavior that are of interest to the researcher.

LCA is useful when the goal is to use an individualized approach while still having the need to understand the general patient population. Additionally, through the exploration of numerous subgroup solutions, various statistical and clinical parameters can be utilized to

determine the best fitting model. Discretion is necessary to determine the preferred model that best presents the data, has a reasonable distribution of individuals across the identified subgroups, has a high certainty of classification and each of the subgroups having clear clinical characteristics (Kongsted & Nielsen, 2017)

This technique is especially useful for researchers in social sciences to explore patterns of shared behaviors between samples. These patterns of interest may be missed when individual variable-centered analyses are conducted. The overarching goal of LCA is to determine subgroups of individuals who share meaningful and interpretable pattern of responses on the measures of interest. This person-orientated approach recovers hidden groups in data through the use of probabilities of individuals belonging to different groups (Ferguson, G. Moore, & Hull, 2019).

An overarching goal of LCA is to identify groups based on responses to a set of observed indicators. LCA, a finite mixture model has been used to identify subgroups in a range of substantive areas to characterize heterogeneity in a population with respect to a given phenomenon. It is a 'person-centered' approach that uses a mathematical evaluation of how well a proposed LCA model represents the data (Nylund-Gibson & Choi, 2018). Additionally, LCA can be used to develop typologies and is utilized in predictive models. LCA can use a wide variety of data with differing variances, and is a powerful alternative to other statistical techniques such as K-means for clustering (Schreiber, 2017).

Analytic algorithms such as LCA allow the use of multiple indicator variables to identify homogenous subgroups within heterogenous populations can be beneficial for the healthcare team. Probabilities are generated for membership in all the identified classes in the model,

indicating which individuals belong to the determined classes (Sinha, Calfee, & Delucchi, 2020). Clinical prediction models are expected to benefit sports medicine practice, but only if they are properly developed and validated. These models may help guide decision making processes in clinical medicine but are not commonly used in sports medicine (Bullock et al., 2021). A focus on the methodology, specifically model development, model performance, and validation must be considered when conducting prediction research.

Collegiate Nutrition Screening Protocols

At this time, a validated and widely used nutrition screening protocol is not available for college athletes. At the NCAA institutional and university level, screening policies and survey tools utilized are dependent on individual policies developed by sports medicine athletic directors, athletic trainers, and nutrition staff if available.

It is unknown at this time if annual screening for low energy syndromes such as RED-S and the Triad, or for eating disorders is conducted routinely at NCAA institutions. The screening and diagnosis of RED-S can be subtle and challenging to uncover, so individuals well versed in the symptomatology should be involved in the screening protocols developed (M. Mountjoy et al., 2014). The shortcomings of currently published screening tools include that there is a lack of consensus on what tool to use and the current tools are limited by lack of validation. Many tools were focused only on males or females and did not target college athletes and team sports.

One of the common screening tools utilized in athletic populations is the Low Energy Availability in Females Questionnaire (LEAF-Q). The LEAF-Q has shown variable results in

identify female athletes at risk of the Female Athlete Triad, but it is limited in the fact that only female athletes can utilize this screening tool (Melin et al., 2014). A recent review published in 2021 on questionnaires as measures for low EA and RED-S found that the LEAF-Q and Eating Disorder Examination Questionnaire (EDE-Q) were the most widely used validated questionnaires, but limitations include that nearly half of the items in the LEAF-Q relate to menstrual function so it cannot be used in males (A. Sim & Burns, 2021). The LEAF-Q was recently used to identify young football players at risk for RED-S in Poland, providing insight into team sports (Łuszczki et al., 2021). The main focus of the EDE-Q is to identify eating disorder risk as a surrogate marker of RED-S, and fails to address the numerous health consequences associated with the syndrome. A narrative review on low EA published in 2020 highlights the need for sport and sex-specific screening tools to identify athletes participating in a variety of sports at risk of RED-S (D. M. Logue et al., 2020).

A review on the Triad and RED-S provides examples of published screening tools, current recommendations for conducting screening for low energy syndromes, and important concepts of the syndromes to include in screening (Tayne, Hrubes, Hutchinson, & Mountjoy, 2019). The authors mention that “the pre-participation physical examinations are a provider’s best chance of detecting a problem before the athlete develops more severe pathology or injury or before there is a negative impact on performance.” The detrimental health consequences of RED-S cannot be understated, and during the screening protocol “if the provider notes one component of RED-S in an athlete, the provider should continue a further, more in-depth evaluation of history, physical examination, and laboratory investigations.” This

recommendation ties back to differentiating the nutrition screening and assessment protocols previously mentioned.

Eating disorders have been shown to occur in higher incidences in athletes compared to the general population, so tools specifically created for the athletes should be utilized as an important component of nutrition screening (Elizabeth Joy, Kussman, & Nattiv, 2016; Sundgot-Borgen & Torstveit, 2004). The Brief Eating Disorder in Athlete Questionnaire BEDA-Q has been validated to identify EDs in the female athlete population (M. Martinsen, I. Holme, A. M. Pensgaard, M. K. Torstveit, & J. Sundgot-Borgen, 2014). A pitfall of ED screening tools can be that they often include an interview portion and can be lengthy, so with 9 items, the BEDA-Q may fill the need for an athletic specific short ED screening tool. The use of the BEDA-Q in male athletes should be investigated since the questions are not sex-specific and the tool has not been previously used in males.

The association between food insecurity and RED-S is yet to be studied. Furthermore, food insecurity as a contributing factor to low EA in the athletic population is currently unknown. The lack of access to nutritious food, or inadequate means to acquire, prepare and consume food is a substantial barrier to proper nutrition. One study found that food insecurity in college athletes was found to be significantly correlated with hoarding food and being preoccupied with food (Poll, Holben, Valliant, & Joung, 2018). Additionally, food insecurity and lack of finances may also contribute to malnutrition in some populations (Burke, Close, et al., 2018). Additionally, in the 2018 IOC Consensus Statement on RED-S, authors state that “cultural, social, psychological, and financial factors contribute to low energy availability” so the

food security status and scholarship status in collegiate athletes warrant further investigation (M. Mountjoy et al., 2018).

A review on nutrition knowledge in athletes highlights the need for future research to use validated tools to measure nutrition knowledge in athletes and to further solidify the understanding of the relationship between nutrition knowledge and dietary intake (Heaney, O'Connor, Michael, Gifford, & Naughton, 2011). Nutrition knowledge has been studied in relation to low EA in female Australian rules football players with results finding low sports nutrition knowledge and a 30% risk of low EA in the 30 athletes studied (Condo, Lohman, Kelly, & Carr, 2019). A study on nutrition knowledge in collegiate athletes found poor nutrition knowledge scores of $57.6\% \pm 18.6\%$ on the survey, with the possible impact on performance and injury risk (Werner, Guadagni, & Pivarnik, 2020). Although nutrition knowledge has not been studied in relation to low energy syndromes like RED-S, assessing nutrition knowledge may be an important component of nutrition screening. Baseline nutrition knowledge measurements can aid in the development of team nutrition education with target interventions. This possible relationship should be explored to determine if the two concepts are interrelated.

Gaps in the Literature

Throughout the review of literature, gaps in knowledge and shortcoming for the compressive understanding of this emerging topic have been mentioned. It is important to note that RED-S was introduced in 2014, so gaps in knowledge for this complex syndrome will continue to be filled as new research emerges. The overarching gap in research at this time is the lack of information on racially diverse athletes from a variety of athletic groups, team sport

athletes, and male athletes. The updated 2018 Consensus Statement on RED-S by the IOC leaves final remarks on future directions for scientific researchers, with a focus on the development of methodology to screen and identify athletes at risk for RED-S that is “scientifically validated and relevant and applicable in clinical sports practice” (M. Mountjoy et al., 2018). Additionally, authors identify that a gap remains in the “understanding of RED-S in specific sports with differing energy demands, performance criteria, ethnicities and cultural perspectives” with the need for ongoing research efforts on male athletes in addition to female athletes, team sport athletes participating in a wide array of sports, and athletes from various cultural backgrounds.

Purpose of the Study

The goal of this study is to detect student-athletes who may be of nutrition-specific health concern related to Relative Energy Deficiency in Sport (RED-S) at the time of pre-participation health evaluations through a latent class analysis predictive model. The profiling of athletes will be done through a latent class analysis approach with the goal of the identification of classes of athletes of concern using probabilities. Due to the lack of a gold standard at this time for nutrition screening, RED-S screening, and collegiate athlete screening, this model will be exploratory in nature with no known classes identified *a priori*.

Furthermore, if classes of athlete of concern are identified, more diagnostic testing can be done to determine if RED-S is present. With the focus on athlete health and safety, it is vital to screen, identify and treat athletes in respect to low EA and RED-S to prevent detrimental short- and long-term health and performance consequences.

CHAPTER III

METHODS

Study Design

The study is a quantitative cross-sectional study utilizing a web-based survey software to explore nutrition-related health concerns including RED-S through nutrition screening in collegiate athletes. Through the Latent Class Analysis model, individuals were profiled to determine classes of individuals of concern. The data for this study were generated using Qualtrics software with electronic administration for the Nutrition Screening Survey (Qualtrics Provo, UT, 2021).

Recruitment and Data Collection Procedures

All participants were current athletes at the University of Mississippi and 18 years of age or older. Information collected on each athlete was protected as a part of the student athletes' personal medical record. Data will be collected and stored in a Health Insurance Portability and Accountability Act (HIPAA) compliant Box account created by the University of Mississippi Athletics Health and Sports Performance Center (Box Redwood City, CA, 2021). Surveys that were administered to athletes will require the use of a unique 4-digit code that will be de-identify the identity of the athlete for all data storage and research purposes. A master Excel sheet

matching the unique 4-digit code to the athletes' identity will be securely stored in the Box account and restricted access to individuals deemed necessary for administering the survey. Data collection occurred during the time of annual preparticipation evaluations concurrent with ImPACT concussion testing during the summer months before the start of the fall semester. Athletic Trainers assisted the sports nutrition staff to assure completion of the nutrition screening. Ethical approval from the University of Mississippi Institutional Review Board was obtained (Protocol # 22x-017) as well as support from the University of Mississippi Athletics Department and Health and Sports Performance Center.

Variables and Measurement

Various nutrition and RED-S components were measured through a variety of previously published screening tools outlined below. Similar survey methodology was used, with reference to a recent study that conducted a cross-sectional study on patients that presented to the Division of Sports Medicine at Boston Children's Hospital (Ackerman et al., 2019). As mentioned in their study, due to the lack of a validated or standard measure for RED-S, survey measures based on validated and/or standard questionnaires for each topic as available were used. The measures used are included in Appendix A.

Low energy availability can be difficult to measure outside of the laboratory setting. Therefore, a surrogate marker for low energy availability was eating disorder risk, self-reported history of eating disorders, and self-reported adherence to special diets. Eating disorder risk was measured through the Brief Eating Disorder in Athlete survey (BEDA-Q) which has 9 questions, 6 pulled from the Eating Disorder Inventory (EDI) survey (Marianne Martinsen, Ingar Holme,

Anne Marte Pensgaard, Monica Klungland Torstveit, & Jorunn Sundgot-Borgen, 2014). The BEDA-Q is scored through a weighted equation score with the six items from the EDI totaling to a maximum of 18 points with an optimal cutoff score of determined by researchers to classify athletes as at-risk or not at-risk for disordered eating . Special diet was considered through the question: Are you currently following or have you ever followed any special dietary considerations for personal reasons, diagnosed conditions, or religious reasons? (vegan, vegetarian, gluten-free, dairy-free, religious fasting, paleo, etc.). Number of meals consumed per day provides insight into if athletes are missing meals and will be assessed through a 24-hour food recall. While a pre-determined number of meals is dependent on individual energy needs, literature has shown that not consuming at least 3 meals per day can be indicative of disordered eating (Adam S Tenforde et al., 2021).

Bone health was assessed through self-reported history of stress fractures including the number of stress fracture and the site of the stress fracture, with high-risk sites include lumbar spine, femoral neck, sacrum, and pelvis. Questions regarding bone health originate from the WHEL Survey (Koltun et al., 2019).

Various questions regarding menstrual function was utilized from the WHEL Survey (Koltun et al., 2019). Through the display function of Qualtrics, menstrual function questions will only appear if the female sex is selected in the demographic section. Questions regarding age of onset menstruation and menstrual irregularity was asked. The goal of these self-reported questions was to determine if delayed menarche or menstrual irregularity is present and if further investigation is warranted through a sports medicine physician or endocrinologist.

The U.S. Household Food Security Survey includes a traditional 10- or 18-item full survey for assessing food insecurity. Adapted from the full survey, a two-item food insecurity screening tool based on Questions 1 & 2 of the U.S. Household Food Security Survey has been validated for use as a screening tool in the health care setting. It has been found to have levels of sensitivity across high-risk population subgroups of $\geq 97\%$ and a specificity of $\geq 74\%$ for food insecurity (Gundersen, Engelhard, Crumbaugh, & Seligman, 2017). Athletes who screened positive for food insecurity should be referred for a nutrition consultation with the nutrition staff.

Nutrition knowledge was assessed through the use of the Abridged Nutrition for Sport Knowledge Questionnaire (A-NSKQ). The A-NSKQ is a valid and reliable brief questionnaire designed to assess general nutrition knowledge (GNK) and sports nutrition knowledge (SNK) in athletic populations (Trakman, Forsyth, Hoye, & Belski, 2018). The full questionnaire is included in the appendix.

Body image was assessed through the Weight Pressures in Sport (WPS) tool developed for male college athletes. It has been validated for use for detecting various sources of weight pressures and body image in the college athlete population (Galli, Petrie, Reel, Chatterton, & Baghurst, 2014; Galli, Reel, Petrie, Greenleaf, & Carter, 2011).

Although there is not a consensus at this time for measuring energy expenditure in free-living college athletes directly related to calculating EA, it is known that athletes expend energy beyond that of the average individual. College athletes participate in a variety of team sports depending on the university or college, the athletic division, and the university budget. This

includes both male and female athletes; fall, winter, and spring sports; and varying levels of intensity and duration of specific sports.

Statistical Analysis

Data were analyzed using a latent class analysis (LCA) model approach to uncover subpopulation structure for the probability of determining athletes at risk of RED-S. The LCA model was introduced as a technique to explore latent classes of individuals in an exploratory manner utilizing a unrestricted model (McCutcheon, 1987). The variables of interest will be included in the linear mixed model with separate male and female models. This method characterizes the possible indicator variables of RED-S to unveil the relationship between the variables of interest and unknown latent classes of individuals who may be of nutrition and RED-S concern, considering each sex separately.

