DISSERTATION

SEEKING OR RISK: MENTAL HEALTH SYMPTOMS AND ASSOCIATED BEHAVIORS IN COLLEGE STUDENT-ATHLETES

Submitted by

Samuel R. Davis

Department of Psychology

In partial fulfillment of the requirements

For the Degree of Doctor of Philosophy

Colorado State University

Fort Collins, Colorado

Summer 2023

Doctoral Committee:

Advisor: Mark A. Prince

Bradley T. Conner
Brian Butki
Randall Swaim

ABSTRACT

SEEKING OR RISK: MENTAL HEALTH SYMPTOMS AND ASSOCIATED BEHAVIORS IN COLLEGE STUDENT-ATHLETES

College mental health symptomatology is highly prevalent on college campuses across the nation. College student-athletes experience mental health issues at similar rates to their non-athlete peers. However, most colleges and universities do not have formal plans to address their student-athletes' mental health concerns. Considering the heterogeneity in experiences with mental health issues like anxiety and depression, applying person-centered analyses may help discern unidentified subgroups of student-athletes at greater risk of negative outcomes. The present study used latent class analysis to discern unidentified subgroups of student-athletes mental health symptoms and determine whether subgroups were associated with varying rates of help-seeking behaviors, health risk behaviors, and performance-related outcomes. Results indicated that a five-class model best fit the data, and that this model did not fit equally well for a comparative sample of non-student-athletes. Patterns of symptom endorsement within these classes ranged from high endorsement of all symptoms within the past month, to recent endorsement of feeling overwhelmed and exhausted, to no current or past-year mental health symptoms. Subsequent auxiliary testing identified classes of mental health symptoms associated with higher likelihood of engagement in health-risk behaviors and issues that could affect athletic performance. This study represented the first effort to discern latent subgroups of student-athletes characterized by varying experiences with mental health symptoms. Findings from the present study can help identify at-risk student-athletes in need of mental health support to attenuate symptom distress and mitigate negative consequences associated with these concerns. Further, athletic departments can use these findings to integrate simple mental health screening tools already circulating at schools across the nation to better support their student-athletes' mental health concerns. Potential application of these screening tools and treatment planning options are discussed.

ACKNOWLEDGEMENTS

There are many people I wish to thank, without whom I would not be where I am today. While I cannot possibly list each person who has contributed and enhanced my personal and professional development over the course of this project and degree, I hope everyone knows the tremendous impact you all have had on my life. To my advisor, Mark Prince, Ph.D., I want to thank you for your unwavering support and mentorship these last six years. I owe so much to you, and I will always be thankful for the opportunity to have been one of your first advisees in this program. I also want to thank each member of my dissertation committee for your thoughtfulness, support, and guidance throughout my project. To Brad Conner, Ph.D., your constant support, balanced with semi-frequent challenges, helped make me the strong clinician and research I am today. Your mentorship truly helped me find my voice in this field. To Randy Swaim, Ph.D., yours and Linda Stanley's, Ph.D., warmth and support, from day one, helped me feel comfortable stretching myself and growing into the person and emerging professional I wanted to be. To Brian Butki, Ph.D., your willingness to support me and offer advice, despite my training happening in a separate department and discipline, has helped shape my continued pursuits of my clinical, research, and teaching goals. I also want to thank my parents, Lisa and Eric Davis, and my brother, Max Davis. Your love and support, through all my ups and downs, are why I am here and who I am today. I can never thank you enough. To my friends and family, it is hard for me to quantify just how much your love, encouragement, and distractions have meant to me over the years. And finally, I want to thank my counseling psychology cohort here at Colorado State University. Brian, Kenzie, Ted, Gereon, Dylan, Shelby, and Gemma, I couldn't imagine going through these last six years with a better group of people.

TABLE OF CONTENTS

INTRODUCTION

College Mental Health

Approximately one out of every three first-year college students across nine countries qualified for at least one anxiety, mood, or substance use disorder diagnosis (Auerbach et al., 2018). Among US college students, findings suggest an increase in reported diagnoses and treatment of insomnia, ADHD, OCD, and panic attack symptoms (Oswalt et al., 2020). Treatment-seeking has increased from 19% in 2007 to 34% in 2017 among US college students and stigma has decreased, but a 14% increase in lifetime mental health diagnoses is hypothesized to be a primary reason why more college students are seeking treatment (Lipson et al., 2019). Rates of depression and suicidality have also increased from 24.8% and 5.8% respectively in 2009 to 29.9% and 10.8% respectively in 2017 (Lipson et al., 2019). Lack of seeking treatment for mental health disorders negatively affects physical health, academic performance, and mental wellbeing (Buchanan, 2012; Eisenberg et al., 2009). Specifically, depression and anxiety are associated with greater physical health issues, lower grade point average, nonsuicidal self-injurious behaviors, suicide, and withdrawal from college (Buchanan, 2012; Eisenberg et al., 2009). While stigma has decreased and service utilization has increased over the last decade, college students are experiencing higher rates of a variety of mental health disorders. This highlights the importance of further understanding the symptoms experienced by college students and associated negative outcomes.

Student-Athlete Mental Health

Despite high prevalence rates of mental health concerns among college students, rates of college student-athlete mental health have been infrequently examined. The National Collegiate

Athletics Association (NCAA) reported that 35% of Division I men's basketball players and 30% of women's basketball players frequently felt overwhelmed by the tasks they needed to complete (NCAA, 2016). Among Division I college athletes, approximately 33% reported experiencing symptoms of depression (Cox et al., 2017). Similarly, a separate study identified that of the 958 Division I student-athletes surveyed, 28.8% and 21.7% of student-athletes reported anxiety and depressive symptoms respectively prior to their season starting (Li et al., 2017). Considering general prevalence of anxiety and depressive symptoms among non-athlete peers was 14.9% and 12.2% respectively (Oswalt et al., 2020), it is key to further understand prevalence and behaviors associated with student-athlete mental health symptoms.

While student-athletes have similar, and in some cases greater, vulnerabilities to mental health problems compared to the general population (Rice et al., 2016), less than 40% of academic institutions reported having a written plan to identify and support student-athlete mental health (Kroshus, 2016). Further, at least 44% of Division I athletes surveyed noted they received no mental health education from their athletic department (Cox et al., 2017). These findings suggest that despite high rates of anxiety, depression, and other mental health issues, student-athletes encounter difficulties accessing mental health care. Mental health issues like anxiety or depression, are associated with decreased motivation (Sheehan et al., 2018), injury (Podlog, 2016), and more frequent heavy episodic drinking (Rexroat, 2014). Considering that student-athletes have different experiences and responsibilities than their non-athlete peers, it is important to discern whether student-athletes have unique patterns of mental health concerns and may therefore require unique plans to get connected with support. While studies have identified rates of mental health symptoms and consequences of these issues, studies have not yet explored ways these symptoms cluster together and whether particular symptoms/patterns of symptoms are associated with different outcomes.

Measurement of College Physical and Mental Health

The American College Health Association's (ACHA) National College Health Assessment (NCHA) survey provides a unique opportunity to examine health behavior within a nationally representative sample of college students. Participation in each semester survey between Fall 2015 and Spring 2019 ranged from 19,664 student participants across 40 schools to over 88,000 student participants across 140 schools totaling at least 426,000 participants (ACHA, 2015, 2016a, 2016b, 2017a, 2017b, 2018a, 2018b, 2019). The survey collects responses regarding physical health issues, mental health issues, substance use, exercise, sex behavior, and academic performance (ACHA, 2015-2019). While these types of surveys may limit the ability to examine specific issues in depth, they can allow researchers to explore a variety of research questions aimed at developing a more comprehensive understanding of health issues, risks, and behaviors. Regarding this project, the NCHA survey provides the rare chance to use secondary data analytic techniques to explore mental health symptoms and associated behavioral outcomes within a generalizable sample of college student-athletes. Through this, we can use commonly asked mental health screener items to explore student-athlete mental health and associated behavioral and performance-related outcomes. These efforts address the present gap in the literature of ways different patterns of symptoms may be associated with varying protective and risky behaviors.

Theoretical Perspectives

Mental Health

Emotions have been described as superordinate programs that direct perceptual processes like attention, memory, motivation, and physiological processes like heart rate and endocrine functions (Cosmides & Tooby, 2000). From an evolutionary psychology perspective, this suggests that emotions and emotional states serve functional purposes in situations from long ago, and likely result in alternate or varied consequences in present-day situations (Cosmides & Tooby, 2000). For example, depressive states can be viewed as an adaptive response to investment in a situation that did not result in an expected return on investment or insufficient investment in a highly valued situation that resulted in a loss. This experience of depression can re-orient the individual to change behavior in efforts to avoid similar consequences in the future (Cosmides & Tooby, 2000). Additionally, anxiety is reported to help an individual identify potential sources of dangers (i.e., stressors) and effective ways to respond to this threat (Marks & Nesse, 1994). For example, an anxiety response to the presence of a predator can help orient the individual to the danger (e.g., the predator) and how to respond to it (e.g., fight, flight, or freeze). Extreme and/or surprise situations can result in panic, leading to less adaptive response patterns in situations (Marks & Nesse, 1994). These studies identify that emotions serve adaptive functions and can help to facilitate effective responses to stimuli.

The anxiety state resulting from hearing the predator rustling the grass behind an individual is no longer as common as the anxiety state resulting from the upcoming deadline to file taxes (Sapolsky, 2004). While the situations have changed, the body's response to anxious and depressive states has remained the same. Regarding anxiety, individuals experiencing anxiety are likely to experience the activation of the sympathetic nervous system and inhibition of systems regulated by the parasympathetic nervous system. Specifically, physiological effects like increased heart rate, muscle tension, increase perspiration, and changes in skin temperature are observed in individuals experiencing anxiety (Kushki et al., 2013). However, the persistence of situations eliciting emotional states and the persistence of the body's stress-response can lead to negative consequences. For example, frequent and/or sustained activation of the stress-response can lead to the development of and/or poorer outcomes related to heart disease (Härter et al., 2003; Konstam et al., 2005). Further, anxiety is associated with greater risk of developing gastrointestinal problems, migraines, and urinary and genital problems (Härter et al., 2003). Similarly, depression is associated with worse outcomes of heart disease and higher rates of mortality (Konstam et al., 2005). Despite the adaptive components of anxiety and depression, findings described above suggest that sustained anxiety and depression are associated with the development of physical health problems and poorer physical health outcomes.

While state anxiety and depression have adaptive features (Cosmides & Tooby, 2000; Marks & Nesse, 1994), sustained or trait anxiety and depression manifest as psychological disorders (Konstam et al., 2005). Major depressive disorder is characterized by the presence of consistently depressed mood, anhedonia, fatigue, sleep disturbances, diminished motor functioning, concentration difficulties, weight loss, and/or suicidal ideation for at least two weeks (American Psychiatric Association, 2013). Prevalence of this disorder is highest among college-aged individuals (18-29 years old; American Psychiatric Association, 2013). Generalized anxiety disorder is characterized as excessive worry most days for at least six months resulting in feelings of restlessness, fatigue, muscle tension, difficulty concentrating, irritability, and sleep disturbances (American Psychiatric Association, 2013). Approximately 19% of college students reported experiencing a major depressive episode within the past year, and 17% reported having a generalized anxiety disorder diagnosis within the past year (Auerbach et al., 2018). These findings suggest that these disorders are both highly prevalent among college students and can have significant effects on daily functioning. Additionally, these findings identify several different symptoms and clusters of symptoms that can characterize disordered anxiety and depression. While surveys such as the ACHA's NCHA do not typically directly assess symptoms of anxiety and depression as defined by diagnostic manuals, they often assess mental health via items reflective of the symptoms listed above. Therefore, it is key to consider the variability in symptom presentation across persons experiencing anxiety and/or depression.

Considering the high prevalence coupled with the effects of symptoms and other outcomes associated with these disorders, it is important to understand why anxiety and depression may be experienced as disorders and not as adaptive. Several theories have been developed to help answer this question, including the role that cognitive and behavioral avoidance plays in the development and sustainment of these psychological disorders (Moulds et al., 2007; Newman & Llera, 2011). Cognitive and behavioral avoidance can be defined as the use of thought or behavioral strategies to avoid content or stimuli related to the depression or anxiety. Given that, in their adaptive forms, anxiety and depression help orient an individual's attention to stimuli and ways to effectively respond to stimuli (Cosmides & Tooby, 2000), avoidance likely limits the ability to respond adaptively to anxious and depressive states. Avoidance has been identified as a significant contributor to depression and anxiety (Moulds et al., 2007; Newman & Llera, 2011). Regarding depression, individuals likely to engage in cognitive avoidance were in turn more likely to engage in rumination (Moulds et al., 2007). Further, avoidance predicted unique variance, above and beyond anxiety and rumination, of depression scores in college students (Moulds et al., 2007). Similarly, avoidance is hypothesized to sustain feelings of worry in anxiety in efforts to avoid the potential outcome of a shift from positive to negative emotion (Newman & Llera, 2011). In support of this, findings suggest that individuals reporting feeling worried prior to exposure to emotional clips helped them feel more able to cope (Llera & Newman, 2010). With both theories of avoidance in anxiety and depression, attention appears oriented towards strategies that sustain symptoms. This suggests that attention to stimuli contributing to anxiety or depression may help lead to adaptive responses.

Evolutionarily, anxiety and depression served to help orient an individual's attention to stimuli to help determine subsequent actions (Cosmides & Tooby, 2000; Marks & Nesse, 1994). The situations eliciting anxiety and depressive states have changed, but the body's response has not, resulting in anxiety and depressive disorders and associated negative outcomes. Theory suggests that avoidance may help to explain present-day anxiety and depressive disorders (Moulds et al., 2007; Newman & Llera, 2011). The avoidance likely sustains anxiety and depressive states through misdirected attentional efforts. Findings indicate that individuals with high levels of anxiety experience attentional bias towards content perceived as threatening (Bar-Haim et al., 2007). This suggests that anxiety can lead to shifts in attention away from relevant stimuli, likely limiting adaptive responses to the anxiety. With depression, findings suggest that slow attentional shifts from negative content and rapid shifts from positive content increased rumination and depression severity (Yaroslavsky et al., 2019). Similarly, greater attentional focus on negative stimuli was associated with quicker MDD onset compared to those focusing less on negative content (Woody et al., 2015). These findings further indicate that when attention shifts from the appropriate stimuli, state anxiety and depression can worsen and develop into pathology. While all anxiety and depression are not maladaptive, it is crucial to determine what characteristics of these states result in greater risk of maladaptive outcomes for individuals. These efforts can help identify those in the greatest need of intervention and treatment.

Student-Athletes

For the purposes of this study, it is necessary to establish operational definitions for student-athletes and non-athlete peers. While approximately 63% of undergraduate college students sampled reported engaging in high intensity cardio/aerobic exercise at least one day in the past week (American College Health Association, 2012), additional factors and stressors are present for student-athletes that help differentiate them from their non-athlete peers. Araujo (2016) proposes several criteria to help define an athlete: training to improve sport performance, active participation in sport competitions, involvement in a local/regional/national sport federation, and that training for sport is a major activity or focus in life. A typical large university will offer several athletic participation levels including varsity and club athletics, with club sports being less competitive and time-consuming than varsity, and not governed by a national body like the NCAA. Division 1 varsity student-athletes engage in 20 hours per week of "countable" athletically related activities and four hours per day, not including optional activities related to their sport participation (NCAA, 2020a). NCAA Division 3 programs, usually smaller schools that do not offer athletic scholarships, can have student-athletes engage in athletic-related activities six days per week for up to 19 weeks while the sport is in its playing season (NCAA, 2020b). Club student-athletes' expectations and experiences often differ by sport and by program, with findings suggesting this population should be examined as separate from the varsity student-athlete and non-student-athlete populations (Marten et al., 2021). The present study defined "student-athletes" as college students reporting participation in varsity Division I, II, and III athletics within the past year, as these are students that train, actively compete, are formally part of the NCAA, and have sport as a major activity in their lives. Regarding their non-athlete peers, this study defined "non-student-athletes" as students that did not endorse any varsity or club sport participation within the past year. Club student-athletes were excluded from analyses, as they are often best grouped as separate from varsity student-athletes and non-athlete students.

Student-Athlete Mental Health. College student-athletes manage similar school-related stressors to their non-athlete peers, in addition to the time- and sport-related stressors discussed above (Araujo, 2016). Therefore, it is important to better understand student-athlete mental health, including potential unique experiences with mental health symptoms compared to their non-athlete peers. For example, the individualized zones of optimal functioning (IZOF) model argues that individual athletes have zones of optimal anxiety levels that lead to best or peak performance (Hanin, 1997). The IZOF model also integrates ways that varying levels of anger and tension can also benefit performance (Hanin, 2007). Within this model, emotional states are considered adaptive at varying levels for individuals. However, it is also indicated that too much or too little emotion can have a detrimental effect on performance. This model is consistent with the general views of mental health presented earlier, that emotional states can be adaptive while sustained emotionality can lead to greater negative outcomes.

Considering the role of attention in both sustainment of anxiety/depression states and symptoms of these disorders, theories related to attention and performance, like attentional control theory (Eysenck et al., 2007), may better differentiate adaptive and maladaptive emotionality in sport. Attentional control theory posits that adverse effects of anxiety depend on ability to control attention through inhibition and shifting cognitive efforts (Eysenck et al., 2007). This theory suggests that not all anxiety negatively affects performance, as it can lead to greater effort and attention to the stimuli. Eysenck et al. (2007) suggest that individuals have two systems: 1) a goal-directed attentional system governed by expectations, knowledge, and goals, and 2) a stimulus-driven attentional system governed by important and/or noticeable stimuli. Increased anxiety can affect the balance between these systems and shift attention to stimuli and away from goals, negatively affecting performance (Eysenk et al., 2007). Further research supports these hypotheses, noting that high anxiety participants had worse motor efficiency when motor tasks required precision and greater attentional resources (Coombes et al., 2009). Similarly, depression was associated poorer attentional flexibility on attentional control tasks (DeJong et al., 2019). However, findings in this study identified that persons with higher depression, rumination, and anxiety were better able to ignore distracting information to complete a specific task (DeJong et al., 2019). Relating these findings to sport, athletic activities often require participants to attend to, synthesize, and react to a variety of information quickly and efficiently. When athletes can focus on fewer pieces of information, whether due to expertise or individual sport-specific factors, anxiety and depression may serve adaptive functions for the athlete. However, when sport tasks require greater attentional flexibility, anxiety and depression affect attentional control which, in turn, affect performance (DeJong et al., 2019). Like the IZOF model described above, these findings underscore the importance of a nuanced, person-centered approach to exploring anxiety and depression in sport.

While the models described above continue to illustrate ways that anxiety and depression can be helpful or harmful to a student-athlete's performance, they fail to explore the potential negative consequences of these states/disorders in greater depth. Focusing first on performance outcomes, depression and anxiety are thought to affect performance in several ways beyond attention. Findings suggest that highly anxious athletes exert greater muscular effort before, during, and after motor tasks and experience significant muscle fatigue related to sport performance than their low anxious peers (Pijpers et al., 2003; Weinberg & Hunt, 1976). Further, athlete's report perceiving anxiety as having a significantly negative effect on their performance (Khan et al., 2017). Depression is associated with fewer competition planning behaviors, suggesting that athletes with depression are less likely to plan and engage in pre-competition behaviors aimed at improving performance (Arruza et al., 2009). Athletes with depression are also more likely to respond negatively to times they do not achieve their performance goals, increasing depression and other negative responses (Hammond et al., 2013). Together, anxiety and depression are major determinants of burnout in athletes (Alexandra et al., 2018). Regarding other negative outcomes associated with depression and anxiety, athletes with anxiety and depression were more likely to use cannabis to cope with these symptoms (Zeigler et al., 2019). Research suggests anxiety is associated with poorer academic performance (Edwards & Froehle, 2021; Petrie & Russell, 1996). Collectively, anxiety and depression can increase risk of several negative outcomes. However, studies generally have not explored whether specific patterns of symptoms are associated with varying levels of risk of these consequences.

Collectively, research suggests that emotional states like anxiety and depression can be adaptive at a variety of levels for athletes (Hanin, 1997, 2007). However, too much or too little can negatively affect an athlete's mental health and sport performance (Hanin, 1997, 2007). In response to decreased athletic performance, athletes may subsequently experience elevated stress and depressive symptoms, further exacerbating and sustaining distress. Considering the variety of negative consequences of anxiety and depression in sport, like performance inhibition, burnout, substance use, and academic struggles, it is key to understand what aspects of anxiety and depression may be more strongly associated with greater risk of negative behavioral and performance outcomes. While IZOF and attentional control models serve to highlight the adaptivity and maladaptively of anxiety and depression in sport, particularly as they relate to sport performance, they fail to identify patterns of these symptoms experienced by groups of student-athletes that are associated with enhanced risk of negative consequences. It is important to understand the unique experiences student-athletes may have with mental health symptoms.

Help-Seeking Behavior in College and Sport

Help-seeking behaviors within the context of mental health were defined as the efforts to seek help and support to address mental health concerns. College student-athletes have access to a variety of additional health-support services, including athletic trainers, coaches, and mental performance consultants (Moreland et al., 2018). Research indicates that a variety of mental health interventions and prevention efforts are effective at reducing mental health problems related to anxiety and depression (Conley et al., 2017; Huang et al., 2018; Lattie et al., 2019). Mental health service utilization has increased to 36% in the last 10 years (Lipson et al., 2019), indicating greater numbers of college students are seeking mental health support than in the past. However, athletes are generally less likely than their nonathlete peers to seek mental health services, 23% to 31%, respectively, despite reporting similar rates of anxiety and depression (Edwards & Froehle, 2021), particularly athletes with higher levels of depression (Drew & Matthews, 2018). Understanding the potential barriers to student-athletes seeking mental health services is essential to develop effective interventions.

There are several barriers to help seeking, including perceived stigma associated with mental health, low mental health literacy, and past negative experiences with mental health services (Castaldelli-Maia et al., 2019). One challenge to effectively assessing student-athlete mental health and service utilization is the variety of ways these services are conceptualized by researchers and institutions. In sport psychology, professionals can receive training to work with athletes on performance-related issues and/or mental health issues. A recent meta-analysis noted several studies conceptualized utilization of services offered by professionals not trained in providing mental health services as athlete mental health utilization (Moreland et al., 2018). making operationalizing student-athlete mental health and help-seeking behaviors difficult. For the present study, help-seeking behaviors were conceptualized as seeking therapy support to address mental health concerns as this better reflects efforts to attend to relevant anxiety and/or depressive symptoms examined in the study.

Health Risk Behavior in College and Sport

In addition to help-seeking behavior, it is also important to explore increased health risk behavior on college campuses associated with anxiety and depression. Health risk behavior is characterized as behaviors that may negatively affect health (Suris et al., 2008). Regardless of the presence of anxiety or depressive symptoms, these health risk behaviors are highly prevalent on college campuses (Dolphin et al., 2017; Huang et al., 2007; Krieger et al., 2018; Mancine et al., 2020). While college students engage in a host of health risk behaviors including substance use, risky sex, disordered eating, and risky driving, among the most prevalent is alcohol use and heavy episodic drinking (four/five drinks in one sitting for women/men; Clarke et al., 2017; Hingson et al., 2009; Krieger et al., 2018; Miech et al., 2016). At least 5% of worldwide deaths in 2016 were attributed to alcohol use and related consequences (World Health Organization, 2018). About 40% of these deaths were due to physical and mental health conditions, while 49% were attributed to injury (World Health Organization, 2018). Greater negative consequences related to use are associated with larger quantities of and more frequent use (Looby & Earleywine, 2007; Patrick et al., 2020). Alcohol use and heavy drinking are also associated with other risk behaviors (e.g., driving under the influence, death from alcohol-related unintentional injuries, physical assault, sexual assault; Hingson et al., 2009; National Institute on Alcohol

Abuse and Alcoholism [NIAAA], 2015; Rexroat, 2014). Mental health is also associated with an increased likelihood of engaging in health risk behavior. Specifically, depression and anxiety are associated with greater alcohol use (Jao et al., 2019) and risky sex behavior (Dolphin et al., 2017; Swanholm et al., 2009). The extant literature indicates these behaviors are highly prevalent among college students and are associated with anxiety and depression.

College student-athletes appear to be at particularly high risk for engaging in health risk behavior (Huang et al., 2007; NCAA, 2018). Approximately 42% of student-athletes endorsed heavy-episodic drinking and 8% reported consuming at least 10 drinks per sitting (NCAA, 2018). Unprotected sex rates appear comparable, and higher for men, between student-athletes and their non-athlete peers (Huang et al., 2007). Finally, disordered eating behaviors, including binging and purging, are highly prevalent among athletes (Huang et al., 2007; Mancine et al., 2020). These findings underscore the importance of further understanding health risk behaviors among college student-athletes and the role that mental health may play in the increased risk. Based on the available data from the ACHA's NCHA, there was insufficient depth to examine all health risk behaviors. While the present study focused on exploring alcohol use-related variables, other health risk variables common among student-athletes were examined (e.g., risky sex, disordered eating, and risky driving).