Latent class analysis is an exploratory modeling technique that allows for the grouping of individuals with similar characteristics (Mori et al., 2020). The aim of this model is to estimate the probability of each athlete being a member of each latent class. Due to the difficulty directly measuring RED-S, this method would help identify the latent variable through the observed variables that serve as indicators. LCA can be a helpful modeling technique that focuses on individuals rather than indicators.

LCA Statistical Analysis

There are a number of considerations when determining which latent class model that best fits the individuals of interest. If many sampling zeros are present in the dataset, sparseness exists. This differs from structural zeros. If sparseness occurs, it leads to difficulties in model

evaluation. Lack of consensus on a general rule of thumb for sample size but it has been established that LCA models are case sensitive and require large sample sizes into the hundreds.

Determining number of classes, also named class enumeration, involves fitting several LCA models with differing numbers of latent classes, collecting fit information for each model, then studying patterns to decide how many classes best describe patterns observed in the data (Nylund-Gibson & Choi, 2018). Information such as goodness of fit statistics can be analyzed to evaluate the model fitness. The Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Sample-size adjusted BIC all are considered for goodness of fit. BIC helps in model selection by penalizing the number of factors, providing insight into the model fit.

The LCA model with the smallest values for AIC, BIC and sample-size adjusted BIC are considered to be the best fitting model. The solution with the largest loglikelihood is considered to be better fitting than a model with lower loglikelihood values.

Lo-Mendell-Rubin Adjusted Likelihood Ratio Test (LMR-LMT) compares models with varying numbers of classes. If $p\text{-value} < 0.05$, the model with one fewer class is a better fit for the data (Lo, Mendell, & Rubin, 2001). If the $p\text{-value}$ is ≥ 0.05 , the model would need to be reclassified with fewer classes. The parametric bootstrapping $p\text{-value}$ is also of interest, with a $p\text{ value} \geq 0.05$ indicating that the model needs to be reduced in class size.

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LIST OF APPENDICES

APPENDIX A

Summary of screening measures for collegiate student-athletes

BEDA-Q	Dietary Practices	Meals Per Day	Bone Health	Menstruation	ANSK-Q	Food Insecurity	WPS
EDI							
I feel extremely guilty after overeating ^a	Are you currently following or have you ever followed any special dietary considerations for personal reasons, diagnosed conditions, or religious reasons? ^b	Please list your food intake for the past 24 hours in each of the categories. Do your best to estimate the amounts (i.e. one handful, one fistful), quantity of food items, if you prepared it at home or out (and list restaurant) and as specific as possible. ^c	Have you ever had a stress fracture? ^b	How old were you when you first menstruated? ^e	Full questionnaire in Appendix	Within the past 12 months I was worried whether my food would run out before I got money to buy more. ^f	In the past year, my coach places an emphasis on team members' weight ^g
I am preoccupied with the desire to be thinner ^a	Options:		How many stress fractures have you had? ^d	Is your menstrual cycle currently regular (period at the same time every month)? ^b			In the past year, my coach encourages athletes to gain muscle mass ^g
I think that my stomach is too big ^a	Options:		What was the site of your stress fracture(s)?			Within the past 12 months the food I bought just didn't last and I didn't have money to get more. ^f	Weigh-ins are held periodically throughout the season ^g
I feel satisfied with the shape of my body ^a	Vegetarian, Semi-		Options: Lumbar spine				Body weight and appearance are important to my coach ^g
My parents have expected excellence of me ^a	Vegetarian, Vegan, Gluten-free, Dairy-free,		Femoral neck Sacrum Pelvis				My teammates notice if I put on weight ^g Any of my body flaws are readily apparent in my uniform ^g
As a child, I tried very hard to avoid disappointing my parents and teachers ^a	Lactose-free, Paleo, Ketogenic, Intermittent Fasting, Low carb, Fasting for religious reasons (Ramadan, etc.), Low FOD-MAP						The crowd scrutinizes my body and makes me concerned about my weight and appearance ^g In the past year, have you lost weight to meet image requirements for your sport? ^g In the past year, have you ever ate in secret? ^g Body weight and appearance are important to my friends outside of sport ^g Body weight and appearance are

important to my
family^g

The leanest athletes
are at a distinct
performance
advantage^g

Note.

Menstruation column excluded for male athletes

Brief Eating Disorder in Athletes Questionnaire (BEDA-Q)

Abridged Nutrition for Sport Knowledge Questionnaire (A-NSKQ)

Weight Pressures in Sport (WPS)

^aAnswer choices: always, usually, sometimes, often, never

^bAnswer choices: yes, no

^cAnswer choices: Breakfast, Lunch, Dinner, Snacks, Beverages

^dAnswer choices: 1, 2, 3, 4, 5, >5

^eAnswer choices: <10, 10, 11, 12, 13, 14, 15, 16, >16

^fAnswer choices: often true, sometimes true, never true

^gAnswer choices: always, usually, often, sometimes, rarely, never

APPENDIX B

A-NSKQ Nutrition Knowledge Questionnaire

General Nutrition Knowledge

1. Eating more energy from protein than you need can make you put on fat.
(agree/disagree/not sure)
2. The body needs fat to fight off sickness. (agree/disagree/not sure)
3. Do you think cheddar cheese is high or low in fat? (high/low/not sure)
4. Do you think margarine is high or low in fat? (high/low/not sure)
5. Do you think honey is high or low in fat? (high/low/not sure)
6. The body has a limited ability to use protein for muscle protein synthesis.
(agree/disagree/not sure)
7. Eggs contain all the essential amino acids needed by the body. (agree/disagree/not sure)
8. Thiamine (Vitamin B1) is needed to take oxygen to muscles. (agree/disagree/not sure)
9. Vitamins contain energy (kilojoules/calories). (agree/disagree/not sure)
10. Do you think alcohol can make you put on weight? (yes/no/not sure)
11. "Binge drinking" (also referred to as heavy episodic drinking) is generally defined as:
(a) having two or more standard alcoholic drinks on the same occasion (b) having four to five
or more standard alcoholic drinks on the same occasion (c) having seven to eight or more
standard alcoholic drinks on the same occasion (d) Not sure

Sport Nutrition Knowledge

12. Do you think 1 medium banana has enough carbohydrate for recovery from intense
exercise? Assume the athlete weighs about 70 kg and has an important training session

again tomorrow. (enough/not enough/not sure)

13. Do you think 1 cup of cooked quinoa and 1 tin of tuna has enough carbohydrate for recovery from intense exercise? Assume the athlete weighs about 70 kg and has an important training session again tomorrow. (enough/not enough/not sure)

14. Do you think 100 g of chicken breast has enough protein to promote muscle growth after a bout of resistance exercise? (yes/no/not sure)

15. Do you think 1 Cup Baked Beans has enough protein to promote muscle growth after a bout of resistance exercise? (yes/no/not sure)

16. Do you think 1/2 Cup Cooked Quinoa has enough protein to promote muscle growth after a bout of resistance exercise? (yes/no/not sure)

17. Eating more protein is the most important dietary change if you want to have more muscle. (agree/disagree/not sure)

18. Which is a better recovery meal option for an athlete who wants to put on muscle? (a) A 'mass gainer' protein shake and 3 - 4 scrambled eggs (b) Pasta with lean beef and vegetable sauce, plus a dessert of fruit, yoghurt and nuts (c) A large piece of grilled chicken with a side salad (lettuce, cucumber, tomato)/ (d) A large steak and fried eggs (e) Not sure

19. When we exercise at a low intensity, our body mostly uses fat as a fuel. (agree/disagree/not sure)

20. Vegetarian athletes can meet their protein requirements without the use of protein supplement. (agree/disagree/not sure)

21. The daily protein needs of a 100 kg (220 lb) well trained resistance athlete are closest to: (a) 100g (1g/kg) (b) 150g (1.5g/kg) (c) 500g (5g/kg) (d) They should eat as much protein as

possible (e) Not sure

22. The optimal calcium intake for athletes aged 15 to 24 years is 500 mg. (agree/disagree/not sure)

23. A fit person eating a balanced diet can improve their athletic performance by eating more vitamins and minerals from food. (agree/disagree/not sure)

24. Vitamin C should always be taken by athletes. (agree/disagree/not sure)

25. Athletes should drink water to: (a) keep plasma (blood) volume stable (b) stop dry mouth (c) allow proper sweating (d) All of the above (e) Not sure

26. Experts think that athletes should: (a) drink 50 - 100 ml (1.7 - 3.3 fluid ounces) every 15 - 20 minutes (b) suck on ice cubes rather than drinking during practice (c) drink sports drinks (e.g. powerade) rather than water when exercising (during intense sessions) (d) drink to a plan, based on body weight changes during training sessions performed in a similar climate (e) Not sure

27. Before competition, athletes should eat foods that are high in: (a) fluids, fat and carbohydrate (b) fluids, fiber and carbohydrate (c) fluids and carbohydrate (d) Not sure

28. In events last 60 - 90 minutes, 30- 60 g (1.0 - 2.0 ounces) of carbohydrates should be consumed per hour. (agree/disagree/not sure)

29. Eating carbohydrates when you exercise will help keep blood sugar levels stable. (agree/disagree/not sure)

30. Which is the best snack to have during an intense 90-minute training session? (a) A protein shake (b) A ripe banana (c) 2 Boiled eggs (d) A handful of nuts (e) Not Sure

31. How much protein do you think experts say athletes should have after completing a

resistance exercise session? (a) 1.5g/kg body weight (~ 150 – 130 g/ 5.3 –10.6 ounces for most athletes) (b) 1.0 g/kg body weight (~ 50 - 100 g /1.9 - 2.3 ounces) for most athletes) (c) 0.3g/kg body weight (~ 15 - 25 g/0.53 - 0.88 ounces) for most athletes) (d) Not sure

32. Supplement labels may sometimes say things that are not true. (agree/disagree/not sure)

33. All supplements are tested to make sure they are safe and don't have any contamination. (agree/disagree/not sure)

34. Which supplement does not have enough evidence in relation to improving body composition or sporting performance? (a) Caffeine (b) Ferulic acid (c) Bicarbonate (d) Leucine (e) Not Sure

35. The WORLD ANTI-DOPING AGENCY (WADA) bans the use of (a) caffeine (b) bicarbonate (c) carnitine (d) testosterone (e) Not Sure

CHAPTER IV

MANUSCRIPT 1

A LATENT CLASS ANALYSIS OF FEMALE COLLEGIATE ATHLETES OF NUTRITION AND RED-S CONCERN

To be submitted to the British Journal of Sports Medicine

Abstract

Relative Energy Deficiency in Sport (RED-S) has been expanded upon creation in 2014 to include a variety of ages and athletes. Female athletes have been the primary focus, but the collegiate female athlete population needs further investigation. Screening collegiate athletes for nutrition-related concerns and low energy syndromes provides insight for practitioners and may lead to necessary referrals in the sports medicine team. Screening may be a part of an athletic department's protocol, but there is a lack of consensus on a validated tool for this population. The goal of this cross-sectional research was to use a Latent Class Analysis (LCA) predictive modeling approach to determine classes of female collegiate athletes who present with nutrition

and RED-S concern. At a Division I university, 144 female athletes competing in various team sports completed a pre- participation nutrition screening survey. Measures such as menstrual function, bone health, disordered eating, restrictive diets, food insecurity, body image, and nutrition knowledge were collected. Some evidence is presented that female athletes can be profiled into a two-class solution, providing practitioners and sports dietitians insight into profiling athletes who may be at risk for low energy syndromes. Future research should consider large sample sizes of athletes to conduct predictive modeling techniques along with high quality, validated measurement tools.

Summary Box

- Latent class analysis is a predictive modeling technique to determine latent classes of individuals through continuous or categorical predictors
- Female collegiate athletes participating in team sports should be screened annually for low energy syndromes such as RED-S
- A validated tool for detecting RED-S in female collegiate athletes is of high importance

Introduction

Relative Energy Deficiency in Sport (RED-S) was introduced in 2014 as a continuation of the Female Athlete Triad by the International Olympic Committee (IOC) to include a number of health and performance related consequences of the syndrome and male athletes as well as females (M. Mountjoy et al., 2014). Additional statements including the 2018 update and comments from the working group have provided further clarification and information regarding

this emerging syndrome (Ackerman et al., 2020; M. Mountjoy et al., 2018; M. Mountjoy et al., 2015). A 2015 publication on a Clinical Assessment Tool (RED-S CAT) provided practitioners guidelines for diagnosing the syndrome, but the screening aspect of this syndrome has not been well established (M. Mountjoy et al., 2015).

The goal of screening differs from the goal of diagnosing because screening implies the identification of risk factors for a specific nutrition condition, while a nutrition assessment is a step further towards the goal of a diagnosis (Correia, 2018). When considering if an athlete may be at risk for RED-S, screening should be done if deemed appropriate by the sports medicine practitioner. This may be useful in settings such as sports medicine clinics and college or university athletics programs.

The screening and diagnosis of RED-S can be subtle and challenging to uncover, so individuals well versed in the symptomatology should be involved in the screening protocols developed (M. Mountjoy et al., 2014). The shortcomings of currently published screening tools include that there is a lack of consensus on what tool to use and the current tools are limited by lack of validation. Many tools developed focus on either males or females entirely, are not targeted to college athletes and team sports. Additionally, in the population of college athletes, a current gold standard for nutrition screening is not established.

It is well established that practitioners look at menstrual function in female athletes to assess endocrine function. The age of onset menstrual cycle, the state of being eumenorrheic, amenorrhoeic or oligomenorrheic, and frequency of missed cycles are often analyzed when assessing menstruation in female athletes. Functional hypothalamic amenorrhea (FHA) is described by the IOC as “disruption of gonadotropin releasing hormone (GnRH) pulsatility at the

hypothalamus, followed by alterations of LH and follicle stimulating hormone release from the pituitary and decreased estradiol and progesterone levels” and is considered the most severe of menstrual dysfunction requiring intervention (M. Mountjoy et al., 2018). Menstrual disorders such as FHA must be diagnosed by a healthcare professional through a clinical evaluation. The 2014 Female Athlete Triad Coalition Consensus Statement outlines an amenorrhea algorithm to follow if an individual is suspected for primary or secondary amenorrhea, and prolonged oligomenorrhoea with the expertise of a physician or endocrinologist if necessary (De Souza et al., 2014). This algorithm may be useful for practitioners to use when examining athletes who may be suspected of menstrual dysfunction. Related to menstrual function, a study found that higher levels of cortisol have been observed in females with menstrual dysfunction, and can indicate physiological stress during intensive training (D. Logue et al., 2018). In junior elite female swimmers, researchers found that ovarian suppression impaired athletic performance, especially when training occurred when the body was in a state of energy conservation so performance was sacrificed (VanHeest et al., 2014).