Measurement of Student-Athlete Mental Health

Typically, college student and student-athlete mental health is assessed via relatively small samples (Arruza et al., 2009; Hammond et al., 2013; Khan et al., 2017; Pijpers et al., 2003; Sheehan et al., 2018) and/or using descriptive statistics to identify prevalence and associations between variables (Cox et al., 2017; Kroshus, 2016; Li et al., 2017; NCAA, 2016; Rexroat, 2014). These variable-centered approaches are largely concerned with identifying levels of variables (e.g., mean or median levels), or relations between variables (e.g., correlations, regression coefficients). These types of analyses are more parsimonious, more familiar to researchers, and can help summarize a population as a whole (Howard & Hoffman, 2018). However, variable centered analyses can fail to identify unobserved or unexpected heterogeneity, limiting the scope of subpopulations observed in the analysis. An alternative to variable centered approaches that explicitly models heterogeneity of key variables within a population are person-centered approaches.

Person-Centered Approaches

In contrast to variable-centered approaches, which examine relations among variables for the entire analytic sample, person-centered analyses are used to identify similar patterns of responses to variables from subsets of individuals (Bergman & Magnusson, 2003). Mixture modeling is a commonly used approach to identify latent subgroups within data. This type of modeling benefits from advantages of parametric and nonparametric modeling, increasing flexibility in the analysis while keeping model parameters reasonable in size (McLachlan & Peel, 2000). For example, some mixture model approaches seek to identify unrecognized or undefined subpopulations based on clustering of responses. These approaches infer probabilistic subpopulation membership based on the data, as these memberships are not observed. Models can be estimated using methods including maximum likelihood by evaluating and comparing the fit of models with varying numbers of latent classes (McLachlan & Peel, 2000). These methods balance applying specific parameters to limit statistical problems and flexibility to identify previously undefined latent subpopulations. Through person-centered approaches like mixture modeling, researchers can identify latent subgroups within a population and subsequently explore differences in variables among these subgroups.

Mixture modeling can be used to address a variety of research questions, including those examined in multivariate, longitudinal, and cross-sectional designs. Finite mixture models, specifically, assume the presence of unobserved subgroups and probabilistically assigns individuals within the data to these subgroups based on patterns of responses within the data (Berlin et al., 2014). Generally, these models can effectively identify latent subgroups within cross-sectional and longitudinal data. Each individual has a probability of belonging in each subgroup, helping to account for uncertainty and measurement error (Muthén, 2001). Within finite mixture modeling, observed variables are inputted as indicators used to identify latent subgroups. These models allow for a variety of types of variables, including continuous, ordered, and dichotomous variable types within cross-sectional data (Muthén & Muthén, 1998-2017). Finite mixture modeling using categorical or dichotomous indicators is referred to as latent class analysis, while models using continuous indicators are called latent profile analysis (Berlin et al., 2014). Latent class or profile models are estimated using theory-informed hypotheses predicting the number of expected classes and/or exploratory approaches allowing researchers to estimate as many classes as allowed by the data (Berlin et al., 2014). With these models, variances across classes are restricted to be equal to reduce statistical problems (Berlin et al., 2014). Interpretation and selection are the final stages of these models, with decisions based on model fit indices, parsimony, and substantive interpretability. Following model identification, researchers can explore differences in outcome variables across these subpopulations (Muthén & Muthén, 1998-2017). Overall, finite mixture models provide flexible ways to identify latent classes/profiles within cross-sectional data and subsequently explore relations between variables across the identified subgroups.

Additionally, these models allow for the inclusion of control and outcome variables which can limit confounding effects and can be used to explore the relation between latent classes and auxiliary variables (Asparouhov & Muthén, 2014). These relations can be tested a variety of ways, depending on the type of auxiliary variable. The BCH method is recommended to explore differences between latent subpopulations in continuous and categorical distal outcomes (Bakk, & Vermunt, 2016; Asparouhov & Muthén, 2015) by accounting for varying probabilities of class membership. The BCH method also uses the Wald test to assess comparisons, global and pairwise, using the Chi-square statistic (Clark & Muthén, 2009).

While researchers have successfully explored student-athlete mental health via variable centered approaches highlighted above (Cox et al., 2017; Hammond et al., 2013; Khan et al., 2017; Kroshus, 2016; Li et al., 2017; NCAA, 2016; Rexroat, 2014), they have yet to explore varying experiences with mental health among student-athlete participants via person-centered approaches. As described throughout this introduction, anxiety and depressive symptoms vary in severity and can often be adaptive for student-athletes. Findings describe the heterogeneity of symptom experiences (Forbes et al., 2023), suggesting the importance of examining unique patterns that may emerge related to symptoms endorsement. Student-athletes are also a heterogeneous group of college students (Harper & Nichols, 2008; Zamboanga et al., 2021), further highlighting the importance of considering this known heterogeneity when exploring symptom expression and associated outcomes. Therefore, applying person-centered methodology to address these considerations will help to describe the heterogeneity of experiences with anxiety and depression that may be associated with greater risk of negative outcomes among student-athletes. Unlike variable-centered approaches that assume a sample is best described by a single set of parameters representing a population, person-centered approaches assume there are multiple subpopulations within a sample that should be described, each with its own set of parameters. Regarding student-athlete anxiety and depression, applying finite mixture models could help to identify unobserved subgroups that are at varying risk for mental health problems and may be in greater need of intervention or treatment services.

Researchers have most often applied person-centered modeling approaches to explore profiles of factors associated with greater risk of athlete burnout from sport (DeFreese & Smith, 2020; Gustafsson et al., 2018a, 2018b; Martinent et al., 2020). These findings have identified profiles associated with greater burnout risk, providing more specific information to help develop effective intervention efforts. Given the variability in experiences with mental health and associated symptoms, exploring student-athlete mental health without first identifying latent subgroups limits the conclusions that could be drawn, and therefore the implications of a study. In the present study, latent classes of anxiety and depressive symptoms experienced by student-athletes were identified, and differences in help-seeking, health risk, and performance-related behaviors across subgroups were evaluated. These efforts will help identify classes of student-athlete mental health symptoms associated with greater risk of negative outcomes.

Study Aim and Outcomes

In the present study, the first aim was to identify patterns of symptoms reported by college student-athletes on a large, national health assessment. The second aim was to determine whether different patterns of symptoms were associated with varying rates of help-seeking, health risk behavior, exercise, and performance-related variables. The final aim was to determine whether the same patterns of symptoms emerge among a comparative sample of non-student-athlete participants. Findings from the present study may help illustrate ways to use traditional, brief symptom measures to help identify classes of student-athlete mental health symptoms that may be associated with more frequent health risk behaviors and less willingness to seek treatment for these symptoms without support.

Given that the ACHA's NCHA survey is already distributed at up to 140 schools across the nation (reaching nearly 500,000 students and student-athletes), findings may help identify ways athletic departments can use the data to identify at-risk student-athletes and connect them with appropriate support services. These efforts may provide essential information to the greater than 60% of schools that do not currently have formal plans to connect their student-athletes with necessary support (Kroshus, 2016). Additionally, findings related to potential similarities or differences in classes of symptom endorsement between student-athletes and non-athletes can help further inform treatment planning and interventions to support student-athletes most effectively on college campuses. The present study also represents the first application of person-centered methods to explore student-athletes' experiences with anxiety and depressive symptoms and associated behavioral outcomes. These efforts addressed an infrequently examined topic among student-athletes, using person-centered methodology for the first time, within a nationally representative sample of college students. The implications of this study may help identify student-athletes at greater risk of negative outcomes associated with mental health and may help schools and athletic departments develop strategies to connect at-risk student-athletes with appropriate support services using surveys already distributed at many schools across the country.

METHOD

Participants

Participants in the present study were college students and student-athletes across the United States that completed the ACHA's NCHA survey between the fall academic semester in 2015 and spring semester in 2019. Between the fall 2015 and spring 2019 semesters, a minimum of 40 and maximum of 140 schools distributed the survey to their students. The dataset includes 426,425 college student participants and 27,642 varsity student-athletes. Regarding age, the median age of the self-identified non-athlete sample was 21 years old, and the median age of the student-athlete sample was 20 years old. Regarding biological sex, 64.4% of student-athlete participants reported they were female and 35.1% reported they were male. Within the non-athlete sample, 69.7% reported they were female, and 29.9% reported they were male. Regarding race, 78.5% of the student-athlete participants identified as White, 9.1% identified as Hispanic or Latino/a, 8.3% identified at Asian or Pacific Islander, and 7.3% identified as Black. Among non-athletes, 65.1% identified as White, 15.2% identified as Hispanic or Latino/a, 15% identified as Asian or Pacific Islander, and 5.8% identified as Black. Further demographic information is presented in Table 1.

Data Collection and Access

For the ACHA's NCHA fall 2015 to spring 2019 data collection, schools self-selected to participate and only schools in the United States that surveyed all students or used random sampling to collect data were included in the study (ACHA, 2015, 2016a, 2016b, 2017a, 2017b, 2018a, 2018b, 2019). Participating schools administered the survey via online or hard-copy formats. Identifying information about participants and participating schools were removed from the data prior to obtaining access. Data collection procedures were approved by the Colorado State University Institutional Review Board. An additional data use request was submitted to acquire permission to use the ACHA-NCHA data for this study.

Measures

This study used measures and items from the Fall 2015-Spring 2019 ACHA-NCHA survey. The following sections highlight the items and describe the measures that were included to address the study aims.

Demographics

Participants responded to several demographics questions as part of their participation in the survey. Survey items asked participants to report typical demographic information, including their age, biological sex, gender identity, race and ethnicity, and year in school. Further, the demographics section included items regarding sport participation and school-specific items like the size of school, geographic location, and setting of campus. These items (See Appendix A) were used to identify the characteristics of the sample to help evaluate generalizability of the findings.

Mental Health Items

The indicators used to help identify latent classes within the student-athlete sample were the mental health screener items within the ACHA-NCHA survey. This mental health screener includes 11 items assessing experiences and symptoms associated with anxiety and depression (See Appendix B). These items were endorsed via a Likert-type scale with response options ranging from *no, never* (0) to *yes, in the last 30 days* (4). Items within this screener include: “Have you ever felt very sad,” “Have you ever felt overwhelming anxiety,” and “Have you ever seriously considered suicide?” These mental health items were entered into the model as indicators to explore and identify latent classes of student-athletes characterized by different patterns of anxiety and depressive symptoms. To keep the type and scale of measurement consistent between indicator and outcome variables, responses to these indicator items were recoded such that a value of "0" represented *no, never or not in the last 12 months*, a value of "1" represented *yes, in the last 12 months*, and a value of "2" represented *yes, in the last 30 days*. Following model identification, auxiliary testing using the items described below addressed whether these latent mental health classes were associated with different rates of health risk, help-seeking, and performance-related behaviors.

Health Risk Items

Several health risk behaviors were assessed within the ACHA-NCHA survey and were included as auxiliary variables (See Appendix C). The behaviors that were included as outcome variables for auxiliary testing were alcohol and cannabis use, risky sex, disordered eating, and risky driving/riding behaviors.

Alcohol Use and Related Consequences. First, several items were included to assess substance use as a health risk behavior. More specifically, this study focused on alcohol use, as this is the most frequently used substance among college students and student-athletes (Buckner et al., 2018; NCAA, 2018). The NCHA survey includes a variety of items assessing alcohol use. However, not all use is problematic and presents as a health risk. Therefore, this study included items related to frequency of use, frequency of heavy episodic drinking, and consequences of alcohol use. Frequency of alcohol use was assessed via the following item: "Within the last 30 days, on how many days did you use?" Participants were given the following response options: *never used, have used but not in the last 30 days, 1-2 days, 3-5 days, 6-9 days, 10-19 days, 20-29 days,* and *used daily*. Heavy episodic drinking was assessed via the following item: "Over the last two weeks, how many times have you had five or more drinks of alcohol at a sitting?" Participants could respond with *none, 1 time, 2 times, 3 times, 4 times, 5 times, 6 times, 7 times, 8 times, 9 times,* and *10 or more times*. Finally, consequences of alcohol use were assessed by several items. The items, "Within the last 30 days, did you drive after drinking any alcohol at all" and "Within the last 30 days, did you drive after drinking five or more drinks of alcohol" were used to assess alcohol use resulting in risky driving behavior. Participants could respond with a *no* or *yes*. Participants also responded to nine items related to other consequences associated with their alcohol use. They were asked "Within the last 12 months, have you experienced any of the following when drinking alcohol" and could respond with a *no* or *yes*. Examples of these items are: "Did something you later regretted" and "Had unprotected sex." These alcohol use items helped assess both frequency of use and use that increases health risk among student-athlete participants.

Risky Sex Behaviors. The ACHA-NCHA survey includes several items assessing sexual intercourse, including items related to risky sex. Risky sex, including unprotected sex and having multiple partners, is a highly prevalent behavior among college students (Buckner et al., 2018) and student-athletes (Huang et al., 2007). To assess risky sex, participants were asked to report "Within the last 12 months, with how many partners have you had oral sex, vaginal intercourse, or anal intercourse?" Additionally, participants were asked "Within the last 30 days, how often did you or your partner(s) use a condom or other protective barrier (e.g., male condom, female condom, dam, glove) during oral sex, vaginal intercourse, or anal intercourse?" They were given the following response options: *never, rarely, sometimes, most of the time,* and *always*. Inclusion of these items helped to represent risky sex among the latent classes of student-athletes identified within this study.

Disordered Eating Behaviors. Another prevalent health risk behavior among college student-athletes is disordered eating behaviors. While not thoroughly assessed within the ACHA's NCHA survey, the following items were included to represent disordered eating behaviors of student-athletes: "Within the last 30 days, did you vomit or take laxatives to lose weight" and "Within the last 30 days, did you take diet pill to lose weight?" Participants could endorse *yes* or *no* as a response. These items represent efforts, beyond exercise and food consumption, to manage weight that can lead to increased risk to physical and mental health. Including these items helped determine whether different mental health symptom patterns experienced by student-athletes were associated with different disordered eating behavior.

Risky Driving. Finally, several additional items within the survey assessed risky driving/riding behaviors. Participants were asked "Within the last 12 months, how often did you wear a seatbelt when you rode in a car, "Within the last 12 months, how often did you wear a helmet when you rode a bicycle," and "Within the last 12 months, how often did you wear a helmet when you rode a motorcycle?" The following were the response options to these items: *never, rarely, sometimes, most of the time,* and *always*. These items helped to expand this study's exploration into college student-athlete health risk behaviors.

Help-Seeking Items

In addition to health risk behaviors, it is important to determine whether different patterns of anxiety/depressive symptoms are associated with varying rates of help-seeking behaviors. In the present study, help-seeking was defined as efforts to seek mental health support in relation to symptoms they are experiencing. Considering mental health symptoms, particularly those associated with anxiety and depression, are persistent and can reappear over time, it was important to consider whether a student-athlete had sought treatment from a trained professional in the past, if they were currently in treatment, and if they would consider seeking treatment in the future. Whether a participant sought help in the past was assessed by the question "Have you ever received psychological or mental health services from a counselor/therapist/psychologist or psychiatrist?" Participants were given *no* and *yes* as response options. Recent and/or current help-seeking was assessed by the question "Have you ever received psychological or mental health services from your current college/university's Counseling or Health Service?" Participants were given *no* and *yes* as response options. Finally, future willingness to seek help was assessed by the question "If in the future you were having a personal problem that was really bothering you, would you consider seeking help from a mental health professional?" Participants were given *no* and *yes* as response options. Collectively, these items (see Appendix D) assessed past help-seeking behaviors and current attitude towards seeking help while in school and beyond.

Performance-Related Items

When considering outcomes important to college student-athletes, it is key to include performance-related outcomes that could affect a student-athletes sport performance and/or ability to compete within their respective sport. These outcomes, represented in the ACHA's NCHA survey, include exercise rates, sleep, and academic performance (See Appendix E).

Exercise. Lower exercise rates among student-athletes may negatively affect athletic performance, underscoring the importance of discerning whether different classes of mental health symptoms may be associated with varying rates of exercise among college student-athletes. This was assessed via self-reported frequency of completing several exercise activities. Participants were asked "On how many of the past 7 days did you do moderate-intensity cardio or aerobic exercise (caused a noticeable increase in heart rate, such as a brisk walk) for at least

30 minutes," "On how many of the past 7 days did you do vigorous-intensity cardio or aerobic exercise (caused large increases in breathing or heart rate, such as jogging) for at least 20 minutes," and "On how many of the past 7 days did you do 8-10 strength training exercises (such as resistance weight machines) for 8-12 repetitions each?" The response options provided for these items were the following: *0 days, 1 day, 2 days, 3 days, 4 days, 5 days, 6 days,* and *7 days*.

Sleep Difficulties. Next, sleep disturbances are associated with poorer athletic performance (Brauer et al., 2019; Fullagar et al., 2014). Sleep issues were assessed by the items "In the past 7 days, how often have you awakened too early in the morning and couldn't get back to sleep," "In the past 7 days, how often have you felt tired, dragged out, or sleepy during the day," "In the past 7 days, how often have you gone to bed because you just could not stay awake any longer," and "In the past 7 days, how often have you had an extremely hard time falling asleep?" The response options provided for these items were the following: *0 days, 1 day, 2 days, 3 days, 4 days, 5 days, 6 days,* and *7 days*. Sleep problems were also assessed by the item "Within the last 12 months, have sleep difficulties been traumatic or very difficult for you to handle?" Participants were given *no* and *yes* as response options.

Academic Performance. Finally, student-athletes are required to maintain a minimum grade point average to be eligible to compete within their sport, underscoring the importance of maintaining academic performance. To assess academic performance, the following item was included as auxiliary variables: "Within the last 12 months, have academics been traumatic or very difficult for you to handle." Participants were given *no* and *yes* as response options for this item.

Collectively, the above listed health risk, help-seeking, and performance outcomes were used to discern ways that patterns of anxiety/depressive symptoms can differentially affect variables directly associated with athletic performance. The inclusion of these variables helps to expand the finding and implications associated with the present study, as interpretations will explore physical, mental, and performance-related outcomes. Means and standard deviation values of indicator and outcome items for the student-athlete and non-athlete samples are presented in Table 2. Additionally, inter-item correlation values for indicators and outcomes for the student-athlete and non-athlete samples are presented in Tables 3 and 4, respectively.

Analysis Plan

Data Preparation

Recoding. Prior to model estimation, I completed several steps to prepare the data. First, I recoded indicator variables so that the time frame of reported mental health symptoms, help seeking, health-risk, and performance related variables better aligned. Initially, participants endorsed whether they had experiences with each mental health symptoms within the last two weeks, the last month, the last year, ever in their lifetime, and never. Since most auxiliary variables assessed behaviors within the past month or year, I recoded indicators so that values represented past month, past year, and never/not in the last year experiences with mental health symptoms. Next, I recoded covariate and auxiliary variables to assist in the interpretability of findings. For example, regarding the item “within the last 30 days, on how many days did you use alcohol,” I recoded the value of the response option “never used” from 1 to 0 and each subsequent response option was recoded to one value lower than it was originally coded. Similarly, I recoded exercise performance variables such that a value of 0 represented “0 days in the past week,” a value of 1 represented “1 day,” and so on to clearly represent exercise activity in the past week. Overall, these recoding and cleaning steps helped increase consistency in measurement and clarity in interpretation during the model estimation and auxiliary testing phases of the analytic plan. Please see Appendix F for the syntax used to clean, compute, and recode variables.

Assumption Testing. The next step before estimating the models was to check model assumptions to determine whether additional transformation steps were needed. The primary assumption for mixture modeling methods like latent class analysis is local independence, which assumes that each observed indicator variable is independent of one another (Sinha et al., 2021). To assess whether this assumption is violated, Sinha et al. (2021) recommends examining the correlation matrix (see Table 3) and eliminating variables which are strongly correlated to another. However, there is no recommended value in the literature that indicates "strong" correlation that would violate the assumption of local independence. While no empirical cut-off value exists, correlation values at or slightly above 0.5 should be evaluated critically since they may impact model estimation and fit indices (Sinha et al., 2021). The assumption of local independence can be relaxed when collinearity is expected and/or if variables are deemed too important to exclude (Braeken, 2011). In the present study, several variables had correlation indices at or above 0.5, with values ranging from 0.5-0.68. I examined item pairs that had correlation values at or above 0.5 to determine whether items should be removed or combined to limit redundancy. I determined that the item pairs with high correlation values were expected to be related and were also too important on their own to remove or combine. For example, the item pair with the highest correlation coefficient (0.68) was "felt very lonely" and "felt very sad." While these symptoms are often experienced together, findings indicated that loneliness and sadness are unique enough on their own to warrant separate assessment (Dahlberg, 2022); therefore, I elected to leave the variables in their original form for model estimation.

Model Estimation

Latent subgroups were derived using person-centered analytic methods with 11 mental health screening items included in the ACHA-NCHA survey (See Appendix B) entered as indicators. To better align measurement types across indicator and outcome variables, the indicator variable was recoded to better represent participant experiences with mental health symptoms within the last year. A value of 0 represented “Never, or not in the past year,” a value of 1 represented “Yes, in the last year,” and a value of 2 (“Yes, in the last 2 weeks”). Latent class analyses (LCAs) were run in Mplus Version 8 using the maximum likelihood with robust standard errors (MLR) estimator, and indicators were specified as “categorical” (Muthén & Muthén, 1998-2017). The MLR estimator can effectively handle analysis of continuous data that may be non-normal and contains missing data (Berlin et al., 2014; Spurk et al., 2020). First, to determine whether potential clustering of responses within the same school and region may affect classification during estimation, intraclass correlation coefficients (ICCs) were generated using Mplus. The average ICCs for the indicators was below 0.05, which suggests that the potential effect of clustering among school region and size may be minimal (Hox, 1998). Additionally, the MLR estimator is as an effective way to handle potential clustering of responses, further limiting the potential impact of clustering by school size and/or location (Spurk et al., 2020). Next, age, biological sex, and variables assessing whether participants had been diagnosed with an anxiety, depressive, or other mental health diagnoses were entered in as covariates to limit potential confounds that may affect discerning latent subgroups of mental health symptoms.

Additionally, I used the full information maximum likelihood (FIML) estimation method to address missing data. This estimation method is recommended for handling missing data because it makes use of all data available and produces unbiased parameter estimates (Cham et al., 2017; Sinha et al., 2021). For categorical variables, FIML uses all the data available, including partial data, to maximize the log-linear likelihood function during model estimation (Enders, 2010). This allows for researchers to make use of variables with missing data, without having to remove large amounts of data and/or impute values where there is missingness. While computationally complex, the FIML method is the default method for models run with MLR in Mplus (Muthén & Muthén, 1998-2017). FIML makes use of all the available data and removes cases where there is no available data. For the present study, there were several instances in which cases were removed during model estimation because there was no available data for the FIML method to pull from. Within the student-athlete sample, there were 13 such cases (approximately 0.05% of the sample) where there was no available mental health symptom data to pull from. Therefore, these cases were removed and not included in model estimation. Additionally, there were 1,813 cases (approximately 6.56% of the sample) where there was no available age, biological sex, or mental health diagnosis data available. Since these variables were entered as covariates in the model, these cases were also removed during model estimation.

I completed a series of LCAs, starting with a single-class model and adding one profile to each subsequent analysis, until model fit began to deteriorate. Model fit was evaluated through interpretation of model fit indices, parsimony, and substantive interpretability. In other words, the best fitting model was the one that had the fewest number of classes while also meeting established statistical criteria and the interpretation of the classes offers novel information and/or fits with the understanding of the theory. Regarding model fit indices, recommendations made by Nylund et al. (2007), Tein et al. (2013), and Muthén and Muthén (2000) were used to identify indices and interpretation cut-offs/criteria. Sample-size adjusted Bayesian Information Criterion (SABIC; Sclove, 1987), entropy (Celeux & Soromenho, 1996), average latent class probabilities

(ALCP), and the Bootstrapped Parametric Likelihood Ratio Test (BLRT; McLachlan & Peel, 2000) were the fit indices interpreted to help select the best fitting model. While no formal rules exist to determine the best stopping point when conducting a series of LCAs, interpretation of these indices helped identify when model fit began to deteriorate.

Prior to discussing these indices in greater detail, it is important to note that model selection was made via collective interpretation of all indices, as they are best used in concert and not as standalone indices. The first index interpreted for model fit was the SABIC. The SABIC is a comparative statistic aimed at identifying the most parsimonious model using maximum likelihood estimates of the model (Sclove, 1987; Tein et al., 2013). This statistic replaces the sample size term used to estimate other information criterion with an adjusted term, preventing overfitting of the model (Tein et al., 2013). When interpreting the SABIC, values closer to zero are preferred and the model with the lowest SABIC compared to other models is preferred (Tein et al., 2013). If a model has a SABIC value lower than a model with one less class, it was viewed as a better fitting model based solely on interpretation of the SABIC. While this index has been identified as the most accurate model fit index, particularly with larger sample sizes (Tein et al., 2013), interpretation of entropy, average latent class probabilities, and the BLRT tests were also critical to final model selection.