While some short-term effects of RED-S have been studied, the long-term health effects are lesser known. In the context of the endocrine system, long-term reproductive health is currently understudied and remains unknown (M. Mountjoy et al., 2014). Reproduction is closely related to EA in relation to survival, so the repercussions of long-term reproductive health should be explored (K. J. Elliott-Sale et al., 2018).

Athletes attending universities and colleges are often 18 to 24 years old, living on their own away from family for the first time, and are required to balance school work and sport obligations. Nutritionally this can be a critical time as growth and development of adolescence is

ending, peak bone mass is reached and fueling demands for college levels sports may increase. These factors relate to energy availability and the importance of meeting nutritional needs for health and performance. Although RED-S and low energy syndromes may be present in college athletes, the current RED-S framework should be critically examined to determine if all 10 health and 10 performance consequences present in this population. Furthermore, the framework should continue to evolve and expand as this syndrome changes over time. This may include considering additional health considerations. This study will examine three additional possible constructs of RED-S: nutrition knowledge, food insecurity, and body image.

A review on nutrition knowledge in athletes highlights the need for future research to use validated tools to measure nutrition knowledge in athletes, and to further solidify the understanding of the relationship between nutrition knowledge and dietary intake (Heaney et al., 2011). Nutrition knowledge has been studied in relation to low EA in female Australian rules football players with results finding low sports nutrition knowledge and a 30% risk of low EA in the 30 athletes studied (Condo et al., 2019). A study on nutrition knowledge in collegiate athletes found poor nutrition knowledge scores $57.6\% \pm 18.6\%$, with the possible impact on performance and injury risk, (Werner et al., 2020). Although nutrition knowledge has not been studied in relation to low energy syndromes like RED-S, assessing nutrition knowledge is an important component of nutrition screening. Baseline nutrition knowledge measurements can aid in the development of team nutrition education with target interventions. This possible relationship should be explored to determine if the two concepts are interrelated.

At this time, food insecurity has not been studied in relation to RED-S. The lack of access to nutritious food, or inadequate means to acquire, prepare and consume food is a substantial barrier to proper nutrition. Food insecurity as a contributing factor to low EA in the athletic population is currently unknown. In the general population, food insecurity may contribute to high or low energy intake dependent on quantity, quality, and the food environment. Although studies for prevalence of food insecurity exist, the relationship between food insecurity and low EA in athletes is not established at this time. Previous research found that food insecurity in college athletes was found to be significantly correlated with hoarding food and being preoccupation with food (Poll et al., 2018). Additionally, food insecurity and lack of finances may also contribute to impaired nutrition in some populations (Burke, Close, et al., 2018). Additionally, in the 2018 IOC Consensus Statement on RED-S, authors state that “cultural, social, psychological, and financial factors contribute to low energy availability” so the food security status and scholarship status in collegiate athletes warrant further investigation (M. Mountjoy et al., 2018).

Body image has been linked to disordered eating and eating disorder behaviors but is not currently included in the RED-S framework. Body image was considered with eating disorder behaviors in elite Icelandic athletes, with 17.9% of the athletes having severe or moderate body image dissatisfaction, and 18.2% of athletes above the clinical cutoff for body image concern, with more women’s scores being higher than the men’s overall (Kristjansdottir et al., 2019). Social media may also play into one’s body image and appearance-related comparisons, which has been looked at in college females (Hendrickse et al., 2017). In college athletes body image may be of concern due to weight pressures from peers, teammates, coaches, fans and other

individuals. The Weight Pressures in Sport (WPS) tool developed for male college athletes has been validated for use for detecting various sources of weight pressures and body image in the college athlete population (Galli et al., 2014; Galli et al., 2011). The WPS tool was developed for male collegiate athletes and the sample included athletes from aesthetic sports such as diving and weight class sports such as wrestling in which body appearance and weight are a focus. Body image is an important component to assess because of the relation to dieting behavior and the psychological component of RED-S that can precede or be a result of RED-S.

A unique aspect of collegiate athletics is the focus on team sports and the subcultures within different institutions and individual teams. It has been speculated that RED-S may occur at an increased rate in high-risk sports, but if all sports including team sports are not included in the body of literature and work, then the prevalence may be unknown. To date, there have been no research publications investigating the incidence of RED-S in team sports highlighting an important need for research efforts (M. L. Mountjoy et al., 2018). At this time, a validated and widely used nutrition screening protocol is not available for college athletes. At the NCAA institutional and university level, screening policies and survey tools utilized are dependent on individual policies developed by sports medicine athletic directors, athletic trainers, and nutrition staff if available.

It is unknown at this time if annual screening for low energy syndromes such as RED-S and the Triad or for eating disorders is conducted routinely at NCAA institutions. The screening and diagnosis of RED-S can be subtle and challenging to uncover, so individuals well versed in

the symptomatology should be involved in the screening protocols developed (M. Mountjoy et al., 2014).

The goal of this research is to determine latent classes of female athletes who may be of nutrition concern related to RED-S. This will be done through a latent class analysis model with various categorical and continuous indicator variables. A variety of measures considered in the traditional framework of RED-S such as bone health, menstruation, disordered eating as well as other measures such as food insecurity and nutrition knowledge may provide insight into individuals of RED-S concern that can be further investigated.

A Latent Class Analysis (LCA model) was introduced as a technique to explore latent classes of individuals in an exploratory manner utilizing an unrestricted model (McCutcheon, 1987). LCA is an explanatory modeling technique that allows for the grouping of individuals with similar characteristics (Mori et al., 2020). The aim of this model is to estimate the probability of each athlete being a member of each latent class. LCA can be a helpful modeling technique that focuses on individuals rather than indicators. Personal behaviors and characteristics are used to determine latent profiles based on similar responses to the indicators and variables of interest (Spurk et al., 2020). The goal is to uncover underlying patterns of shared behavior that are of interest to the researcher.

This technique is especially useful for researchers in social sciences to explore patterns of shared behaviors between samples. These patterns of interest may be missed when individual variable-centered analyses are conducted (Ferguson et al., 2019). Furthermore, LCA can be useful in medical disciplines. Syndromic clinical conditions are frequently reliant on rigid, yet broad definitions. Clinical prediction models are expected to benefit sports medicine practice, but

only if they are properly developed and validated. These models may help guide decision making processes in clinical medicine but are not commonly used in sports medicine (Bullock et al., 2021). A focus on the methodology, specifically model development, model performance, and validation must be considered when conducting prediction research. The goal of this research is to explore the use of such prediction models to uncover latent classes of athletes of RED-S concern.

Research Question

The goal of this study is to detect student-athletes who may be of nutrition-specific health concern related to Relative Energy Deficiency in Sport (RED-S) at the time of pre-participation health evaluations through a latent class analysis predictive model. This study will explore and answer the following question:

1. What conceptual groups exist that distinctly categorize female student-athletes that are of nutrition-specific health concern related to Relative Energy Deficiency in Sport (RED-S)?

The question will be answered through a latent class analysis model that identifies levels of a latent categorical variable through the analysis of observed continuous and categorical variables. The observed variables include measures consistent with the traditional framework of RED-S with the addition of three variables of interest. Eating disorder risk, restrictive diets/dieting, menstruation, bone health, as well as nutrition knowledge, food insecurity, and body image will

be included in this model. This model will examine female student-athletes at a division I college.

The following hypothesis will be tested:

H1: Female student-athletes can be categorized into classes ranging from low nutrition and RED-S concern to high nutrition and RED-S concern using traditional RED-S framework indicators and three additional indicators.

Methods

Study Design

The study is a quantitative cross-sectional study utilizing a web-based survey software to explore nutrition-related health concerns including RED-S through nutrition screening in collegiate athletes. Through a latent class analysis, individuals will be profiled to determine classes of individuals of concern. The data for this study will be generated using Qualtrics software with electronic administration for the Nutrition Screening Survey (Qualtrics Provo, UT, 2021).

Setting

The setting is at a Division I university in the southeast of the United States. Athletes range from 18-24 years old and participate in a variety of team sports. Team sport female athletes will be screened with sports outlined in the table below.

Table 1

Study participants and team sports

n	Sports
---	--------

Female	144	Basketball, Golf, Rifle, Softball, Soccer, Tennis, Track & Field, Volleyball
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Measurement Tools

Nutrition and RED-S components will be measured through a variety of previously published screening tools outlined below. Similar survey methodology was used as a recent study that conducted a cross-sectional study on patients that presented to the Division of Sports Medicine at Boston Children’s Hospital (Ackerman et al., 2019). As mentioned in their publication, due to the lack of a validated or standard measure for RED-S survey measures were based on validated and/or standard questionnaires for each topic as available were used. The measurement tool is included in the Appendix.

Eating disorder and disordered risk will be measured through the Brief Eating Disorder in Athlete Questionnaire (BEDA-Q) screening tool, restrictive dieting, and number of meals consumed per day. The BEDA-Q has been used in adolescent female athletes, but it has not been validated for use in collegiate male and female athletes. Restrictive dieting will be measured through the question: “Are you currently following or have you ever followed any special dietary considerations for personal reasons, diagnosed conditions, or religious reasons? (vegan, vegetarian, gluten free, dairy free, religious fasting, paleo, etc.)” with options including: “Vegetarian” “Semi-Vegetarian” “Vegan” “Gluten-free” “Dairy-free” “Lactose-free” “Paleo” “Ketogenic” “Intermittent Fasting” “Low carb” “Fasting for religious reasons (Ramadan, etc.)”

“Low FOD-MAP.” While the diets mentioned are not necessarily low-energy diets, the purpose is to see if any restrictions may be followed for any reason that may lead to energy restriction if not properly planned. This screening question may provide insight into diets athletes follow for a variety of reasons. Number of meals consumed per day provides insight into if athletes are missing meals and will be assessed through a 24-hour food recall. While a pre-determined number of meals is dependent on individual energy needs, literature has shown that not consuming at least 3 meals per day can be indicative of disordered eating (Adam S Tenforde et al., 2021). With low energy availability (LEA) at the core of RED-S, it is more traditionally measured in a laboratory setting. Through screening forms, it is important to assess possibility of LEA in collegiate athletes through disordered eating behaviors such as skipping meals or following a restrictive diet. Dependent on resources, the diagnosis of LEA may need to follow through more complex equations, body composition testing, and indirect calorimetry testing.

Bone health will be measured through self-reported history of the number of stress fractures and a follow-up question on high-risk sites (sacrum, pelvis, lumbar spine, femoral neck).

Menstrual function will be measured through the age of onset menses, which will be asked through “What age did you get your first period?” and menstrual irregularity which will be asked through “Does your menstrual cycle appear at the same time every month?” to determine if evidence of primary or secondary amenorrhea is present. If amenorrhea is suspected, confirmation through an endocrinologist or OBGYN should follow.

Food insecurity will be measured through the United States Department of Agriculture (USDA) 2-question measure for food insecurity. The two questions include: “Within the past 12

months I was worried whether my food would run out before I got money to buy more” and “Within the past 12 months the food I bought just didn't last and I didn't have money to get more” with answer choices as “often true” “sometimes true” or “never true.” The variable was operationalized through a positive answer to “often true” or “sometimes true” to either question to be coded as food insecure.

Nutrition knowledge will be measured through the Abridged Nutrition for Sport Knowledge Questionnaire (ANSK-Q) tool that assesses general nutrition knowledge as well as sport nutrition knowledge. Items will be scored and individuals will be scored on a range of 0-100 with higher values indicating higher nutrition knowledge.

Weight pressures in sport will be measured through the Weight Pressures in Sport (WPS) tool that was developed to assess weight pressures and body image in male collegiate athletes (Galli et al., 2014; Galli et al., 2011). With no question specific to sex, the tool is appropriate for use in female athletes as well but has yet to be validated in this population. The authors recommend a 6-point Likert scale, but the survey included an extra measure of “neutral” or “neither agree or disagree” increasing the scale to a 7-point Likert scale for athletes that may have not been comfortable answering questions about coaches, peers, or family. To account for this, the data was linearly transformed to convert responses in a weighted manner to match the recommended 6-point scale. The following formula was utilized:

$$Y = (B - A) * (x - a) / (b - a) + A$$

$$Y = (6 - 1) * (x - 1) / (7 - 1) + 1$$

Data Analysis

Data were analyzed through a latent class analysis model (LCA) to determine classes of individuals who may be of heightened nutrition and RED-S concern. This exploratory modeling technique is often utilized in the psychological or health science field as an approach to patient-centered analysis. The LCA technique was introduced in 1987 as a method to determine classes of individuals (McCutcheon, A.C., 1987). Data were analyzed with Mplus software (Muthén, L. K., & Muthén, B. O., 2021). A conceptual map of the model is outlined below with each of the indicator variables with C latent classes.

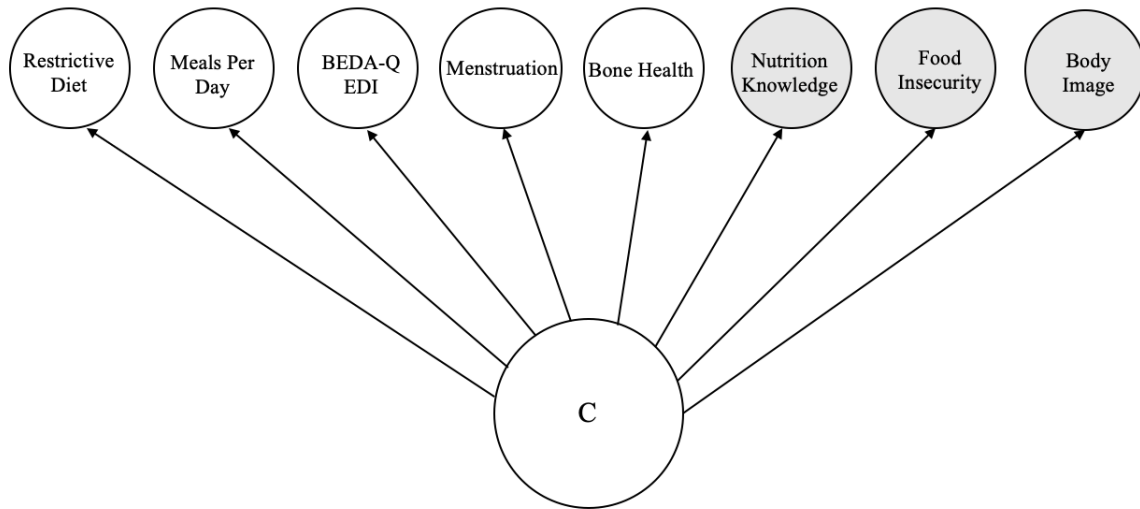


Figure 1: Proposed Latent Class Analysis Model for Collegiate Female Athletes

There are a number of considerations when determining which latent class model that best fits the individuals of interest. If many sampling zeros are present in the dataset, sparseness exists. This differs from structural zeros. If sparseness occurs, it leads to difficulties in model evaluation. Lack of consensus on a general rule of thumb for sample size but it has been established that LCA models are case sensitive and require large sample sizes into the hundreds.