Next, entropy is the collection of classification uncertainty within the model. When uncertainty is high, it indicates that posterior probabilities are relatively similar across classes (Celeux & Soromenho, 1996; Tein et al., 2013). Entropy values range from 0 to 1. Values at or greater than 0.80 suggest adequate classification quality, with values closer to 1 being preferred (Celeux & Soromenho, 1996; Jung & Wickrama, 2008). While a commonly used index when selecting a best fitting model, it is unreliable when used as a standalone index for model selection (Tein et al., 2013).

Third, the BLRT evaluates model improvement by comparing each model with a model with one fewer class (Nylund et al., 2007). This test generates a *p*-value by using a bootstrap resampling method, with a significant *p*-value indicating the current model represents a significant improvement over a model with one less class (McLachlan & Peel, 2000). The BLRT may be a more stable and reliable index than other measures, like the Lo-Mendell-Rubin likelihood ratio test (LMR), when conducting LCAs with large samples. This test helps in the process of identifying the best-fitting model.

Finally, ALCPs represent the probability that individuals belong within each class identified within the model. ALCP values on the primary diagonal indicate the probability that individuals likely characterizing the class were correctly categorized within the class. Values closer to 1 on the primary diagonal are preferred. The off-diagonal values indicate the probability an individual was incorrectly categorized. In the off-diagonal, values close to 0 are preferred. For example, a value of 0.90 on the primary diagonal for class one indicates that an individual that is most likely to respond similarly to the pattern of responses characterized by class one has a 90% chance of being correctly categorized within class one and a 10% chance of being incorrectly categorized within the remaining classes. While no specific cut-off criteria have been identified, the model where ALCPs on the primary diagonal are closest to one is preferred.

Overall, identifying a model requires considering multiple model fit indices, parsimony, and the interpretability of the model. A model with a SABIC lower than a model with one fewer class, an entropy value greater than 0.80, a statistically significant BLRT test, and average latent class probability values on the primary diagonal close to 1 would indicate good model fit. Taking interpretability and parsimony into account, if a model with one fewer class has the same model fit index conditions listed above and has interpretability that fits with the theory, then that model was selected as the final, best-fitting model. Ultimately, final model selection involved consideration of several pieces of information. Once the final model was selected, analyses were conducted to determine whether a similar model would best fit a randomly selected subset of non-athlete college students. Finally, outcome variables were introduced into the final student-athlete model to conduct post-hoc auxiliary difference testing.

Post-Hoc Difference Auxiliary Tests

Mplus Version 8 (Muthén & Muthén, 1998-2017) was used to determine whether the identified latent classes were associated with differences in help-seeking behaviors, health risk behaviors, and academic/athletic performance-related outcomes. The BCH method was used because it is more effective than other methods when examining differences among outcomes within mixture models (Bakk, & Vermunt, 2016; Asparouhov & Muthén, 2015). The BCH method best accounts for the probabilistic nature of membership to given classes, a known limitation of other methodology like distal continuous (DCON) methods (Asparouhov & Muthén, 2015). The BCH method uses the Wald test to assess global and pairwise comparisons based on a Chi-square statistic (Clark & Muthén, 2009). For dichotomous distal outcome variables, the BCH method was still used. Results of the BCH auxiliary tests for dichotomous outcomes were interpreted as the probability of endorsing a value of "1" and not "0."

Multigroup and Confirmatory Latent Class Analyses

Once the number of latent classes was identified within the student-athlete sample, testing was conducted to determine whether the same model fit equally well for the non-athlete sample as it fit the student-athlete sample. Mplus Version 8 (Muthén & Muthén, 1998-2017) was used to compare whether the best fitting model identified for student-athletes (see person-centered analyses plan listed above) fit equally well for a randomly selected sub-population of ACHA college student participants that identified as not competing in varsity or club athletics within the past year. These comparisons are akin to invariance testing in factor analytic methodology. However, unlike the variable-centered approaches to invariance testing, person-centered approaches to invariance evaluate whether observed groups have similar probabilistic class membership across latent classes and similar likelihood of endorsement across model indicators.

While variable-centered approaches have clearly established procedures and recommendations, there are no such procedures and recommendations to test for model invariance using mixture modeling methods like latent class analysis. While studies have used methods to identify invariant items when constructing tests via differential item functioning (Sawatzky et al., 2018), these studies do not evaluate and compare overall model fit across groups. Other methods, like multigroup and confirmatory latent class analyses, better evaluate whether latent class models are similar between groups (e.g., Davis et al., 2019; Finch & Bronk, 2011). These methods allow for direct comparisons of model structure across observed groups (e.g., male and female) and the application of model constraints to evaluate differences in class probabilities and threshold values. Class probability refers to the probability that a given participant belongs within each class in the estimated model. Threshold values for each indicator in the model refer to the likelihood of endorsement of "1," with lower threshold values indicating high likelihood of endorsement within the class and higher values indicating low likelihood of endorsement. For latent class models, multigroup and confirmatory analytic methods most effectively identify differences in class probability and thresholds across observed groups.

To determine whether the best-fitting model for student-athletes fits equally well for non-student-athletes, several models consistent with multigroup and confirmatory latent class analytic methodology were estimated. First, several “knownclass” analyses (i.e., multi-group analyses in a mixture modeling framework) were conducted in Mplus, one constraining class probabilities to be equal across groups and one freeing probabilities, to determine whether class probabilistic membership was equal across groups using the number of classes identified to be best-fitting to the student-athlete sample. Mplus code for these “knownclass” models can be referenced in Appendix G. Second, two latent class models were estimated using the non-student-athlete sample, one constraining threshold values to be equal to those in the student-athlete model and one allowing thresholds to be freely estimated. Mplus code for these constrained and free threshold models can be referenced in Appendix H. Consistent with previous studies (Davis et al., 2019; Finch & Bronk, 2011) and model fit recommendations listed above, differences in comparative model fit indices like SABIC and entropy were observed to determine whether differences in class probabilities and thresholds existed between student-athlete and non-student-athletes. While there are no statistical tests to determine whether differences in SABIC or entropy values are statistically significant, rules of thumb exist regarding how to interpret differences in BIC values. Jeffreys (1961) reports that a difference of greater than 100 in BIC values between models suggests the model with the smaller BIC value is decisively better fitting. Considering that the SABIC index is the sample size-adjusted version of the BIC index and that no rule of thumb exists for the SABIC at this time, models with a delta SABIC (ΔSABIC) of greater than 100 were interpreted as the decisively better fitting model. Delta entropy (Δentropy) values were used to provide additional statistical support when comparing models.

RESULTS

Latent Class Analysis

A series of one- to seven-class LCA models was estimated, with age, biological sex, and previous diagnostic history entered in as covariates. Model fit results for the series of LCAs conducted using the student-athlete sample of the ACHA NCHA survey are presented in Table 5. Several models provided good model fit based solely on interpretation of model fit indices. For the one- to seven-class models, SABIC values were consistently lower for each model when compared to a model with one fewer class. Entropy values for the two- through seven-class models fell above the recommended cut off value of 0.80 (Celeux & Soromenho, 1996; Jung & Wickrama, 2008). ALCP values for the two- and three-class models were above 0.90, indicating a high likelihood of individuals being correctly categorized within the class most representative of their response patterns. ALCP values remained high for the four- (0.88-0.95) and five-class (0.85-0.92) models, also suggesting a high likelihood of individuals being correctly categorized within the class representing their response patterns. Finally, the BLRT test was significant for the three-, four-, and five-class models, indicating these models represented statistically significant improvements over the two-, three-, and four-class solutions, respectively. Collectively, these results suggest that a three-, four-, or five-class model all present good model fit based on the interpretation of model fit indices. Final model selection among these three solutions was made considering parsimony and substantive interpretability of the models.

The three-, four-, and five-class models were each evaluated based on parsimony and interpretability of the model being consistent with theories of college student and student-athlete mental health. The three-class model was the most parsimonious solution since it had the fewest number of classes, and the model had strong fit indices. Interpretation of the probability estimate patterns of mental health symptom endorsement for the three-class model revealed three distinct class patterns of mental health symptom endorsement. While these three classes presented unique patterns of mental health symptom endorsement, each class was characterized by the presence of a moderate-to-high likelihood of endorsing several mental health symptoms. However, these patterns are inconsistent with student-athlete mental health symptom prevalence (Li et al., 2017; NCAA, 2016) as no class emerged that was characterized by little-to-no endorsement of current or past mental health symptoms.

The next-most parsimonious model was the four-class model. Like the three-class solution, this model had strong model fit indices and the fewer number of classes compared to the five-class model. However, this model also suffered from similar substantive interpretability concerns. Specifically, no class emerged that was characterized by low-to-no endorsement of current and past mental health symptoms. Additionally, two classes appeared to be characterized by similar patterns of responses. While one class was characterized by high endorsement of current feelings of exhaustion and overwhelmingness, a separate class was characterized by moderate endorsement of current feelings of exhaustion and overwhelmingness. Despite these emerging as two distinct classes, it did not appear to offer substantive and unique interpretability and did not align with student-athlete mental health symptom patterns (Li et al., 2017; NCAA, 2016).

While the five-class model was not the most parsimonious solution, it provided strong overall fit to the data. The five-class model had a lower SABIC than each model with fewer classes, and the BLRT indicated that the five-class model was a significant improvement over the four-class model. Additionally, the five-class model was the most substantively interpretable model when compared to the three- and four-class models, and the pattern of responses characterizing each class was consistent with extant theory of student-athlete mental health. Class one (*n* = 4,045) was characterized by a high likelihood of endorsement of all mental health symptoms and low-to-moderate suicidal ideation and nonsuicidal self-injurious behavior within the past 30 days. This class was labeled the high symptoms class (HS). Class two (*n* = 2,979) was characterized by a high likelihood of endorsement of all mental health symptoms and low-to-moderate suicidal ideation and nonsuicidal self-injurious behavior within the past year, but not in the past 30 days. This class was labeled the past symptom class (PS). Class three (*n* = 6,139) was characterized by a high likelihood of endorsement of mental health symptoms most consistent with anxiety and was labeled the anxiety class (ANX). Class four (*n* = 7,676) was characterized by a high likelihood of endorsement of feeling overwhelmed and exhausted within the past 30 days and was labeled the overwhelmed and exhausted class (OE). Class five (*n* = 4,964) was characterized by a high likelihood of endorsing no current or recent mental health symptoms and was labeled the no symptom class (NS). Figures 1, 2, and 3 illustrate latent class probabilities of endorsing each level of the mental health indicators in the final model. Considering model fit indices, parsimony, and substantive interpretability, the five-class model was identified as the best fitting model. Next, auxiliary testing was completed to explore whether the latent classes differed in help-seeking, health risk, and other performance-related outcomes.

BCH Tests of Equality, 5-Class Model

The results of the overall BCH tests of equality for the five-class model are described below and presented in Table 6. BCH class comparison results are illustrated in Figures 4-30, which shows the model-estimated means for the help-seeking, health risk, and performance-related outcomes for the five latent classes.

Help-Seeking Behaviors

Regarding overall tests, the BCH tests were significant for past therapy with a licensed mental health provider ($\chi^2(4) = 3{,}394.73$, $p < .01$), past services with a psychiatric provider ($\chi^2(4) = 1{,}285.81$, $p < .01$), past services from their current university counseling center ($\chi^2(4) = 1{,}684.32$, $p < .01$), and future willingness to seek treatment ($\chi^2(4) = 311.26$, $p < .01$).

For likelihood of seeking past services from a licensed mental health provider, comparisons (See Figure 4) revealed that the HS class reported a significantly higher likelihood of endorsing receiving past services with a mental health provider ($M = 0.61$) than the PS ($M = 0.49$), ANX ($M = 0.36$), OE ($M = 0.21$), and NS ($M = 0.12$) classes. The PS class had a significantly higher likelihood of seeking past services from a mental health provider than the ANX, OE, and NS classes. The ANX class was significantly more likely to have endorsed seeking past services from a mental health provider than the OE and NS classes. Finally, the OE class was significantly more likely to have endorsed past services from a mental health provider than the NS class.

Regarding likelihood of seeking past services from a psychiatric provider, comparisons revealed (See Figure 5) that the HS class reported a significantly higher likelihood of endorsing past services with a psychiatric provider ($M = 0.26$) than the PS ($M = 0.15$), ANX ($M = 0.08$), OE ($M = 0.03$), and NS ($M = 0.02$) classes. The PS class had a significantly higher likelihood of past services with a psychiatric provider than the ANX, OE, and NS classes. The ANX class was significantly more likely to have endorsed past services with a psychiatric provider than the OE and NS classes. Finally, the OE class was significantly more likely to have endorsed past services with a psychiatric provider than the NS class.

Regarding likelihood of seeking past services from their current university counseling center (UCC), comparisons revealed (See Figure 6) that the HS class reported a significantly higher likelihood of endorsing receiving past services with a mental health provider ($M = 0.39$) than the PS ($M = 0.28$), ANX ($M = 0.20$), OE ($M = 0.11$), and NS ($M = 0.07$) classes. The PS class had a significantly higher likelihood of past services with their UCC than the ANX, OE, and NS classes. The ANX class was significantly more likely to have endorsed past services with their UCC than the OE and NS classes. Finally, the OE class was significantly more likely to have endorsed past services with their UCC than the NS class.

Regarding likelihood of seeking future mental health services, comparisons revealed (See Figure 7) that the HS ($M = 0.77$), PS ($M = 0.78$), ANX ($M = 0.76$), and OE ($M = 0.76$) classes reported a significantly higher likelihood of seeking future services than the NS ($M = 0.62$) class. All other classes were not significantly different in their likelihood of seeking future mental health services.

Health Risk Behaviors

Regarding overall tests, the BCH tests were significant for wearing a seatbelt while driving ($\chi^2(4) = 102.71$, $p < .01$), wearing a helmet while riding a bike ($\chi^2(4) = 27.83$, $p < .01$), wearing a helmet while riding a motorcycle ($\chi^2(4) = 48.49$, $p < .01$), alcohol use in the past 30 days ($\chi^2(4) = 414.23$, $p < .01$), heavy episodic drinking over the past two weeks ($\chi^2(4) = 42.45$, $p < .01$), driving after consuming alcohol ($\chi^2(4) = 47.41$, $p < .01$), driving after heavy episodic drinking ($\chi^2(4) = 39.76$, $p < .01$), alcohol-related consequences ($\chi^2(4) = 858.46$, $p < .01$), number of sexual partners in the past over the past year ($\chi^2(4) = 289.18$, $p < .01$), use of a condom during oral intercourse ($\chi^2(4) = 70.06$, $p < .01$), use of a condom during vaginal intercourse ($\chi^2(4) = 71.40$, $p < .01$), past 30-day purging behaviors ($\chi^2(4) = 420.99$, $p < .01$), and use of diet pills in the past 30 days ($\chi^2(4) = 189.82$, $p < .01$). The overall test for use of a condom during anal intercourse was not significant ($\chi^2(4) = 7.03$, $p = .13$).

Risky Driving. Regarding risky driving behaviors, class comparisons (See Figures 8-10) revealed that the HS class reported wearing a seatbelt less frequently ($M = 3.57$) than the PS ($M = 3.66$), ANX ($M = 3.69$), OE ($M = 3.72$), and NS ($M = 3.67$) classes. The PS and ANX classes reported wearing a seatbelt less frequently than the OE class. The OE class reported wearing a seatbelt more frequently than the NS class. Tests revealed no significant differences in frequency of wearing a seatbelt between the PS and ANX classes ($p = 0.08$), the PS and NS classes ($p = 0.36$), and the ANX and NS classes ($p = 0.36$).

Additionally, class comparisons revealed that the HS ($M = 1.52$), PS ($M = 1.56$), ANX ($M = 1.50$), and OE ($M = 1.56$) classes reported wearing a helmet while biking less frequently than the NS ($M = 1.71$) class. Tests revealed no significant differences in frequency of wearing a helmet while biking between the HS and PS classes ($p = 0.44$), the HS and ANX classes ($p = 0.71$), the HS and OE classes ($p = 0.40$), the PS and ANX classes ($p = 0.25$), the PS and OE classes ($p = 0.91$), and the ANX and OE classes ($p = 0.19$).

Finally, class comparisons revealed that the HS class ($M = 3.07$) reported wearing a helmet while riding a motorcycle less frequently than the ANX ($M = 3.27$) and OE ($M = 3.49$) classes. The PS ($M = 3.18$), ANX, and NS ($M = 3.15$) classes reported wearing a helmet while riding a motorcycle less frequently than the OE class. Tests revealed no significant differences in frequency of wearing a helmet while riding a motorcycle between the HS and PS classes ($p = 0.23$), the HS and NS classes ($p = 0.27$), the PS and ANX classes ($p = 0.31$), the PS and NS classes ($p = 0.71$), and the ANX and NS classes ($p = 0.08$).

Overall, these results suggest that, across several outcomes, the HS class engaged in more frequent risky driving behaviors than most other classes of mental health symptoms.

Alcohol Use. Regarding alcohol use outcomes, class comparisons (See Figures 11-15) revealed that the HS class reported consuming alcohol on significantly more days in the past 30 days ($M = 2.52$) than the ANX ($M = 2.35$), OE ($M = 2.33$), and NS ($M = 1.81$) classes. The PS class ($M = 2.49$) reported consuming alcohol on more days in the past month than the ANX, OE, and NS classes. The ANX and OE classes reported consuming alcohol on more days in the past month than the NS class. Tests revealed no significant differences in alcohol consumption in the past month between the HS and PS classes ($p = 0.53$), and the ANX and OE classes ($p = 0.5$).

Regarding heavy episodic drinking, class comparisons revealed that the HS ($M = 1.28$) and NS ($M = 1.26$) classes reported more days of heavy episodic drinking in the past two weeks than the PS ($M = 1.14$), ANX ($M = 1.05$), and OE ($M = 1.09$) classes. Tests revealed no significant differences in heavy episodic drinking between the HS and NS classes ($p = 0.72$), the PS and ANX classes ($p = 0.07$), the PS and OE classes ($p = 0.34$), and the ANX and OE classes ($p = 0.24$).

Tests indicated that the HS ($M = 0.15$) and PS ($M = 0.16$) classes were more likely to endorse driving after consuming alcohol than the ANX ($M = 0.12$), OE ($M = 0.12$), and NS ($M = 0.09$) classes. The ANX and OE classes reported a greater likelihood of driving after drinking than the NS class. Tests revealed no significant differences in the likelihood of driving after drinking alcohol between the HS and PS classes ($p = 0.73$) and the ANX and OE classes ($p = 0.54$). Comparison tests indicated that the HS class ($M = 0.03$) was more likely to endorse driving after engaging in heavy episodic drinking than the ANX ($M = 0.01$), OE ($M = 0.01$), and NS ($M = 0.02$) classes. The PS ($M = 0.02$) and NS classes were significantly more likely to report driving after heavy episodic drinking than the ANX and OE classes. Tests revealed no significant differences in the likelihood of driving after heavy episodic drinking between the HS and PS classes ($p = 0.48$), the PS and NS classes ($p = 0.26$), and the ANX and OE classes ($p = 0.15$).

Finally, tests indicated that the HS class ($M = 1.82$) experienced significantly more alcohol-related consequences than the PS ($M = 1.51$), ANX ($M = 1.28$), OE ($M = 1.03$), and NS ($M = 0.82$) classes. The PS class reported experiencing significantly more alcohol-related consequences than the ANX, OE, and NS classes. The ANX class reported more alcohol-related consequences than the OE and NS classes. Finally, the OE class reported more alcohol-related consequences than the NS class.

Overall, these results suggest that the HS class generally consumed alcohol more often, were more likely to engage in risky driving behavior following alcohol use, and experienced more consequences associated with their alcohol use than other mental health symptoms classes. Additionally, the PS class appeared to demonstrate similar patterns among alcohol-related outcomes when compared to the ANX, OE, and NS classes, suggesting that riskier alcohol use behaviors were associated with classes of individuals endorsing larger numbers of current and/or past mental health symptoms.

Risky Sex. Comparison tests (See Figures 16-19) revealed that the HS ($M = 2.17$) and PS ($M = 2.04$) classes reported having significantly more sexual partners in the past year than the ANX ($M = 1.60$), OE ($M = 1.52$), and NS ($M = 1.48$) classes. Additionally, comparisons revealed that the ANX class endorsed more sexual partners than the OE and NS classes. Tests revealed no significant differences in the number of sexual partners within the last year between the HS and PS classes ($p = 0.06$) and the OE and NS classes ($p = 0.33$).

Regarding condom or protective barrier use during oral intercourse in the past 30 days, the HS ($M = 0.30$), PS ($M = 0.26$), ANX ($M = 0.26$), and OE ($M = 0.26$) classes endorsed significantly less frequency of using protection during oral intercourse than the NS class ($M = 0.50$). Tests revealed no significant differences in frequency of using protection during oral intercourse between the HS and PS classes ($p = 0.20$), the HS and ANX classes ($p = 0.3$), the HS and OE classes ($p = 0.15$), the PS and ANX classes ($p = 0.87$), the PS and OE classes ($p = 0.93$), and the ANX and OE classes ($p = 0.77$).

For condom use during vaginal intercourse in the past 30 days, tests indicated that the HS class ($M = 2.10$) reported significantly less frequent use of protection during vaginal intercourse than the PS ($M = 2.27$), ANX ($M = 2.30$), OE ($M = 2.44$), and NS ($M = 2.43$) classes. Additionally, the PS class reported less frequent condom use than the OE and NS classes. Finally, the ANX class reported less frequent condom use than the OE and NS classes. Tests revealed no significant differences in frequency of condom use during vaginal intercourse between the PS and ANX classes ($p = 0.68$) and the OE and NS classes ($p = 0.77$).

Finally, while the overall test for the frequency of use of protection during anal intercourse in the past 30 days was not statistically significant, two differences were observed between classes. First, the HS class ($M = 1.20$) reported significantly less frequent use of protection during anal intercourse than the NS class ($M = 1.45$). Second, the OE class ($M = 1.20$) reported significantly less frequent use of protection during anal intercourse than the NS class. All other tests were not statistically significant.

Collectively, these results suggest that the HS class was engaged in more frequent risky sex behaviors than other classes of mental health symptoms. Consistent with the alcohol-related findings described above, the PS class was also associated with more risk sex behaviors than the

ANX, OE, and NS classes, indicating that classes experiencing a greater number of mental health symptoms may be at greater risk of engaging in risky sex and experiencing associated negative consequences.

Disordered Eating Behaviors. Finally, class comparisons (See Figures 20 and 21) of disordered eating behaviors revealed that the HS class ($M = 0.10$) was more likely to endorse vomiting or taking laxatives to lose weight in the past 30 days than the PS ($M = 0.04$), ANX ($M = 0.03$), OE ($M = 0.01$), and NS ($M = 0.01$) classes. Additionally, the PS class was more likely to endorse purging behaviors than the ANX, OE, and NS classes. The ANX class was more likely to endorse purging in the last 30 days than the OE and NS classes. There was no significant difference between the OE and NS classes ($p = .81$). Regarding taking diet pills to lose weight, the HS class ($M = 0.07$) was more likely to endorse taking diet pills to lose weight in the past 30 days than the PS ($M = 0.04$), ANX ($M = 0.02$), OE ($M = 0.01$), and NS ($M = 0.02$) classes. The PS class was more likely to endorse taking diet pills than the ANX, OE, and NS classes. The ANX class was more likely to take diet pills than the OE class. Tests revealed no significant differences in likelihood of taking diet pills in the last 30 days between the ANX and NS classes ($p = 0.19$) and the OE and NS classes ($p = 0.51$). Together, these findings suggest that the HS class is at the greatest risk of engaging in disordered eating behavior to manage weight. Like the above findings, the PS class also was associated with greater likelihood of disordered eating behaviors when compared to the ANX, OE, and NS classes.

Performance-Related Outcomes

The overall BCH tests were significant for engagement in moderate cardiovascular exercise within the past week ($\chi^2(4) = 102.11$, $p < .01$), engagement in vigorous cardiovascular exercise in the past week ($\chi^2(4) = 181.48$, $p < .01$), weightlifting in the past week ($\chi^2(4) = 428.61$,

$p < .01$), sleep difficulties in the past year ($\chi^2(4) = 4889.83$, $p < .01$), trouble falling back asleep within the past week ($\chi^2(4) = 848.07$, $p < .01$), feeling tired, dragging, or sleepy during the day within the past week ($\chi^2(4) = 4470.60$, $p < .01$), feeling unable to stay awake due to fatigue in the past week ($\chi^2(4) = 1545.91$, $p < .01$), difficulties falling asleep in the past week ($\chi^2(4) = 2200.28$, $p < .01$), and academic difficulties in the past year ($\chi^2(4) = 6663.89$, $p < .01$).