Determining number of classes, also named class enumeration, involves fitting several LCA models with differing numbers of latent classes, collecting fit information for each model, then studying patterns to decide how many classes best describe patterns observed in the data (Nylund-Gibson & Choi, 2018). Information such as goodness of fit statistics can be analyzed to evaluate the model fitness. The Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Sample-size adjusted BIC all are considered for goodness of fit. BIC helps in model selection by penalizing the number of factors, providing insight into the model fit.

The LCA model with the smallest values for AIC, BIC and sample-size adjusted BIC are considered to be the best fitting model. The solution with the largest loglikelihood is considered to be better fitting than a model with lower loglikelihood values.

Lo-Mendell-Rubin Adjusted Likelihood Ratio Test (LMR-LMT) compares models with varying numbers of classes. If $p\text{-value} < 0.05$, the model with one fewer class is a better fit for the data (Lo et al., 2001). If the $p\text{-value} \geq 0.05$, the model would need to be reclassified with fewer classes. The parametric bootstrapping $p\text{-value}$ is also of interest, with a $p\text{ value} \geq 0.05$ indicating that the model needs to be reduced in class size.

Results

The descriptive statistics of the data of interest is in Table 2, providing insight into some variables of interest. The average age for onset of menstruation for the female athletes sampled was 13.26 years old. Nutrition knowledge scores for this population were 38.175, indicating poor knowledge.

Table 2

Descriptive Statistics for Female Participants

	N	Minimum	Maximum	Mean	Std. Deviation	Variance
Restrictive Diet	144	0	1	0.19	0.397	0.158
Number of Meals Per Day	144	1	3	2.83	0.392	0.154
Eating Disorder Inventory (EDI)	144	0	15	4.64	3.148	9.911
Age Onset Menses	144	10	17	13.26	1.491	2.224
Irregular Menstrual Cycle	144	0	1	0.26	0.438	0.192
Stress Fractures	144	0	5	0.26	0.697	0.486
Food Insecurity	144	0	1	0.12	0.324	0.105
Nutrition Knowledge	144	2.857	77.143	38.175	14.735	217.110
Body Image	144	1	4.333	2.126	0.722	0.521

To test the classification of female collegiate athletes, a latent class analysis was run on 144 participants. The number of optimal classes in the data set are determined by the researcher based on a number of criteria. The best fitting LCA model is determined based on fit statistics such as Bayesian Information Criterion (BIC), adjusted BIC, and Akaike Information Criterion

(AIC), as well as interpretability, and non-information-criterion such as the Lo-Mendell-Rubin fit index, Vuong-Lo-Mendell-Rubin (VLMR), and the Bootstrapped likelihood ratio test (BLRT).

The following fit information for the two- and three-class models is included in Table 3:

Table 3

Latent class analysis model fit criteria

Model	Number of classes	Loglikelihood	Entropy	AIC	BIC	Adjusted BIC	Number of free parameters	VLMR	Lo-Mendell-Rubin Bootstrapped LRT	BLRT
1	2	-1770.732	0.851	3591.464	3665.709	3586.603	25	0.6764	0.6764	0.000*
2	3	-1570.654	1.000	3211.309	3315.252	3204.503	35	0.7858	0.7858	0.000*

Note. * $p < .05$

Akaike information criterion (AIC)

Bayesian information criterion (BIC)

Vuong-Lo-Mendell-Rubin (VLMR)

Likelihood ratio test (LRT)

Bootstrapped likelihood ratio test (BLRT)

The analysis provided information regarding two and three-class models that emerged from the data. The first model provided insight into profiling female student-athletes into a two-class solution with no errors. The three-class solution provided model fit information, but class enumeration was not trustworthy due to a higher-class size and model error. The three-class model showed poor absolute model fit and poor relative fit. The two-class model identified the following counts for the latent classes based on the estimated model:

Table 4

Two-class latent class assignment results

Latent Class	Number of individuals	Percentage of individuals
1	23	15.972%
2	121	84.028%

The three-class model identified the following counts for the latent classes based on the estimated model:

Table 5

Three-class latent class assignment results

Latent Class	Number of individuals	Percentage of individuals
1	23	15.972%
2	115	79.861%
3	6	4.167%

Fit Indices

A practitioner’s guide was utilized to examine the following information of fit indices, model testing, and model characteristics (Sinha et al., 2020). When analyzing a latent class analysis for fit indices, several considerations should be looked at. For smaller sample sizes of less than 300, both Akaike information criteria (AIC) and Bayesian information criteria (BIC) should be considered. A decreasing value indicates better model fit. Through the fit statistics table, Table 3, AIC and BIC are an index of model fit, balance the complexity of the model against the sample size.

Model Testing

Comparing models with varying classes is also an important consideration for LCA. The VLMR test compares a model with k classes to one with $k-1$ classes. If the p -value is greater than 0.05, like in this circumstance, clinical relevance may be worth considering. Additionally, the Lo-Mendel-Rubin test and BLMR can be considered.

Model Characteristics

Number of classes, class size, and separation are considered with looking at LCA model characteristics. Entropy is a measure of class separation between the latent classes with values above 0.80 considered a good fit. Table 3 provides two and three-class model values, but it is important to consider that higher values do not necessarily mean that a model is the best fit and may indicate an overfit model. The two-class model provides an acceptable value. When considering the number of classes and class size, a small class size of less than 15% of the sample is a concern. The two-class model revealed a class size just above that value. If a class contains less than 15%, it is possible whether outliers of a single indicator may be determining the class. In the three-class model, the smaller classes are less likely to be externally generalizable than models with fewer, well-distributed classes and the classes contain less than 10% of the sample which is indicative of a poor fit.

Class Characteristics

Tables 6 through 9 provide insight into the two- and three-class models. The results in probability scale tables outline the categorical variables of interest in the model and the model results table outlines the continuous variables. The results of the table do not provide distinction between classes two and three on a variable level. If variables distinctly were consistent between

groups, then there would be shared characteristics in the participants. While latent class 1 in the two-class model had high reported restrictive dieting, disordered eating, stress fractures, and body image concern, with low nutrition knowledge scores; there was not a clear distinction into the other group.

Table 6

Results in probability scale two-class latent class female model

Latent Class 1	Estimate	Standard Error	Estimate/Standard Error	P-Value
Restrictive Diet				
Category 1	0.812	0.124	6.559	0.000
Category 2	0.188	0.124	1.517	0.129
Irregular Menses				
Category 1	0.664	0.394	2.261	0.024
Category 2	0.336	0.294	1.142	0.253
Food Insecurity				
Category 1	0.623	0.127	4.923	0.000
Category 2	0.377	0.127	2.978	0.003
Latent Class 2	Estimate	Standard Error	Estimate/Standard Error	P-Value

Restrictive Diet				
Category 1	0.804	0.042	19.376	0.000
Category 2	0.196	0.042	4.718	0.000
Irregular Menses	Estimate	Standard Error	Estimate/Standard Error	P-Value
Category 1	0.759	0.080	9.515	0.000
Category 2	0.241	0.080	3.017	0.003
Food Insecurity	Estimate	Standard Error	Estimate/Standard Error	P-Value
Category 1	0.925	0.047	19.909	0.000
Category 2	0.065	0.047	1.378	0.168

Table 7

Model results two-class latent class female model

Latent Class 1	Estimate	Standard Error	Estimate/Standard Error	P-Value
Means				
Meals Per Day	2.549	0.254	10.027	0.000
BEDAQ EDI	8.551	6.180	1.384	0.166
Age Menses	12.350	0.400	30.873	0.000

Stress Fractures	0.050	0.049	1.033	0.307
Nutrition Knowledge	34.873	3.614	9.649	0.000
Body Image	3.087	0.376	8.216	0.000
<hr/>				
Variances				
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Meals Per Day	0.136	0.029	4.777	0.000
BEDAQ EDI	6.690	6.468	1.034	0.301
Age Menses	2.036	0.366	5.561	0.000
Stress Fractures	0.474	0.176	2.697	0.007
Nutrition Knowledge	213.357	22.038	9.681	0.000
Body Image	0.327	0.304	1.076	0.282
<hr/>				
Latent Class 2	Estimate	Standard Error	Estimate/Standard Error	P-Value
<hr/>				
Means				
<hr/>				
Meals Per Day	2.892	0.039	74.767	0.000
BEDAQ EDI	3.833	0.450	8.525	0.000
Age Menses	13.452	0.271	49.709	0.000
Stress Fractures	0.300	0.078	3.845	0.000

Nutrition Knowledge	38.855	1.767	21.993	0.000
Body Image	1.927	0.267	7.217	0.000
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Variances				
<hr/>				
Meals Per Day	0.136	0.029	4.777	0.000
BEDAQ EDI	6.690	6.468	1.034	0.301
Age Menses	2.036	0.366	5.561	0.000
Stress Fractures	0.474	0.176	2.697	0.007
Nutrition Knowledge	213.357	22.038	9.681	0.000
Body Image	0.327	0.304	1.076	0.282
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Table 8

Results in probability scale three-class latent class female model

Latent Class 1	Estimate	Standard Error	Estimate/Standard Error	P-Value
Restrictive Diet				
Category 1	0.826	0.079	10.452	0.000
Category 2	0.174	0.079	2.200	0.028

Irregular Menses	Estimate	Standard Error	Estimate/Standard Error	P-Value
Category 1	0.652	0.099	6.567	0.000
Category 2	0.348	0.099	3.502	0.000
Food Insecurity	Estimate	Standard Error	Estimate/Standard Error	P-Value
Category 1	0.826	0.079	10.452	0.000
Category 2	0.174	0.079	2.200	0.028
Latent Class 2 Restrictive Diet	Estimate	Standard Error	Estimate/Standard Error	P-Value
Category 1	0.800	0.037	21.449	0.000
Category 2	0.200	0.037	5.362	0.000
Irregular Menses	Estimate	Standard Error	Estimate/Standard Error	P-Value
Category 1	0.765	0.040	19.360	0.000
Category 2	0.235	0.040	5.362	0.000
Food Insecurity	Estimate	Standard Error	Estimate/Standard Error	P-Value
Category 1	0.887	0.030	30.040	0.000

Category 2	0.113	0.030	3.828	0.000
Latent Class 3	Estimate	Standard Error	Estimate/Standard Error	P-Value
Restrictive Diet				
Category 1	0.833	0.153	5.452	0.000
Category 2	0.167	0.153	1.092	0.275
Irregular Menses	Estimate	Standard Error	Estimate/Standard Error	P-Value
Category 1	0.667	0.192	3.472	0.001
Category 2	0.333	0.192	1.733	0.083
Food Insecurity	Estimate	Standard Error	Estimate/Standard Error	P-Value
Category 1	1.000	0.000	0.000	1.000
Category 2	0.000	0.000	0.000	1.000

Table 9

Model results three-class latent class female model

Latent Class 1	Estimate	Standard Error	Estimate/Standard Error	P-Value
Means				
Meals Per Day	1.957	0.043	46.011	0.000

BEDAQ EDI	5.174	0.614	8.429	0.000
Age Menses	12.652	0.279	45.327	0.000
Stress Fractures	0.000	0.000	-3.038	0.002
Nutrition Knowledge	33.168	2.954	11.228	0.000
Body Image	2.286	0.150	15.212	0.000
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Variances				
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Meals Per Day	0.007	0.006	1.076	0.282
BEDAQ EDI	9.541	1.372	6.953	0.000
Age Menses	2.064	0.241	8.551	0.000
Stress Fractures	0.152	0.034	4.433	0.000
Nutrition Knowledge	210.067	21.325	9.851	0.000
Body Image	0.508	0.069	7.373	0.000
<hr/>				
Latent Class 2	Estimate	Standard Error	Estimate/Standard Error	P-Value
Means				
<hr/>				
Meals Per Day	3.000	0.000	*****	0.000
BEDAQ EDI	4.661	0.296	15.753	0.000

Age Menses	13.313	0.135	98.271	0.000
Stress Fractures	0.165	0.035	4.758	0.000
Nutrition Knowledge	38.908	1.358	28.654	0.000
Body Image	2.111	0.067	31.375	0.000

Variances

Meals Per Day	0.007	0.006	1.076	0.282
BEDAQ EDI	9.541	1.372	6.953	0.000
Age Menses	2.064	0.241	8.551	0.000
Stress Fractures	0.152	0.034	4.433	0.000
Nutrition Knowledge	210.067	21.325	9.851	0.000
Body Image	0.508	0.069	7.373	0.000

Latent Class 3	Estimate	Standard Error	Estimate/Standard Error	P-Value
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Means

Meals Per Day	3.000	0.000	*****	0.000
BEDAQ EDI	2.166	0.684	3.122	0.002
Age Menses	14.677	0.610	24.040	0.000

Stress Fractures	3.001	0.412	7.262	0.000
Nutrition Knowledge	43.318	5.965	7.262	0.000
Body Image	1.787	0.196	9.101	0.000
<hr/>				
Variances				
<hr/>				
Meals Per Day	0.007	0.006	1.076	0.282
BEDAQ EDI	9.541	1.372	6.953	0.000
Age Menses	2.064	0.241	8.551	0.000
Stress Fractures	0.152	0.034	4.433	0.000
Nutrition Knowledge	210.067	21.325	9.851	0.000
Body Image	0.508	0.069	7.373	0.000

Note. ***** indicates that the estimate/standard error value was not computed.

When a one-class model was conducted, few model characteristic statistics are provided by the statistical software Mplus. Fit indices for a one-class model include an AIC of 3639.257, a BIC of 3683.804, and an adjusted BIC of 3636.340. For the one-class model compared to the two-class model, AIC is higher, BIC is higher, and Adjusted BIC is higher. The values are close, but the two-class model performs better for these values. Other considerations include that sample size of female athletes included in the model is into the hundreds, but is low for LCA and there is some difficulty in interpreting the overall model fit criteria. Due to limited theory for this

population, given the current model there is some evidence to show that a two-class solution is better than a one-class solution. Therefore, H1 is supported and the null hypothesis can be rejected.

Discussion

Main Findings

This study aimed to profile female student-athletes in collegiate athletics for nutrition and RED-S concern. Categorical and continuous indicators consistent with the RED-S framework and new considerations such as food insecurity, nutrition knowledge, and body image were included in the model with the goal of uncovering an unknown latent variable of classes. At a Division I university, 144 female student-athletes completed a pre-participation physical evaluation that included a cross-sectional nutrition screening survey. Data from the evaluation was utilized in a latent class analysis predictive model. RED-S is an emerging syndrome with few studies in the population of team sport athletes and collegiate athletes.

Descriptive statistics outlined in Table 1 provide some insight into the indicators of interest. For females, the mean age of onset menses was 13.26 ± 1.491 with a range of age 10 to 17. The mean nutrition knowledge score was 38.175 ± 14.735 , indicating poor nutrition knowledge. The results of the statistical analysis provide information to support a two-class model solution to profile the athletes of interest into separate latent classes.

Energy Availability

With consideration to previous RED-S research and the goal of screening, energy availability has been typically assessed through disordered eating and eating disorder risk. At this time no validated tool has been specifically designed for the collegiate athlete population, with

very few available for the female athlete population. The BEDA-Q tool has been utilized in the female athlete population, specifically for adolescents, when screening for disordered eating related to RED-S. This tool was utilized in this study due to the short length of the questionnaire and the ease of distribution without the need for an interview, which is common in disordered eating and eating disorder screening tools. When considering disordered eating risk, other surrogate markers were also considered due to the lack of energy availability measurements in a laboratory setting and the lack of validated tools for the college population. Number of meals per day and restrictive dieting were also considered to also consider low energy availability.

Clinical Application

A main consideration of this topic is the complexity of RED-S and the difficulty of screening athletes for a syndrome when limited tools exist for athletes of consideration that have not been typically studied. College athletes that are not considered traditionally high risk are often overlooked in the research. The questions that still stands at this time is does the traditional RED-S framework apply to athletes outside of high-risk classification. Additionally, what additional factors beyond the traditional framework may contribute to RED-S and low energy syndromes and which of them may be specific to college athletes. Food insecurity, body image, and nutrition knowledge were included in the LCA model to expand beyond the traditional framework. As research evolves, the conceptual model for RED-S may change. An aim of this study was to explore RED-S and low energy syndromes in a new population: non-high risk collegiate athletes. Some findings were of interest beyond the LCA profiling.

Of the 144 female athletes included in the study, 19.4% followed a restrictive diet, 16.7% reported eating less than 3 meals per day, 20.2% reported starting their menstrual cycle at or after

age 15, 25.7% had an irregular menstrual cycle, 17.4% reported at least one stress fracture, 11.8% had food insecurity, and 77.1% scored less than a 50 out of 100 on nutrition knowledge. From the reported frequencies, it is important to note that many of the athletes have nutrition and RED-S related issues of concern that need clinical consideration and further investigation through consultations and referrals.

Specific to the statistical modeling technique, LCA has been previously utilized in the healthcare setting as a clinical tool. Predictive modeling techniques as well as machine learning have potential to assist clinicians. This exploratory study highlights a number of clinical considerations and offers a starting point for others in the field to explore LCA and predictive modeling techniques to explore RED-S.

Class Characteristics

In Tables 6 through 9, individual characteristics based on the indicator variables included in the model did not clearly define class characteristics. This provides insight into the indicator variables. A future model may consider using different tools to measure some of the RED-S variables of interest. Additionally, for the variable meals per day, the estimate/standard error value was not computed. This indicates model disruption at the three-class level. This may indicate that the value could not be estimated due to the variable being similar across participants. While some validated tools currently exist for female athletes, there is still a need for high-quality validated tools for the college athlete population. This research provides a starting point for other researchers to consider utilizing predictive modeling for RED-S and highlights the need for more research.

Other Considerations

When a researcher is considering model fit and the number of classes for a population of interest, their expertise regarding clinical insight is important. Classes should be separate from a clinical standpoint through the discretion of the researcher. To prevent bias, the best fitting model should be determined before linking the variables of interest to the classes identified. It is possible that a 1-class model may be the best fit for a population and latent classes may not be possible to distinguish using the indicators selected. As LCA is utilized in varying disciplines, the application of LCA algorithms will evolve through understanding best conditions, interpreting the information to the field, and clinical investigation.

There is evidence of poor model fit for the three-class solution due to two errors that occurred. First, one or more logit thresholds approached extreme values of -15.000 and 15.000 and were fixed to stabilize model estimation. This resulted in parameters with 0 standard errors and unknown z-score and p-values. Second, the standard errors of the model parameter estimates may not be trustworthy for some parameters due to a non-positive definite first-order derivative product matrix. This may be indicative of model nonidentification. This is likely due to poor class enumeration with a higher class number. The sample size is likely the culprit for this model. There are no guidelines for calculating sample size requirement *a priori* with recommendations suggesting the larger the better, and into the hundreds. Smaller sample sizes may perform well for estimating two-classes as long as the indicators are of high quality. There is a suggestion that a three-class model may require up to 12 high quality indicators to perform well if the sample size is under 200 (Wurpts, 2012). If indicators are of low quality, sample size is recommended to be at least $N = 500$ for 12, and if $N = 1000$ if there are 6 low quality indicators. Some possible recommendations if working with a smaller sample size is to include a

higher number and quality of indicators and adding a covariate. Sample size may be limited in a university setting with a range of athletes depending on athletic conference, division, and school funding and size.

Another consideration for LCA is zero variances. Due to data sparseness with the BEDA-Q disordered eating indicator, an alternate value from the tool was used. The EDI sum of 6 values was used in place of a binary, yes or no classification to reduce data sparseness and to raise variance values away from zero. The BEDA-Q may need to be reconsidered for use in the college athletic population because it at this time has only been validated in adolescent female athletes. Results from the BEDA-Q tool include that only one athlete screened positive for eating disorder risk, leading to a close to zero variance in the data set. This presents valuable information that highlights a need for screening tools specific to male athletes and college athletes and a validated tool specific to this population. Future research efforts should ensure the model has few missing values relative to sample size and the sample size is large enough for indicators of interest.

The main consideration at this time is the lack of validated nutrition screening surveys for the collegiate athlete population. While some RED-S surveys may be in progress, at this time there is a need for comprehensive nutrition screening tools with a focus on RED-S to be created specific to this population. Utilizing a validated screening tool with a LCA approach may have resulted in a model with more use of interpretation. This exploratory approach of LCA modeling may provide health care practitioners valuable information in the future if the measures are reliable and validated for the population of interest.

Strengths and Limitations

A strength of this study is that it provided insight into a predictive modeling technique to identify classes of athletes who may be of nutrition and RED-S concern. This technique may prove to be useful in the future to provide sports medicine practitioners and sports dietitians information. This would ideally be used in the first step of a treatment plan to then move forward with additional diagnostic tests such as the DEXA, bloodwork, body composition testing, and additional consultations and interviews to make the diagnosis of RED-S. This would be helpful in settings with limited sports medicine staff or high patient loads where each individual may not be able to be diagnostically tested. As previously mentioned, the goal of screening differs from the goal of diagnosing. All the individuals screened for RED-S may not present with diagnostic criteria for RED-S, but the opposite end of the spectrum of flagging athletes of concern prior to detrimental outcomes is worth the time and effort.

A predictive screening approach is proactive in nature rather than the reactive approach of treating individuals when they present with RED-S symptoms. Ultimately this approach may flag individuals of concern before decremental health and psychological outcomes appear such as stress fractures. With athlete health and wellbeing in mind, practitioners should consider predictive model screening as a piece of their healthcare practice. Another strength of this study is that it is one of the few studies that explores RED-S screening and the first study to do so in the collegiate setting.

A limitation of this study is that it is a cross-sectional study so athletes are only measured at one point in time. Using screening data from incoming and returning athletes at the time of pre-participation physicals does not account for athletes who may present with nutrition concerns or RED-S throughout the duration of the academic year. A possible solution is multiple time

points of screening which could then be used in a longitudinal LCA model. It is necessary to have practitioners well-versed in RED-S symptomology to be diligent about detecting behaviors of concern and impaired health outcomes related to the syndrome. Another limitation is the sample size. Future research should consider high sample sizes when utilizing LCA. Finally, the study just examined the energy intake portion of EA due to the lack of tools available to capture energy expenditure through survey or screening tools.

Conclusion

This research provided insight into a predictive modeling technique for a complex syndrome in female collegiate athletes. The bulk of RED-S research is conducted on female athletes, but few studies exist in the collegiate population. Additionally, predictive modeling has not been utilized for this syndrome. This person-centered approach is exploratory in nature and differs from most clustering techniques. This profiling technique differs from traditional screening methodology. The evidence is premature to determine how this person-centered approach of LCA will aid in the detection, prevention, and care of athletes. As further research emerges, more insight may lead to the impact of athlete care through preventative measures.

The goal of this research was to employ an exploratory and predictive modeling technique to profile athletes at risk for nutrition and RED-S concern. A two-class model was determined the best fit to uncover classes of individuals of concern. It was difficult to explore the class characteristics related to the indicator variables. With more accurate and validated tools, this modeling technique may provide insight into a cost-effective and timely technique to identify individuals of concern at pre-participation evaluations. Additionally, screening information from multiple universities or universities with larger student-athlete populations may

provide a more stable LCA model to allow for higher class enumeration. Nutrition and RED-S screening should be the first step before diagnosis to allow for the allocation of time and resources to athletes of identified concern. Future studies should consider sport specific surveys due to differing dynamics in individual and team sports. In the collegiate setting, a RED-S screening tool and eventually a RED-S diagnostic tool with consideration to female and team sport athletes is of high importance. Overall, this predictive modeling technique provides some insight into individual athletes who may need to be monitored and evaluated for RED-S. It is important to note that many of the athletes have nutrition and RED-S related issues of concern that need clinical consideration and further investigation through consultations and referrals through the reported frequencies. Three additional indicators of RED-S were included in the model, providing additional considerations beyond the RED-S framework. As research emerges, the RED-S framework may need to be restructured but further studies should examine food insecurity, nutrition knowledge, and body image and RED-S. At this time, a validated screening tool and RED-S protocol for distribution is of high importance in the collegiate setting but until one is validated, predictive modeling through models such as LCA may provide insight to best detect athletes of RED-S concern.

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APPENDIX

Summary of screening measures for female student-athletes

BEDA-Q	Dietary Practices	Meals Per Day	Bone Health	Menstruation	ANSK-Q	Food Insecurity	WPS
EDI							
I feel extremely guilty after overeating ^a	Are you currently following or have you ever followed any special dietary considerations for personal reasons, diagnosed conditions, or religious reasons? ^b	Please list your food intake for the past 24 hours in each of the categories. Do your best to estimate the amounts (i.e. one handful, one fistful), quantity of food items, if you prepared it at home or out (and list restaurant) and as specific as possible. ^c	Have you ever had a stress fracture? ^b	How old were you when you first menstruated? ^e	Full questionnaire in Appendix	Within the past 12 months I was worried whether my food would run out before I got money to buy more. ^f	In the past year, my coach places an emphasis on team members' weight ^g
I am preoccupied with the desire to be thinner ^a	Options:		How many stress fractures have you had? ^d	Is your menstrual cycle currently regular (period at the same time every month)? ^b			In the past year, my coach encourages athletes to gain muscle mass ^g
I think that my stomach is too big ^a	Options:		What was the site of your stress fracture(s)?				Weigh-ins are held periodically throughout the season ^g
I feel satisfied with the shape of my body ^a	Vegetarian, Semi-		Options: Lumbar spine			Within the past 12 months the food I bought just didn't last and I didn't have money to get more. ^f	Body weight and appearance are important to my coach ^g
My parents have expected excellence of me ^a	Vegetarian, Vegan, Gluten-free, Dairy-free,		Femoral neck Sacrum Pelvis				My teammates notice if I put on weight ^g
As a child, I tried very hard to avoid disappointing my parents and teachers ^a	Lactose-free, Paleo, Ketogenic, Intermittent Fasting, Low carb, Fasting for religious reasons (Ramadan, etc.), Low FOD-MAP						Any of my body flaws are readily apparent in my uniform ^g
							The crowd scrutinizes my body and makes me concerned about my weight and appearance ^g
							In the past year, have you lost weight to meet image requirements for your sport? ^g
							In the past year, have you ever ate in secret? ^g
							Body weight and appearance are important to my friends outside of sport ^g
							Body weight and appearance are

important to my
family^g

The leanest athletes
are at a distinct
performance
advantage^g

Note.

Brief Eating Disorder in Athletes Questionnaire (BEDA-Q)
Abridged Nutrition for Sport Knowledge Questionnaire (A-NSKQ)
Weight Pressures in Sport (WPS)

^aAnswer choices: always, usually, sometimes, often, never

^bAnswer choices: yes, no

^cAnswer choices: Breakfast, Lunch, Dinner, Snacks, Beverages

^dAnswer choices: 1, 2, 3, 4, 5, >5

^eAnswer choices: <10, 10, 11, 12, 13, 14, 15, 16, >16

^fAnswer choices: often true, sometimes true, never true

^gAnswer choices: always, usually, often, sometimes, rarely, never

Latent Class Analysis Syntax

Title:

Dissertation Female New Model LCA;

Variable:

```
names = RESdiet Meals BEDAQEDI Agemens  
Irrmens SF FoodIns ANSKQ WPS;  
usevariables = RESdiet Meals BEDAQEDI  
Agemens Irrmens SF FoodIns ANSKQ WPS;  
categorical = RESdiet Irrmens FoodIns;  
classes = c(3);
```

Analysis:

```
type = mixture;  
STARTS = 0;  
LRTSTARTS = 0 0 300 20;
```

Savedata:

```
file = Female_Model_Mplus_save_test.txt;  
save = cprob;  
format = free;
```

Output:

```
tech11 tech14;
```


CHAPTER V
MANUSCRIPT II
A LATENT CLASS ANALYSIS OF MALE COLLEGIATE ATHLETES OF NUTRITION
AND RED-S CONCERN

To be submitted to the Journal of American College Health

Abstract

Relative Energy Deficiency in Sport (RED-S) has been expanded upon creation in 2014 to include a variety of ages and athletes. The traditional female athlete triad was expanded to include male athletes in the RED-S definition as well. Research on the male athlete population needs further investigation. The goal of this cross-sectional research was to use a Latent Class Analysis (LCA) predictive modeling approach to determine classes of male collegiate athletes who present with nutrition and RED-S concern. At a Division I university, 72 male athletes competing in various team sports completed a pre- participation nutrition screening survey. Measures such as bone health, disordered eating, restrictive diets, food insecurity, body image, and nutrition knowledge were collected. At this time, there is a lack of evidence presented to support that male athletes can be profiled into a two-class solution. In order to provide practitioners and sports dietitians insight into profiling athletes who may be at risk for low energy syndromes, larger samples of male athletes should be collected when utilizing LCA.

Future research should consider large sample sizes of athletes to conduct predictive modeling techniques along with high quality, validated measurement tools. This research highlights the need for more research on low energy syndromes in male collegiate team sport athletes.