Exercise. Comparison tests (See Figures 22-24) revealed that the HS ($M = 3.89$) class reported significantly fewer days of moderate cardiovascular exercise in the past week than the PS ($M = 4.07$), ANX ($M = 4.06$), OE ($M = 4.20$), and NS ($M = 4.37$) classes. Tests also indicated that the PS class reported significantly fewer days of moderate cardiovascular exercise than the OE and NS classes. Additionally, the ANX class endorsed fewer days of moderate cardiovascular exercise than the OE and NS classes. Finally, the OE class reported fewer days of moderate cardiovascular exercise than the NS class. Tests revealed no significant differences in the number of moderate cardiovascular exercise days within the last week between the PS and ANX classes ($p = 0.85$).

Regarding vigorous cardiovascular exercise, comparison tests revealed that the HS ($M = 3.47$) class reported significantly fewer days of vigorous cardiovascular exercise in the past week than the PS ($M = 3.70$), ANX ($M = 3.67$), OE ($M = 3.85$), and NS ($M = 4.11$) classes. Tests also indicated that the PS class reported significantly fewer days of vigorous cardiovascular exercise than the OE and NS classes. Additionally, the ANX class endorsed fewer days of vigorous cardiovascular exercise than the OE and NS classes. Finally, the OE class reported fewer days of vigorous cardiovascular exercise than the NS class. Tests revealed no significant differences in the number of vigorous cardiovascular exercise days within the last week between the PS and ANX classes ($p = 0.63$).

Finally, tests indicated that the HS (*M* = 2.68) class reported significantly fewer days of weightlifting training in the past week than the PS (*M* = 2.87), OE (*M* = 2.91), and NS (*M* = 3.50) classes. Tests also indicated that the PS class reported significantly fewer days of weightlifting training than the ANX (*M* = 2.66) and NS classes. Additionally, the ANX class endorsed fewer days of weightlifting training than the OE and NS classes. Finally, the OE class reported fewer days of weightlifting training than the NS class. Tests revealed no significant differences in the number of weightlifting training days within the last week between the HS and ANX classes ($p = 0.68$) and the PS and OE classes ($p = 0.51$).

Overall, these results suggest that the HS class engaged in significantly less exercise than the other classes of mental health symptoms. Notably, the PS class and the ANX class were not significantly different across all exercise behaviors. This finding deviates from previous auxiliary findings that the ANX class was at significantly less risk of other health-risk and greater likelihood of engagement in help seeking behaviors compared to the PS class.

Sleep Difficulties. Regarding likelihood of experiencing sleep difficulties, comparison tests (See Figures 25-29) revealed that the HS (*M* = 0.60) class had a significantly higher likelihood of reporting sleep difficulties in the past year than the PS (*M* = 0.35), ANX (*M* = 0.31), OE (*M* = 0.12), and NS (*M* = 0.05) classes. Additionally, the PS class was more likely to report sleep difficulties than the ANX, OE, and NS classes. The ANX class was more likely to report sleep difficulties than the OE and NS classes. Finally, the OE class was more likely to report sleep difficulties than the NS class.

Regarding experiences associated with sleep difficulties, the HS class reported significantly more days of having trouble falling back asleep (*M* = 1.80), feeling tired/dragging/sleepy during the day (*M* = 4.54), having trouble staying awake due to fatigue (*M*

= 2.80), and having trouble falling asleep (*M* = 2.79) in the past seven days than the PS (*M* = 1.28, *M* = 3.38, *M* = 1.99, *M* = 1.82), ANX (*M* = 1.26, *M* = 3.73, *M* = 2.12, *M* = 1.79), OE (*M* = 0.91, *M* = 2.87, *M* = 1.59, *M* = 1.17), and NS (*M* = 0.83, *M* = 1.93, *M* = 1.19, *M* = 0.90) classes. Further, the PS class endorsed significantly more days of having trouble falling back asleep, feeling tired or dragging during the day, having trouble staying awake, and having trouble falling asleep than the OE and NS classes. The PS class also reported more days of feeling tired and having trouble staying awake than the ANX class. The ANX class reported significantly more days of having trouble falling back asleep, feeling tired or dragging during the day, having trouble staying awake, and having trouble falling asleep than the OE and NS classes. Finally, the OE class endorsed more days of having trouble falling back asleep, feeling tired, trouble staying awake, and trouble falling asleep than the NS class. Tests revealed no significant differences between the PS and ANX classes in the number of days reported having trouble falling back asleep ($p = 0.70$) and the number of days having trouble falling asleep ($p = 0.52$).

Overall, these results suggest that, across all sleep outcomes, the HS class experienced significantly more sleep concerns than all other classes of mental health symptoms. Notably, the OE class consistently endorsed significantly fewer sleep-related concerns despite the latent class being characterized by high endorsement of feeling overwhelmed and exhausted.

Academic Performance. Regarding impairments to academic performance, comparison tests (See Figure 30) revealed that the HS (*M* = 0.76) class had a significantly higher likelihood of reporting academic difficulties in the past year than the PS (*M* = 0.53), ANX (*M* = 0.55), OE (*M* = 0.29), and NS (*M* = 0.11) classes. The PS and ANX classes were more likely to report academic difficulties than the OE and NS classes. Finally, the OE class was more likely to report academic difficulties than the NS class. Tests revealed no significant differences between the PS and ANX classes in likelihood of endorsing academic difficulties (p = 0.15).

Multigroup and Confirmatory Latent Class Analyses

After selection of the five-class model for the student-athlete sample, a series of single-group and multigroup latent class analyses were conducted using a random sample of non-student-athlete participants to determine whether the five-class model identified using the student-athlete sample fit equally well for the non-student-athlete sample. Using IBM SPSS 25.0 (IBM Corp., 2017), 27,642 student participants that endorsed no varsity and club athletic participation were randomly selected from the ACHA-NCHA dataset to match the number of student-athlete identified participants in the same dataset. Several models were then estimated to compare the student-athlete and non-student-athlete models. Like the originally estimated latent class models, age, biological sex, and past mental health diagnoses were entered in as covariates to limit potential confounds.

Two multigroup latent class models were estimated, one with constrained class probabilities across groups and one with freely estimated class probabilities (See Table 7 for model fit indices). The difference between the SABIC from the unconstrained model and constrained model was greater than 100 (ΔSABIC = 384.79) indicating the unconstrained model was the decisively better fitting model. In support of this conclusion, the difference between the entropy values from the unconstrained model and constrained model was small and positive (Δentropy = 0.002). Collectively, these results suggest that the model where class probabilities were freely estimated across groups was the better fitting model. Finally, another two latent class models were estimated using the non-student-athlete sample. The first model estimated was one where threshold values for each indicator in all five classes were constrained to be equal to the respective values from the five-class student-athlete model. This model was compared to one where a five-class model was freely estimated for the non-student-athlete sample (See Table 8 for model fit indices). The difference between the SABIC from the unconstrained and constrained models was greater than 100 (ΔSABIC = 829.88) indicating unconstrained model was the decisively better fitting model than the constrained model. In support of this conclusion, the difference between the entropy values from the unconstrained model and constrained model was small and positive (Δentropy = 0.008). Overall, results indicated that the five-class model identified for student-athletes did not fit equally well for the non-student-athlete sample.

DISCUSSION

Summary of Findings

The aims of this study were to discern whether there were unobserved patterns of general mental health symptoms endorsed by college student-athletes, whether these classes were differentially associated with help seeking, health-risk, and performance-related variables, and whether similar patterns of symptoms were observed among non-student-athletes. The findings from the present study are summarized below.

Overall Model

Results from this study discerned previously unidentified latent subgroups of student-athletes, characterized by varying patterns of depressive and anxiety symptoms, that are associated with varying risk of experiencing negative physical and mental health and performance-related outcomes, and associated with varying likelihood of seeking support to address these concerns. I ran a series of latent class analyses and identified that a five-class model best fit the data. Class one was characterized by a pattern of high likelihood of endorsement of past 30-day general mental health symptoms and higher likelihood of suicidal ideation and nonsuicidal self-injurious behavior (HS class). The pattern of responses that was characterized by the HS class was the most likely class for approximately 4,045 student-athlete participants (~16%). Class two was characterized by a pattern of high likelihood of endorsement of past 12-month general mental symptoms (PS class). The pattern of responses that was characterized by the PS class was the most likely class for approximately 2,979 student-athlete participants (~11%). Class three was characterized by a pattern of high likelihood of endorsement of symptoms consistent with anxiety (ANX class). The pattern of responses that was characterized by the ANX class was the most likely class approximately 6,139 student-athlete participants (~24%). Class four was characterized by a pattern of high likelihood of endorsement of experiences feeling overwhelmed and exhausted (OE class). The pattern of responses that was characterized by the OE class was the most likely class for approximately 7,676 student-athlete participants (~30%). Finally, class five was characterized by a pattern of no endorsement of past 30-day and 12-month mental health symptoms (NS). The pattern of responses that was characterized by the NS class was the most likely class for approximately 4,964 student-athlete participants (~19%). The presence of these five latent profiles further strengthens claims that college student-athletes and mental health experiences are heterogeneous (Forbes et al., 2023; Zamboanga et al., 2021), underscoring the need to understand the unique patterns of symptom experiences.

While limited research has explored classes or profiles of mental health symptoms, several previous studies identified similar patterns of mental health symptoms. Several studies have identified three classes or profiles characterized by low, moderate, and high mental health symptom endorsement (Gerber et al., 2014; McFadden et al., 2020; Petersen et al., 2019; Reinhardt et al., 2020). My findings strengthen the extant literature, identifying varying experiences with a variety of mental health experiences. Additionally, researchers have identified six robust profiles characterized by moderate-to-high stress and high mental health concerns, high stress and high resilience, moderate stress and high resilience, high stress and low resilience, moderate stress and low resilience, and low stress and low mental health concerns (Gerber et al., 2014). While these studies do not include similar mental health symptoms used in the present study, my findings align with the overall conclusions of robust and varying patterns of mental health symptom endorsement. However, previous findings have not identified a unique pattern of mental health symptoms characterized by high endorsement of exhaustion and overwhelmed symptom endorsement. Whether this is a class unique to student-athletes or is capturing a pattern that has not been previously assessed, it is important to consider potential implications associated with this class. Persistent and pervasive feelings of exhaustion and overwhelmedness often indicate burnout, which for student-athletes relates to greater likelihood of withdrawal from sport (Gustafsson et al., 2016). Considering the consequences associated with exhaustion, feeling overwhelmed, and burnout could lead to withdrawal from sport and short- and long-term health problems (Bayes et al., 2021). Identifying student-athletes that likely belong to this class could help attenuate symptoms and mitigate consequences. By relying on traditional variable-centered approaches to explore student-athlete mental health symptoms, like reporting individual symptom endorsement rates (Edwards et al., 2021), researchers and clinicians lacked critical information regarding unique patterns of symptoms and differential associations with a variety of health- and performance related outcomes.

Auxiliary Testing

To evaluate whether latent classes differ on a variety of mental- and performance-related outcomes, BCH auxiliary tests were conducted. Results indicated that these identified latent classes described above were differentially associated with various help seeking, health-risk, and performance-related variables.

Help Seeking. The classes characterized by endorsement of mental health symptoms within the past month or year (HS, PS, ANX, OE) were associated with greater likelihood of seeking services from mental health providers in the past than the class characterized by minimal-to-no endorsement (NS class) of mental health symptoms in the past year. Further, classes characterized by mental health symptom endorsement reported greater likelihood to seek future mental health services in the future as compared to the NS class. Several differences in help seeking behaviors between classes are important to highlight. Specifically, the HS class was significantly more likely to endorse seeking past mental health support (0.26-0.61) than all other classes. While the HS class did not differ in willingness to seek future support from the PS, ANX, and OE classes, the likelihood was high (0.77) suggesting high willingness to seek help if/when needed. Considering that seeking mental health support has been identified as effective at reducing symptoms and mitigating negative consequences associated with expressed symptoms (Moreland et al., 2018), my findings suggest that continued connection to mental health resources may be effective at addressing immediate symptom presentation.

Additionally, I found that the OE class was equally likely to endorse willingness to seek future mental health services when compared to other classes of mental health symptoms and were significantly less likely to seek mental health services in the past. While these results may suggest student-athletes with the highest likelihood of being in the OE class are experiencing greater situational stress exacerbating feelings of exhaustion, they may also capture student-athletes with more chronic experiences of feeling overwhelmed and exhausted characteristic of burnout. Considering this class was associated with high willingness to seek future support and low likelihood of past mental health seeking behaviors, it may be of particular importance to consider ways to connect student-athletes with this pattern of symptoms to appropriate consultation resources to better understand their experiences with these symptoms.