Keywords: Relative Energy Deficiency in Sport (RED-S), Collegiate Athletes, Nutrition Screening, Latent Class Analysis

Main Text Introduction

The National Collegiate Athletic Association (NCAA) is comprised of 1,098 colleges and universities, 102 athletics conferences, nearly 500,000 college athletes on 19,886 teams in 24 sports across 3 divisions (NCAA, 2021). Student-athletes participating in NCAA athletics in the United States receive academic support, medical care, access to coaching, facilities, and equipment at their respective university. Annually, NCAA schools award nearly \$3.5 billion dollars in athletic scholarships with some Division I schools offering additional funds to cover costs not covered by a scholarship. NCAA Division I and II schools can provide unlimited meals to support the nutritional needs of student-athletes, but only some schools have registered dietitians (RD), nutritionists, and other health professionals designated to work with athletes. A study found that nutrition education from a registered dietitian improved energy intake, macronutrient intake, and nutrition knowledge in 11 NCAA Division I female volleyball athletes (Valliant et al., 2012).

When energy availability and fueling demands for sport are not met, a syndrome called Relative Energy Deficiency in Sport (RED-S) can occur. The syndrome was introduced by the

International Olympic Committee (IOC) as a “broader, more comprehensive term” in 2014 to describe the previously known low energy condition of the Female Athlete Triad (M. Mountjoy et al., 2014). Various health systems such as bone health, menstrual function, and others along with performance parameters may be affected by this syndrome. A publication on male athletes and RED-S suggested looking at additional factors that may be contributing to RED-S beyond just those for females (Burke, Close, et al., 2018). Male athletes are more likely to suffer from disordered eating compared to non-athletes (Chapman & Woodman, 2016).

Athletes attending universities and colleges are often 18 to 24 years old, living on their own away from family for the first time, and are required to balance school work and sport obligations. Nutritionally this can be a critical time as growth and development of adolescence is ending, peak bone mass is reached, and fueling demands for college levels sports may increase. These factors relate to energy availability and the importance of meeting nutritional needs for health and performance. Although RED-S and low energy syndromes may be present in college athletes, the current RED-S framework should be critically examined to determine if all 10 health and 10 performance consequences present in this population. Furthermore, the framework should continue to evolve and expand as this syndrome changes over time. This may include considering additional health considerations. This study will examine three additional possible constructs of RED-S: nutrition knowledge, food insecurity, and body image.

A review on nutrition knowledge in athletes highlights the need for future research to use validated tools to measure nutrition knowledge in athletes, and to further solidify the understanding of the relationship between nutrition knowledge and dietary intake (Heaney et al., 2011). Nutrition knowledge has been studied in relation to low EA in female Australian rules

football players with results finding low sports nutrition knowledge and a 30% risk of low EA in the 30 athletes studied (Condo et al., 2019). A study on nutrition knowledge in collegiate athletes found poor nutrition knowledge scores $57.6\% \pm 18.6\%$, with the possible impact on performance and injury risk, (Werner et al., 2020). Although nutrition knowledge has not been studied in relation to low energy syndromes like RED-S, assessing nutrition knowledge is an important component of nutrition screening. Baseline nutrition knowledge measurements can aid in the development of team nutrition education with target interventions. This possible relationship should be explored to determine if the two concepts are interrelated.

At this time, food insecurity has not been studied in relation to RED-S. The lack of access to nutritious food, or inadequate means to acquire, prepare and consume food is a substantial barrier to proper nutrition. Food insecurity as a contributing factor to low EA in the athletic population is currently unknown. One study found that food insecurity in college athletes was found to be significantly correlated with hoarding food and being preoccupation with food (Poll et al., 2018). Additionally, food insecurity and lack of finances may also contribute to impaired nutrition in some populations (Burke, Close, et al., 2018). Additionally, in the 2018 IOC Consensus Statement on RED-S, authors state that “cultural, social, psychological, and financial factors contribute to low energy availability” so the food security status and scholarship status in collegiate athletes warrant further investigation (M. Mountjoy et al., 2018).

Body image has been linked to disordered eating and eating disorder behaviors but is not currently included in the RED-S framework. Body image was considered with eating disorder behaviors in elite Icelandic athletes, with 17.9% of the athletes having severe or moderate body image dissatisfaction, and 18.2% of athletes above the clinical cutoff for body image concern,

with more women's scores being higher than the men's overall (Kristjansdottir et al., 2019). Social media may also play into one's body image and appearance-related comparisons, which has been looked at in college females (Hendrickse et al., 2017). In college athletes body image may be of concern due to weight pressures from peers, teammates, coaches, fans and other individuals. The Weight Pressures in Sport (WPS) tool developed for male college athletes has been validated for use for detecting various sources of weight pressures and body image in the college athlete population (Galli et al., 2014; Galli et al., 2011). The WPS tool was developed for male collegiate athletes and the sample included athletes from aesthetic sports such as diving and weight class sports such as wrestling in which body appearance and weight are a focus. Body image is an important component to assess because of the relation to dieting behavior and the psychological component of RED-S that can precede or be a result of RED-S.

A unique aspect of collegiate athletics is the focus on team sports and the subcultures within different institutions and individual teams. It has been speculated that RED-S may occur at an increased rate in high-risk sports, but if all sports including team sports are not included in the body of literature and work, then the prevalence may be unknown. To date, there have been no research publications investigating the incidence of RED-S in team sports highlighting an important need for research efforts (M. L. Mountjoy et al., 2018).

At this time, a validated and widely used nutrition screening protocol is not available for college athletes. At the NCAA institutional and university level, screening policies and survey tools utilized are dependent on individual policies developed by sports medicine athletic directors, athletic trainers, and nutrition staff if available.

It is unknown at this time if annual screening for low energy syndromes such as RED-S and the Triad or for eating disorders is conducted routinely at NCAA institutions. The screening and diagnosis of RED-S can be subtle and challenging to uncover, so individuals well versed in the symptomatology should be involved in the screening protocols developed (M. Mountjoy et al., 2014). The shortcomings of currently published screening tools include that there is a lack of consensus on what tool to use and the current tools are limited by lack of validation. Many tools developed focus on either males or females entirely, are not targeted to college athletes and team sports. A narrative review on low EA published in 2020 highlights the need for sport and sex-specific screening tools to identify athletes participating in a variety of sports at risk of RED-S (D. M. Logue et al., 2020).

A Latent Class Analysis (LCA model) was introduced as a technique to explore latent classes of individuals in an exploratory manner utilizing a unrestricted model (McCutcheon, 1987). LCA is an explanatory modeling technique that allows for the grouping of individuals with similar characteristics (Mori et al., 2020). The aim of this model is to estimate the probability of each athlete being a member of each latent class. LCA can be a helpful modeling technique that focuses on individuals rather than indicators. Personal behaviors and characteristics are used to determine latent profiles based on similar responses to the indicators and variables of interest (Spurk et al., 2020). The goal is to uncover underlying patterns of shared behavior that are of interest to the researcher.

This technique is especially useful for researchers in social sciences to explore patterns of shared behaviors between samples. These patterns of interest may be missed when individual variable-centered analyses are conducted (Ferguson et al., 2019). Furthermore, LCA can be useful in medical disciplines. Syndromic clinical conditions are frequently reliant on rigid, yet

broad definitions. Clinical prediction models are expected to benefit sports medicine practice, but only if they are properly developed and validated. These models may help guide decision making processes in clinical medicine but are not commonly used in sports medicine (Bullock et al., 2021). A focus on the methodology, specifically model development, model performance, and validation must be considered when conducting prediction research.

Research Question

The goal of this study is to detect student-athletes who may be of nutrition-specific health concern related to Relative Energy Deficiency in Sport (RED-S) at the time of pre-participation health evaluations through a latent class analysis predictive model. This study seeks to explore and answer the following question:

1. What conceptual groups exist that distinctly categorize male student-athletes that are of nutrition-specific health concern related to Relative Energy Deficiency in Sport (RED-S)?

This question will be answered through a latent class analysis model that identifies levels of a latent categorical variable through the analysis of observed continuous and categorical variables. The observed variables include measures consistent with the traditional framework of RED-S for male athletes such as disordered eating, restrictive diets/dieting, and bone health, will be included in this model. Along with the traditional indicators, three additional measures will be considered. Food insecurity, nutrition knowledge, and body image will be included in the model to explore how the RED-S framework can evolve in the future with additional research efforts.

The following hypothesis will be tested:

H1: *Male student-athletes can be categorized into classes ranging from low nutrition and RED-S concern to high nutrition and RED-S concern using traditional RED-S framework indicators and three additional new indicators.*

Materials and Methods

Study Design

This study is a quantitative cross-sectional study utilizing a web-based survey software to explore nutrition-related health concerns including RED-S through nutrition screening in collegiate athletes. Through a latent class analysis, individuals will be profiled to determine classes of individuals of concern. The data for this study will be generated using Qualtrics software with electronic administration for the Nutrition Screening Survey (Qualtrics Provo, UT, 2021).

Setting

The setting is at a Division I university in the southeast of the United States. Athletes range from 18-24 years old and participate in a variety of team sports. Team sport female athletes will be screened with sports outlined in the table below.

Table 1

Study participants and team sports

	n	Sports
Male	72	Baseball, Basketball, Tennis, Track & Field

Measurement Tools

Due to the lack of consensus on RED-S screening tools, no current validated screening tools for this population, and the subtle nature of low energy syndromes and how they may be detected through screening forms, no current tool was available for use. Various nutrition and RED-S components will be measured through a variety of previously published screening tools outlined below. Similar survey methodology was used, with reference to a recent study that conducted a cross-sectional study on patients that presented to the Division of Sports Medicine at Boston Children's Hospital (Ackerman et al., 2019). As mentioned in their study, due to the lack of a validated or standard measure for RED-S, survey measures based on validated and/or standard questionnaires for each topic as available were used. The survey tools are outlined in the Appendix.

Eating disorder and disordered risk will be measured through self-reported history of a diagnosed eating disorder, self-reported history of professional counseling for eating problems (disordered eating), and the BEDA-Q screening tool. The BEDA-Q has been used in adolescent female athletes, but it has not been validated for use in collegiate male and female athletes. Restrictive dieting will be measured through the question: "Are you currently following or have you ever followed any special dietary considerations for personal reasons, diagnosed conditions, or religious reasons? (vegan, vegetarian, gluten free, dairy free, religious fasting, paleo, etc.)" with options including: "Vegetarian" "Semi-Vegetarian" "Vegan" "Gluten-free" "Dairy-free" "Lactose-free" "Paleo" "Ketogenic" "Intermittent Fasting" "Low carb" "Fasting for religious reasons (Ramadan, etc.)" "Low FOD-MAP." While the diets mentioned are not necessarily low-energy diets, the purpose is to see if any restrictions may be followed for any reason that may lead to energy restriction if not properly planned. This screening question may provide insight into diets athletes follow for a variety of reasons. Number of meals consumed per day provides

insight into if athletes are missing meals and will be assessed through a 24-hour food recall.

While a pre-determined number of meals is dependent on individual energy needs, literature has shown that not consuming at least 3 meals per day can be indicative of disordered eating (Adam S Tenforde et al., 2021). With low energy availability (LEA) at the core of RED-S, it is more traditionally measured in a laboratory setting. Through screening forms, it is important to assess possibility of LEA in collegiate athletes through eating disorders/disordered eating and dieting with the diagnosis of LEA at a later time through more complex equations, body composition testing, and indirect calorimetry.

Bone health will be measured through self-reported history of number of stress fractures, and if answered yes to having history of a stress fracture, a follow-up question on high-risk sites (sacrum, pelvis, lumbar spine, femoral neck) will be asked.

Food insecurity will be measured through the United States Department of Agriculture (USDA) 2-question measure for food insecurity. The two questions include: “Within the past 12 months I was worried whether my food would run out before I got money to buy more” and “Within the past 12 months the food I bought just didn't last and I didn't have money to get more” with answer choices as “often true” “sometimes true” or “never true.” If the athlete answered with the choice of “often true” or “sometimes true” that indicated a positive screen for food insecurity.

Nutrition knowledge will be measured through the Abridged Nutrition for Sport Knowledge Questionnaire ANSK-Q tool that assesses general nutrition knowledge as well as sport nutrition knowledge. Items will be scored and individuals will be scored on a range of 0-100 with higher values indicating higher nutrition knowledge.

Weight pressures in sport will be measured through the Weight Pressures in Sport (WPS) tool that was developed to assess weight pressures and body image in male collegiate athletes (Galli et al., 2014; Galli et al., 2011). With no questions specific to sex, the tool is appropriate for use in female athletes as well but has yet to be validated in this population. The authors recommend a 6-point Likert scale, but the survey included an extra measure of “neutral” increasing the scale to a 7-point Likert scale. To account for this, the data underwent a linear transformation to convert responses in a weighted manner to match the recommended 6-point scale. The following formula was utilized:

$$Y = (B - A) * (x - a) / (b - a) + A$$

$$Y = (6 - 1) * (x - 1) / (7 - 1) + 1$$

Statistical Analysis

A latent class analysis approach will determine classes of individuals who may present with nutrition related and RED-S concerns. Mplus statistical software will be utilized to discover underlying latent classes of individuals (Muthén, L. K., & Muthén, B. O., 2021). This exploratory modeling technique is often utilized in the psychological or health science field as an approach to patient-centered analysis. The LCA technique was introduced in 1987 as a method to determine classes of individuals (McCutcheon, A.C., 1987). A conceptual map of the model is outlined below with each of the indicator variables on the top and the covariate sex off to the side with C latent classes.

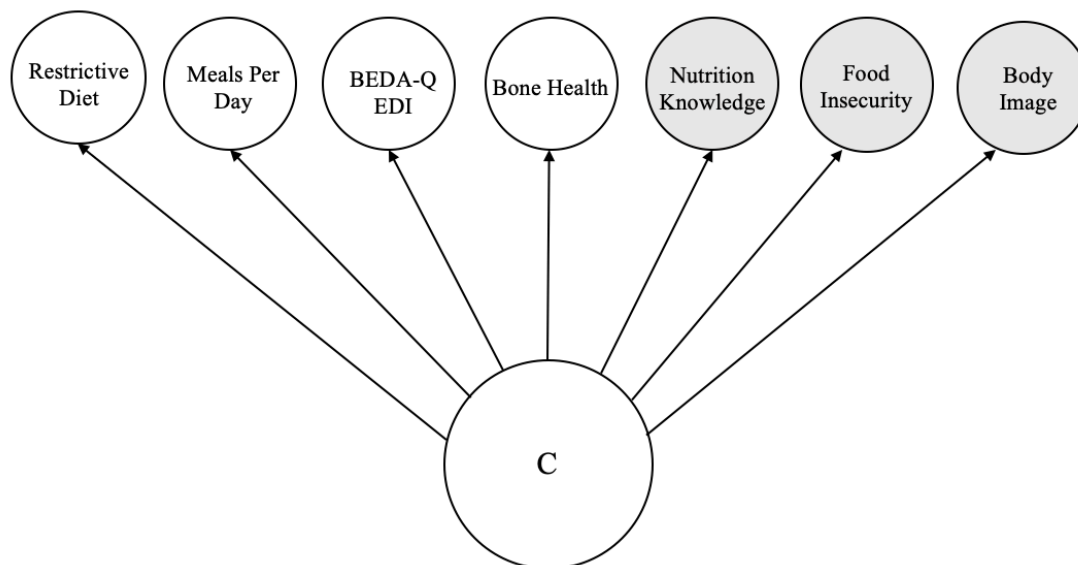


Figure 1: Proposed Latent Class Analysis Model for Collegiate Male Athletes

LCA Statistical Analysis

There are a number of considerations when determining which latent class model that best fits the individuals of interest. If many sampling zeros are present in the dataset, sparseness exists. This differs from structural zeros. If sparseness occurs, it leads to difficulties in model evaluation. Lack of consensus on a general rule of thumb for sample size but it has been established that LCA models are case sensitive and require large sample sizes into the hundreds.

Determining number of classes, also named class enumeration, involves fitting several LCA models with differing numbers of latent classes, collecting fit information for each model, then studying patterns to decide how many classes best describe patterns observed in the data (Nylund-Gibson & Choi, 2018). Information such as goodness of fit statistics can be analyzed to evaluate the model fitness. The Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Sample-size adjusted BIC all are considered for goodness of fit. BIC helps in model selection by penalizing the number of factors, providing insight into the model fit.

The LCA model with the smallest values for AIC, BIC and sample-size adjusted BIC are considered to be the best fitting model. The solution with the largest loglikelihood is considered to be better fitting than a model with lower loglikelihood values.

Lo-Mendell-Rubin Adjusted Likelihood Ratio Test (LMR-LMT) compares models with varying numbers of classes. If $p\text{-value} < 0.05$, the model with one fewer class is a better fit for the data (Lo et al., 2001). If the $p\text{-value} \geq 0.05$, the model would need to be reclassified with fewer classes. The parametric bootstrapping $p\text{-value}$ is also of interest, with a $p\text{ value} \geq 0.05$ indicating that the model needs to be reduced in class size.

Results

The descriptive statistics of the data of interest is included in Table 2. From the male athletes included in the study, the average nutrition knowledge score was a 30.00 out of 100, indicating poor nutrition knowledge. The average number of stress fractures was less than 1 at 0.56.

Table 2

Descriptive Statistics for Male Participants

	N	Minimum	Maximum	Mean	Std. Deviation	Variance
Restrictive Diet	72	0	1	0.08	0.278	0.077
Number of Meals Per Day	72	0	3	2.76	0.569	0.324
Eating Disorder Inventory (EDI)	72	0	16	4.31	2.881	8.300

Stress Fractures	72	0	4	0.56	0.870	0.757
Food Insecurity	72	0	1	0.22	0.419	0.175
Nutrition Knowledge	72	0	68.571	30	18	324.001
Body Image	72	1	4.472	2.647	0.990	0.980

To test the classification of collegiate athletes, a latent class analysis was run on 72 participants. The number of optimal classes in the data set are determined by the researcher based on a number of criteria. The best fitting LCA model is determined based on fit statistics such as Bayesian Information Criterion (BIC), adjusted BIC, and AIC, as well as interpretability, and non-information-criterion such as the Lo-Mendell-Rubin fit index and the Bootstrapped likelihood ratio test (BLRT).

The following fit information for the two and three-class models are included in Table 3:

Table 3

Latent class analysis model fit criteria

Model	Number of classes	Loglikelihood	Entropy	AIC	BIC	Adjusted BIC	Number of free parameters	VLRT	Lo-Mendell-Rubin Bootstrapped LRT	BLRT
1	2	-782.480	0.800	1604.961	1650.494	1587.481	20	0.1169	0.1169	0.000*
2	3	-762.898	0.977	1581.795	1645.542	1557.323	28	0.3734	0.3803	0.000*

Note. * $p < .05$

- Akaike information criterion (AIC)
- Bayesian information criterion (BIC)
- Vuong-Lo-Mendell-Rubin (VLMR)
- Likelihood ratio test (LRT)
- Bootstrapped likelihood ratio test (BLRT)

The analysis provided information regarding two and three-class models that emerged from the data. The first model provided insight into profiling male student-athletes into a two-class solution with no errors. The three-class solution provided model fit information, but class enumeration was not trustworthy due to a higher class size and model error. The three-class model showed poor absolute model fit and poor relative fit.

Table 4

Two class latent class assignment results

Latent Class	Number of individuals	Percentage of individuals
1	38	52.778%
2	34	49.752%

The three-class model identified the following counts for the latent classes based on the estimated model:

Table 5

Three class latent class assignment results

Latent Class	Number of individuals	Percentage of individuals
1	3	4.167%
2	60	83.333%
3	9	12.500%

Class Characteristics

Tables 6 through 9 provide insight into the two- and three-class models. The results in probability scale tables outline the categorical variables of interest in the model and the model results table outlines the continuous variables. The results of the table do not provide distinction between classes two and three on a variable level. If variables distinctly were consistent between groups, then there would be shared characteristics in the participants.

Table 6

Results in probability scale two-class latent class male model

Latent Class 1	Estimate	Standard Error	Estimate/Standard Error	P-Value
Restrictive Diet				
Category 1	0.917	0.046	19.891	0.000
Category 2	0.083	0.046	1.793	0.073
	Estimate	Standard Error	Estimate/Standard Error	P-Value
Food Insecurity				
Category 1	0.900	0.051	17.481	0.000
Category 2	0.100	0.051	1.952	0.051
Latent Class 2	Estimate	Standard Error	Estimate/Standard Error	P-Value
Restrictive Diet				
Category 1	0.916	0.049	18.521	0.000
Category 2	0.084	0.049	1.699	0.089

Food Insecurity	Estimate	Standard Error	Estimate/Standard Error	P-Value
Category 1	0.641	0.091	7.079	0.000
Category 2	0.359	0.091	3.957	0.000

Table 7

Model results two-class latent class male model

Latent Class 1	Estimate	Standard Error	Estimate/Standard Error	P-Value
Means				
Meals Per Day	2.765	0.107	25.871	0.000
BEDAQ EDI	3.003	0.340	8.835	0.000
Stress Fractures	0.629	0.169	3.748	0.000
Nutrition Knowledge	32.565	3.309	9.841	0.000
Body Image	1.871	0.134	13.920	0.000
Variances				
Meals Per Day	0.319	0.120	2.671	0.008
BEDAQ EDI	6.285	1.735	3.624	0.000
Stress Fractures	0.741	0.179	4.141	0.000
Nutrition Knowledge	312.137	43.020	7.256	0.000

Body Image	0.291	0.051	5.711	0.000
Latent Class 2	Estimate	Standard Error	Estimate/Standard Error	P-Value
Means				
Meals Per Day	2.763	0.091	30.479	0.000
BEDAQ EDI	5.764	0.558	10.324	0.000
Stress Fractures	0.474	0.133	3.574	0.000
Nutrition Knowledge	27.129	2.837	9.563	0.000
Body Image	3.517	0.123	28.636	0.000
Variances				
Meals Per Day	0.319	0.120	2.671	0.008
BEDAQ EDI	6.285	1.735	3.624	0.000
Stress Fractures	0.741	0.179	4.141	0.000
Nutrition Knowledge	312.137	43.020	7.256	0.000
Body Image	0.291	0.051	5.711	0.000

Table 8

Results in probability scale three-class latent class male model

Latent Class 1	Estimate	Standard Error	Estimate/Standard Error	P-Value
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Restrictive Diet				
Category 1	1.000	0.000	0.000	1.000
Category 2	0.000	0.000	0.000	1.000
Food Insecurity	Estimate	Standard Error	Estimate/Standard Error	P-Value
Category 1	0.667	0.274	2.434	0.015
Category 2	0.333	0.274	1.214	0.225
Latent Class 2	Estimate	Standard Error	Estimate/Standard Error	P-Value
Restrictive Diet				
Category 1	0.900	0.039	23.179	0.000
Category 2	0.100	0.039	2.579	0.010
Food Insecurity	Estimate	Standard Error	Estimate/Standard Error	P-Value
Category 1	0.766	0.055	13.958	0.000
Category 2	0.234	0.055	4.260	0.000
Latent Class 3	Estimate	Standard Error	Estimate/Standard Error	P-Value
Restrictive Diet				
Category 1	1.000	0.000	0.000	0.000

Category 2	0.000	0.000	0.000	1.000
Food Insecurity	Estimate	Standard Error	Estimate/Standard Error	P-Value
Category 1	0.891	0.109	8.145	0.000
Category 2	0.109	0.109	0.998	0.318

Table 9

Model results three-class latent class male model

Latent Class 1	Estimate	Standard Error	Estimate/Standard Error	P-Value
Means				
Meals Per Day	0.667	0.273	2.442	0.015
BEDAQ EDI	3.997	0.951	4.202	0.000
Stress Fractures	1.334	0.548	2.433	0.015
Nutrition Knowledge	32.364	15.471	2.092	0.036
Body Image	2.156	0.579	3.727	0.000
Variances				
Meals Per Day	0.128	0.029	4.348	0.000
BEDAQ EDI	8.029	2.122	3.784	0.000
Stress Fractures	0.258	0.057	4.490	0.000

Nutrition Knowledge	312.440	38.640	8.086	0.000
Body Image	0.956	0.104	9.191	0.000
Latent Class 2	Estimate	Standard Error	Estimate/Standard Error	P-Value
Means				
Meals Per Day	2.850	0.046	61.343	0.000
BEDAQ EDI	4.473	0.371	12.052	0.000
Stress Fractures	0.251	0.060	4.182	0.000
Nutrition Knowledge	30.936	2.252	13.716	0.000
Body Image	2.672	0.128	20.891	0.000
Variances				
Meals Per Day	0.128	0.029	4.348	0.000
BEDAQ EDI	8.029	2.122	3.784	0.000
Stress Fractures	0.258	0.057	4.490	0.000
Nutrition Knowledge	312.440	38.640	8.086	0.000
Body Image	0.956	0.104	9.191	0.000
Latent Class 3	Estimate	Standard Error	Estimate/Standard Error	P-Value
Means				

Meals Per Day	2.891	0.105	27.637	0.000
BEDAQ EDI	3.300	1.015	3.250	0.001
Stress Fractures	2.306	0.260	8.883	0.000
Nutrition Knowledge	23.045	5.289	4.357	0.000
Body Image	2.649	0.335	7.916	0.000
Variances				
Meals Per Day	0.128	0.029	4.348	0.000
BEDAQ EDI	8.029	2.122	3.784	0.000
Stress Fractures	0.258	0.057	4.490	0.000
Nutrition Knowledge	312.440	38.640	8.086	0.000
Body Image	0.956	0.104	9.191	0.000

Fit Indices

When analyzing a latent class analysis for fit indices, several considerations should be looked at. For smaller sample sizes of less than 300, both Akaike information criteria (AIC) and Bayesian information criteria (BIC) should be considered. A decreasing value indicates better model fit. Through the fit statistics table, Table 3, AIC and BIC are an index of model fit, balance the complexity of the model against the sample size.

Model Testing

Comparing models with varying classes is also an important consideration for LCA. The VLMR test compares a model with k classes to one with $k-1$ classes. If the p -value is greater than 0.05, like in this circumstance, clinical relevance may be worth considering. Additionally, the Lo-Mendel-Rubin test and BLMR can be considered.

Model Characteristics

Number of classes, class size, and separation are considered with looking at LCA model characteristics. Entropy is a measure of class separation between the latent classes with values above 0.80 considered a good fit. Table 3 provides two and three-class model values, but it is important to consider that higher values do not necessarily mean that a model is the best fit and may indicate an overfit model. The two-class model provides an acceptable value. When considering the number of classes and class size, a small class size of less than 15% of the sample is a concern. The two-class model revealed a class size well above that, with individuals close to being split in half. If a class contains less than 15%, it is possible whether outliers of a single indicator may be determining the class. In the three-class model, the smaller classes are less likely to be externally generalizable than models with fewer, well-distributed classes and the classes contain less than 10% of the sample which is indicative of a poor fit.

When a one-class model was conducted, few model characteristic statistics are provided by the statistical software Mplus. Fit indices for a one-class model include an AIC of 1624.117, a BIC of 1651.437, and an adjusted BIC of 1613.630. For the one-class model compared to the two-class model, AIC is lower, BIC is lower, and Adjusted BIC is higher. The values are extremely close, and due to the lack of other model fit criteria it is difficult to differentiate what the best-fitting model is for this population. Due to the small sample size of male athletes included in the model and the difficulty in interpreting the model fit criteria, more information is

needed at this time to definitely conclude that a two-class solution is superior to a one-class solution. Therefore, H1 cannot be supported and we fail to reject the null hypothesis.

Discussion

Main Findings

This study aimed to profile male student-athletes in collegiate athletics for nutrition and RED-S concern. Categorical and continuous indicators consistent with the RED-S framework and new considerations such as food insecurity, nutrition knowledge, and body image were included in the model with the goal of uncovering an unknown latent variable of classes. At a Division I university, 72 male student-athletes completed a pre-participation physical evaluation that included a cross-sectional nutrition screening survey. Data from the evaluation was utilized in a latent class analysis predictive model. RED-S is an emerging syndrome with few studies in the population of team sport athletes and collegiate athletes. Very limited information is available for male athletes, especially male collegiate team sport athletes, regarding RED-S.

Descriptive statistics outlined in Table 1 provide some insight into the indicators of interest. For males, the mean number of meals consumed per day was 2.760 ± 0.569 . The mean nutrition knowledge score was 30.000 ± 18.000 , indicating poor nutrition knowledge. The results of the statistical analysis provide information to support a two-class model solution to profile the athletes of interest into separate latent classes. A practitioner's guide was utilized to examine the following information of fit indices, model testing, and model characteristics (Sinha et al., 2020).

Class Characteristics

In Tables 6 through 9, individual characteristics based on the indicator variables included in the model did not clearly define class characteristics. This provides insight into the indicator variables. A future model may consider using different tools to measure some of the RED-S

variables of interest. This highlights the need for high quality variables to measure RED-S health and performance parameters in male athletes. Due to the lack of tools available for this population, this study provides some insight into predictive modeling for this topic and population as a starting point for other researchers.

Energy Availability

With consideration to previous RED-S research and the goal of screening, energy availability has been typically assessed through disordered eating and eating disorder risk. At this time no validated tool has been specifically designed for the collegiate athlete population, with very few available for the female athlete population. The BEDA-Q tool has been utilized in the female athlete population, specifically for adolescents, when screening for disordered eating related to RED-S. This tool was utilized in this study due to the short length of the questionnaire and the ease of distribution without the need for an interview, which is common in disordered eating and eating disorder screening tools. When considering disordered eating risk, other surrogate markers were also considered due to the lack of energy availability measurements in a laboratory setting and the lack of validated tools for the college population. Number of meals per day and restrictive dieting were also considered to also consider low energy availability.

Clinical Application

A main consideration of this topic is the complexity of RED-S and the difficulty of screening athletes for a syndrome when limited tools exist for athletes of consideration that have not been typically studied. College athletes that are not considered traditionally high risk are often overlooked in the research. The questions that still stands at this time is does the traditional RED-S framework apply to athletes outside of high-risk classification. Additionally, what additional factors beyond the traditional framework may contribute to RED-S and low energy

syndromes and which of them may be specific to college athletes. Food insecurity, body image, and nutrition knowledge were included in the LCA model to expand beyond the traditional framework. As research evolves, the conceptual model for RED-S may change. An aim of this study was to explore RED-S and low energy syndromes in a new population: non-high risk collegiate athletes. Some findings were of interest beyond the LCA profiling.

Of the 72 male athletes included in the study, 8.3% followed a restrictive diet, 18.1% reported eating less than 3 meals per day, 36.1% reported at least one stress fracture, 22.2% had food insecurity, and 87.5% scored less than a 50 out of 100 on nutrition knowledge. From the reported frequencies, it is important to note that many of the athletes have nutrition and RED-S related issues of concern that need clinical consideration and further investigation through consultations and referrals.

Specific to the statistical modeling technique, LCA has been previously utilized in the healthcare setting as a clinical tool. Predictive modeling techniques as well as machine learning have potential to assist clinicians. This exploratory study highlights a number of clinical considerations and offers a starting point for others in the field to explore LCA and predictive modeling techniques to explore RED-S.

Other Considerations

When a researcher is considering model fit and the number of classes for a population of interest, their expertise regarding clinical insight is important. Classes should be separate from a clinical standpoint through the discretion of the researcher. To prevent bias, the best fitting model should be determined before linking the variables of interest to the classes identified. It is possible that a 1-class model may be the best fit for a population and latent classes may not be possible to distinguish using the indicators selected. In this model, a higher sample size and

higher quality indicator variables were necessary to distinctly categorize the male athletes into latent classes. Additionally, specific variables were difficult to extract and name to each profile. As LCA is utilized in varying disciplines, the application of LCA algorithms will evolve through understanding best conditions, interpreting the information to the field, and clinical investigation.

There is evidence of poor model fit for the three-class solution due to two errors that occurred. First, one or more logit thresholds approached extreme values of -15.000 and 15.000 and were fixed to stabilize model estimation. This resulted in parameters with 0 standard errors and unknown z-score and p-values. Second, the standard errors of the model parameter estimates may not be trustworthy for some parameters due to a non-positive definite first-order derivative product matrix. This may be indicative of model nonidentification. This is likely due to poor class enumeration with a higher-class number. The sample size is likely the culprit for this model. With only 72 participants, a higher-class model can be difficult to interpret. There are no guidelines for calculating sample size requirement *a priori* with recommendations suggesting the larger the better, and into the hundreds. Smaller sample sizes may perform well for estimating two-classes as long as the indicators are of high quality. There is a suggestion that a three-class model may require up to 12 high quality indicators to perform well if the sample size is under 200 (Wurpts, 2012). If indicators are of low quality, sample size is recommended to be at least $N = 500$ for 12, and if $N = 1000$ if there are 6 low quality indicators. Some possible recommendations if working with a smaller sample size is to include a higher number and quality of indicators and adding a covariate. Sample size may be limited in a university setting with a range of athletes depending on athletic conference, division, and school funding and size. Especially in male athletes, many coaches and support staff may be biased towards male athletes

not being of RED-S concern. This warrants further investigation in male team sport athletes beyond those considered at risk.

Another consideration for LCA is zero variances. Due to data sparseness with the BEDA-Q disordered eating indicator, an alternate value from the tool was used. The EDI sum of 6 values was used in place of a binary, yes or no classification to reduce data sparseness and to raise variance values away from zero. The BEDA-Q may need to be reconsidered for use in the college athletic population because it at this time has only been validated in adolescent female athletes. Results from the BEDA-Q tool include that only no male athletes screened positive for eating disorder risk, leading to zero variance in the data set. This presents valuable information that highlights a need for screening tools specific to male athletes and college athletes and a validated tool specific to this population to determine true eating disorder risk. Future research efforts should ensure the LCA model has few missing values relative to sample size and the sample size is large enough for indicators of interest.

The main consideration at this time is the lack of validated nutrition screening surveys for the collegiate athlete population. While some RED-S surveys may be in progress, at this time there is a need for comprehensive nutrition screening tools with a focus on RED-S to be created specific to this population. Utilizing a validated screening tool with a LCA approach may have resulted in a model with more use of interpretation. This exploratory approach of LCA modeling may provide health care practitioners valuable information in the future if the measures are reliable and validated for the population of interest.

Strengths and Limitations

A strength of this study is that it provided insight and a starting point into a predictive modeling technique to identify classes of athletes who may be of nutrition and RED-S concern.

This technique may prove to be useful in the future to provide sports medicine practitioners and sports dietitians information. This would ideally be used in the first step of a treatment plan to then move forward with additional diagnostic tests such as the DEXA, bloodwork, body composition testing, and additional consultations and interviews to make the diagnosis of RED-S. This would be helpful in settings with limited sports medicine staff or high patient loads where each individual may not be able to be diagnostically tested. As previously mentioned, the goal of screening differs from the goal of diagnosing. All the individuals screened for RED-S may not present with diagnostic criteria for RED-S, but the opposite end of the spectrum of flagging athletes of concern prior to detrimental outcomes is worth the time and effort.

Another strength of this study is that it is one of the few studies that explores RED-S screening and the first study to do so in the collegiate setting. Male athletes are rarely studied and athletes of concern may not be identified as a result of bias, so an approach such as LCA may provide evidence of the grouping of individuals of concern into a class based on indicators used.

A limitation of this study is that the athletes were only measured at one point in time at pre-participation physicals. Using screening data from incoming and returning athletes at the time of pre-participation physicals does not account for athletes who may present with nutrition concerns or RED-S throughout the duration of the academic year. A possible solution is multiple time points of screening which could then be used in a longitudinal LCA model. It is necessary to have practitioners well-versed in RED-S symptomology to be diligent about detecting behaviors of concern and impaired health outcomes related to the syndrome, especially for male athletes who may not traditionally be considered at risk. Another limitation is the sample size. Future research should consider higher sample sizes when utilizing LCA if participants are accessible.

Another limitation is that a screening tool for male athletes is not available at this time. For female athletes, menstrual function is commonly used, but there are no validated, equivalent measures at this time. As the body of literature expands, considering male athlete endocrine function through a screening tool is of high importance.

Conclusion

This research provided insight into a predictive modeling technique for a complex syndrome in male collegiate athletes. This person-centered approach is exploratory in nature and differs from most clustering techniques. This approach can be utilized when the aim is on the individual, and when exploring an unknown latent variable which can be common in healthcare or sports science.

The goal of this research was to employ an exploratory and predictive modeling technique to profile athletes at risk for nutrition and RED-S concern. A two-class model was not determined the best fit to uncover classes of individuals of concern, leading to the conclusion that the model fit criteria did not provide enough evidence that male athletes included in the model could be profiled into distinct classes. With more accurate and validated tools, this modeling technique may provide insight into a cost-effective and timely technique to identify individuals of concern at pre-participation evaluations. Additionally, screening information from multiple universities or universities with larger student-athlete populations may provide a more stable LCA model to allow for higher class enumeration. Male athletes may be difficult to study and screen because staff may not consider male team sport athletes of concern. Nutrition and RED-S screening should be the first step before diagnosis to allow for the allocation of time and resources to athletes of identified concern. Future studies should consider sport specific surveys due to differing dynamics in individual and team sports. In the colligate setting, a RED-S

screening tool and eventually a RED-S diagnostic tool with consideration to male and team sport athletes is of high importance. Overall, this predictive modeling technique provides insight into individual athletes who may need to be monitored and evaluated for RED-S. Three additional indicators of RED-S were included in the model, providing insight into additional considerations beyond the RED-S framework. At this time, a validated screening tool and RED-S protocol for distribution is of high importance in the collegiate setting but until one is validated, predictive modeling through models such as LCA may provide insight to best detect athletes of RED-S concern.

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APPENDIX

Summary of screening measures for male student-athletes

BEDA-Q	Dietary Practices	Meals Per Day	Bone Health	ANSK-Q	Food Insecurity	WPS
EDI						
I feel extremely guilty after overeating ^a	Are you currently following or have you ever followed any special dietary considerations for personal reasons, diagnosed conditions, or religious reasons? ^b	Please list your food intake for the past 24 hours in each of the categories. Do your best to estimate the amounts (i.e. one handful, one fistful), quantity of food items, if you prepared it at home or out (and list restaurant) and as specific as possible. ^c	Have you ever had a stress fracture? ^b	Full questionnaire in Appendix	Within the past 12 months I was worried whether my food would run out before I got money to buy more. ^e	In the past year, my coach places an emphasis on team members' weight ^f
I am preoccupied with the desire to be thinner ^a	Options:		How many stress fractures have you had? ^d		Within the past 12 months the food I bought just didn't last and I didn't have money to get more. ^e	In the past year, my coach encourages athletes to gain muscle mass ^f
I think that my stomach is too big ^a	Options:		What was the site of your stress fracture(s)?			Weigh-ins are held periodically throughout the season ^f
I feel satisfied with the shape of my body ^a	Vegetarian, Semi-		Options: Lumbar spine			Body weight and appearance are important to my coach ^f
My parents have expected excellence of me ^a	Vegetarian, Vegan, Gluten-free, Dairy-free,		Femoral neck Sacrum Pelvis			My teammates notice if I put on weight ^f
As a child, I tried very hard to avoid disappointing my parents and teachers ^a	Lactose-free, Paleo, Ketogenic, Intermittent Fasting, Low carb, Fasting for religious reasons (Ramadan, etc.), Low FOD-MAP					Any of my body flaws are readily apparent in my uniform ^f
						The crowd scrutinizes my body and makes me concerned about my weight and appearance ^f
						In the past year, have you lost weight to meet image requirements for your sport? ^f
						In the past year, have you ever ate in secret? ^f
						Body weight and appearance are important to my friends outside of sport ^f
						Body weight and appearance are important to my family ^f
						The leanest athletes are at a distinct performance advantage ^f

Note.
Brief Eating Disorder in Athletes Questionnaire (BEDA-Q)

Abridged Nutrition for Sport Knowledge Questionnaire (A-NSKQ)
Weight Pressures in Sport (WPS)

^aAnswer choices: always, usually, sometimes, often, never

^bAnswer choices: yes, no

^cAnswer choices: Breakfast, Lunch, Dinner, Snacks, Beverages

^dAnswer choices: 1, 2, 3, 4, 5, >5

^eAnswer choices: often true, sometimes true, never true

^fAnswer choices: always, usually, often, sometimes, rarely, never

Latent Class Analysis Syntax

Title:

Dissertation Male New Model LCA;

Variable:

names = RESdiet Meals BEDAQEDI

SF FoodIns ANSKQ WPS;

usevariables = RESdiet Meals BEDAQEDI

SF FoodIns ANSKQ WPS;

categorical = RESdiet FoodIns;

classes = c(2);

Analysis:

type = mixture;

STARTS = 0;

LRTSTARTS = 0 0 300 20;

Savedata:

file = Male_Model_Mplus_save_test.txt;

save = cprob;

format = free;

Output:

tech11 tech14;

VITA

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Academic Preparation

University of Mississippi, Oxford, Mississippi
Doctor of Philosophy, 2019-2021; Field of Study: Nutrition and Hospitality Management
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Concentration: Sports Nutrition

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Dietetic Internship Rotations: January-August 2017, Foodservice, University of Kentucky
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Professional Credentials and Experience

Licenses/Credentials/Certifications

Licenses/Credentials

Registered Dietitian (RD), ID: 86090133. Academy of Nutrition and Dietetics, January 2018-
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Board Certified Specialist in Sports Dietetics (CSSD), ID: 86090133. Academy of Nutrition and
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Certifications

International Society for the Advancement of Kinanthropometry (ISAK) Level 1 Anthropometrist, University of Mississippi, 2018.

Electronic Learning Endorsement Program (eEP) Online Course Training, University of Mississippi, (May 2020).

Professional Positions

Graduate Instructor, The University of Mississippi, University, MS
NHM 319: Foundations in Sports Nutrition (2021)

Graduate Assistant Sports Dietitian, The University of Mississippi, University, MS
Ole Miss Athletics (2017-2021)
Team Dietitian: Baseball, Soccer, Men's Tennis, Women's Tennis, Rifle, Track & Field (2017-2021)
Student Volunteer Coordinator: August 2017- May 2019
Gillom Olympic Sport Fueling Station Manager: 2017-2021
Baseball Fueling Station Manager: 2020

Scholarly and Creative Activities/Accomplishments

Presentations

Non-Refereed Poster Presentations

Delventhal M, Valliant MW, Callaway K, Franks C, Slatniske M. Comparison of ADP and ISAK body composition assessment in D1 collegiate athletes. SCAN Annual Conference Symposium, Phoenix, AZ, April 26, 2019.

Guest Lectures

Health Promotion (HP 313) Guest Lecture. The Career of a Sports Dietitian and Nutrition Related to Injury Recovery. September 2020. The University of Mississippi.

Invited Guest Speaking

Student Dietetic and Nutrition Association (SDNA) Guest Speaker. SDNA Alumni Panel. November 2020. The University of Kentucky.

Student Dietetics Association (SDA) Guest Speaker. The Career Path of a Sports Nutrition Graduate Assistant. October 2017. The University of Mississippi.

Professional Association Memberships and Service

Academy of Nutrition and Dietetics
(2014-Present)

- Sports and Human Performance Nutrition (SHPN)
(2018-Present)

Collegiate and Professional Sports Dietitian Association (CPSDA)
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- Research and Education Committee

American Society of Nutrition (ASN)
(March 2020-March 2021)

Instruction and Advisement

a. Courses Taught (University of Mississippi, 2018-2021)

University of Mississippi, Fall 2021

NHM 319 Foundations in Sports Nutrition (graduate instructor)

University of Mississippi, Spring 2018 (March-May 2018)

NHM 311 Introduction to Nutrition (graduate instructor)