Health-Risk. Overall, my results indicated that classes characterized by endorsement of mental health symptoms were associated with greater likelihood or endorsement of a variety of health-risk behaviors compared to the NS class. Regarding comparisons across classes characterized by different mental health patterns, the HS and PS classes were associated with greater likelihood of endorsing risky driving behaviors, endorsed consuming more alcohol and heavy episodic drinking, endorsed greater frequency of risky sex behaviors, and endorsed more purging and risky dieting behaviors. These results indicated that patterns of endorsement of both anxiety and depressive symptoms, in both the past month and past year, were associated with increased risk of engagement in health-risk behaviors. Considering I identified that these classes were associated with greater willingness to seek future support, outreach and treatment planning efforts may successfully connect these student-athletes with support. Outreach efforts may provide the support necessary to limit engagement in and attenuate negative consequences of these health-risk behaviors. These outreach and treatment efforts will be further discussed below when exploring treatment planning and future directions.

Performance-Related. Traditional and direct performance outcomes, such as competition factors (e.g., times, wins, statistics), were not assessed in the present study. However, I evaluated outcomes associated with performance, like exercise rates, sleep, and academic success (for sport eligibility). The HS class was associated with engaging in significantly fewer days of moderate exercise, vigorous exercise, and weightlifting activities per week than all other mental health classes. Further, the HS class was associated with significantly more days of sleep issues and a higher likelihood of academic difficulties than the other mental health classes. This finding further underscores the importance of targeting outreach and treatment efforts to student-athletes that may be presenting with this pattern of current anxiety and depressive symptom endorsement. Previous research suggests that consistent sleep disturbances and sleep loss can significantly decrease athletic performance (Fullagar et al., 2015). Additionally, aerobic exercise and weightlifting can further enhance athletic performance (Armstrong et al., 2011; Hori et al., 2005), suggesting that less exercise may limit performance in sport. Finally, academic success is significantly associated with athletic success, and that academic struggles are related to poorer sport performance (Bailey, 2017). Since student-athletes must maintain "good academic standing," often defined as a grade point average of 2.0, to remain eligible to participate in sport (NCAA, 2023), sustained academic issues could prevent a student-athlete from competing in their sport. While not a direct effect, the HS class may be at greater risk of exercise, sleep, and academic difficulties which may subsequently hurt their sport performance. This finding further underscores the importance of identifying these patterns of mental health symptoms and connecting these student-athletes with additional supports.

Finally, the OE class was associated with fewer sleep issues than all other classes besides the no-symptom class. This is notable, as it may indicate that the exhaustion student-athletes that belong to this class may not be physical exhaustion due to decreased sleep quality/quantity. This finding may further demonstrate that some student-athletes that belong to this class of symptoms may be experiencing burnout, since burnout is primarily associated with emotional exhaustion as opposed to exhaustion brought on by sleep concerns (Maslach & Jackson, 1981). Further exploration into the role that burnout may play in this class's experiences feeling overwhelmed and fatigue may help inform more targeted interventions.

Student-Athletes Versus Non- Athletes

Past studies often examined rates of college mental health symptoms, treatment seeking, and negative outcomes without separating groups like student-athletes from their non-athlete peers. This study represented one of the first, and largest, comparisons between student-athlete and non-athlete mental health symptom experiences. To determine whether non-student-athletes had similar patterns of mental health symptom endorsement, a series of multigroup and confirmatory latent class analyses were run. Results indicated that the five-class model identified within the student-athlete sample fit well for a comparative sample of non-athletes. However, comparisons revealed that the five-class solution allowing for differences between student-athletes and non-athletes fit decisively better. These findings suggest that student-athletes experience a unique pattern of mental health symptoms as compared to their non-athlete peers. Since student-athletes report feelings of isolation from the general college student population and that unique barriers to accessing services meant for the whole college student community exist for student-athletes (Ishaq & Bass, 2019; Srivastava, 2019), The lack of evaluation regarding whether college student and student-athlete mental health should be treated separately may limit researchers' and stakeholders' ability to address barriers to receiving support.

Considering that student-athlete mental health service utilization rates are lower compared to their non-athlete peers (Kilcullen et al., 2022), this study represents a key step in recognizing the importance of developing athlete-specific resources for mental health support to improve access to services. Since this study's findings highlight the differences in patterns of mental health symptoms between student-athletes and their non-athlete peers, student-athletes may benefit from unique and targeted intervention and prevention efforts to address these patterns and associated consequences. Specifically, efforts focused on barriers like university/athletic department control of resources and student-athlete time constraints (Ishaq & Bass, 2019) may help student-athletes receive supports that may uniquely benefit their experiences with mental health symptoms patterns. This study underscores the importance of viewing the mental health experiences of student-athletes, and therefore allocation of services to address these experiences, as separate from their non-student-athlete peers.

Implications on Prevention and Intervention Efforts

This study represents the first application of person-centered analyses to explore mental health symptoms of college student-athletes. As such, findings from the present study provide several valuable contributions to the field.

First, these findings can inform prevention and intervention efforts to help university athletic departments draft plans to better address their student-athlete mental health concerns. Considering ways to identify which class of mental health symptoms a student-athlete may likely belong, and adapting stepped care approaches to athletic settings may help departments evaluate and connect at-risk student-athletes with appropriate levels of support. For example, findings identified that a student-athlete experiencing a pattern of mental health symptoms characterized by high likelihood of endorsement of all depressive and anxiety symptoms within the past month may be at greater risk of engaging in health-risk behaviors and other experiences that may negatively affect performance compared to a student-athlete with a pattern of responses characterized by only anxiety symptoms. Athletic departments can identify at-risk student-athletes and connect them with resources to prevent or reduce negative outcomes like academic concerns or health risk behaviors. They may also conserve resources by focusing appropriate levels of outreach to those student-athletes experiencing certain patterns of symptoms. Through treatment aimed at reducing symptom distress, student-athletes may engage in fewer health risk behaviors that could be detrimental to their performance and recovery (i.e., heavy episodic drinking) and improve areas of life that may affect performance and eligibility (i.e., sleep quality, weekly exercise, academic performance).

Next, results presented here may also help schools identify student-athletes at risk of negative outcomes due to mental health concerns without relying on the athlete seeking support and implement simple and empirically supported ways to identify these at-risk student-athletes.

Considering that, in the present study, I identified that student-athletes across all mental health symptom classes endorsed a high willingness to seek future services, proactive efforts by athletic departments can enhance help-seeking behaviors. Athletic departments, particularly the greater than 60% that have not yet developed formal plans to address student-athlete mental health concerns (Kroshus, 2016), may use this study's findings to implement simple mental health screeners aimed at identifying at-risk athletes they could connect with trained mental health professionals. Since this study is the first to identify these latent classes and associated help seeking, health-risk, and performance-related outcomes, it is important to note study limitations and future directions that may replicate and enhance my findings.

Limitations

The present study had several limitations to note. First, the present study was cross-sectional, so conclusions regarding the direction of relations and potential stability of class membership over time cannot be made. Therefore, this study is unable to discern whether student-athletes were experiencing mental health symptoms due to their engagement in health-risk behaviors or if they were engaging in health-risk behaviors due to the mental health symptoms they were experiencing. The study also cannot tell how long a student-athlete may belong in their respective mental health symptom class, and at what point they may transition to a different class. Future longitudinal studies may explore the directionality of these identified relations and evaluate transitions across classes over time.

Second, this study was a secondary data analysis, which limited the ability to select what indicator and auxiliary variables could be used in the present study. While the mental health symptoms included in the ACHA-NCHA dataset represent a short and simple way to evaluate depressive and anxiety-related symptoms, there are empirically validated brief measures for depression, anxiety, and other mental health concerns that may more effectively assess mental health concerns of college students and student-athletes. For example, the Patient Health Questionnaire-9 (PHQ-9) is a nine-item depression questionnaire that has been validated and is given in a variety of medical and mental health settings (Kroenke et al., 2001). Additionally, the Generalized Anxiety Disorder-7 (GAD-7) is a seven-item measure assessing symptoms consistent with generalized anxiety disorder (Spitzer et al., 2006). While using both tools, in lieu of the existing measure, would add an additional five items that student-athletes would be required to complete, the addition may strengthen assessment due to the use of reliable and valid measures. However, these measures were designed to assist in the diagnosis of disordered experiences with these symptoms, rather than general experiences with these mental health experiences. Therefore, the variables present in the ACHA-NCHA survey were adequate to address this study's aims.

Regarding auxiliary variables, I was limited because the ACHA-NCHA survey did not include empirically validated measures to evaluate health-risk and performance outcomes more comprehensively and effectively. For example, alcohol use rates may be more effectively evaluated using measures like the Daily Drinking Questionnaire (DDQ; Collins et al., 1985). Disordered eating behaviors were limited to purging and diet pill consumption, which does not fully evaluate the domain of disordered eating. Additionally, including assessment of specific performance outcomes, such as points scored or times in respective competition, could help further strengthen conclusions on differential impacts of mental health on sport performance. While including more questions and empirically validated measures may increase burden to participants, it may also strengthen the quality and generalizability of findings. Future studies may consider ways to evaluate changes in sport performance and validate ACHA-NCHA measures and/or evaluate whether the present findings are confirmed using empirically validated measures.

Third, several factors may limit the generalizability of these findings. This study was of a sample of predominantly White-identified college students and student-athletes. This may limit our ability to generalize findings to youth and post-collegiate athletes. Since this was a population-based data set that pulled from a large sample of college students across the United States, findings likely generalize to college student-athletes in the United States. While the purpose of this study was to explore college student-athlete mental health patterns and differential associations with help seeking, health-risk, and performance-related outcomes, it may be important to evaluate whether similar patterns exist among pre- and post-collegiate athletes. Additionally, the data used in the present study was collected between fall 2015 and spring 2019. Since this data was collected prior to the COVID-19 pandemic, it is important to replicate findings using more recent data collected during/post-pandemic. This step may further increase generalizability of these findings.

Future Directions

To further expand on findings from the present study, it is planned to examine ways for mental health professionals in athletic departments to use the brief mental health screening from the ACHA-NCHA survey. Specifically, future studies will focus on efforts to develop simple, cost-effective ways to determine the likelihood a student-athlete may belong to a class associated with high risk of engagement in health-risk behaviors and other issues that may affect athletic performance. These efforts could help athletic departments effectively tailor intervention and prevention efforts to the individual student-athlete. This process, referred to as precision medicine, uses data-driven and empirically supported decision-making processes to help inform individualized support (Kosorok & Laber, 2019). While this may appear to be an ambitious and inefficient process, machine learning algorithms can be used to help clinicians classify student-athletes more effectively to individualize support. Specifically, the k-nearest neighbors algorithm (Cover & Hart, 1967; Fix & Hodges, 1951) can help researchers and clinicians classify student-athletes based on their proximity to one of the classes of mental health patterns I identified in the present study. It is possible that machine learning applications of this algorithm could be an effective method to classify individuals based on their proximity to respective latent classes/profiles. Developing a tool within which clinicians may enter student-athlete mental health symptoms and identify which class they most likely belong to may provide university athletic departments with simple and effective ways to identify levels of support most appropriate for each student-athlete. Following these classification efforts, researchers and clinicians should consider ways to adapt stepped care approaches to university athletic settings to effectively apply precision medicine and individualize support recommendations.

Treatment Planning with Stepped Care Approach

A recent application of the social ecological framework to college athletic counseling identified several roles and recommendations for sport counselors to enhance student-athlete help seeking and retention efforts (Reich et al., 2021). Including an emphasis on the administration of annual mental health screenings, these researchers noted the importance of counselor's advocating for and educating student-athletes inside and outside the individual counseling setting (Reich et al., 2021). Immediate next steps from the present study may help departments classify students based on their proximity to mental health symptom classes identified in this study and connect students with consultation, advocacy, and educational resource to best address their individual concerns. Considering ways to integrate stepped care treatment approaches in athletic settings may help athletic departments develop more formal plans to support student-athletes' mental health needs on an individualized basis.

Stepped care treatment models in the United States were adapted from models first developed in the United Kingdom (Cornish et al., 2017). These models were developed to help connect larger groups of treatment-seeking college students with effective support, appropriate for their presentation, without requiring significant wait times on ever growing counseling center waitlists. These programs have been designed to allow individuals to be "stepped up" or down depending on symptom severity and need (Cornish et al., 2017). Additional studies have noted eight treatment "tracks" for students: online information, online assisted self-help, biofeedback, consultation, brief therapy, outpatient therapy, more frequent outpatient therapy, and group therapy (Bailey et al., 2021). While each track has a variety of benefits and limitations, this approach has helped connect students with a wider variety of helpful services and reduce clinician burnout (Bailey et al., 2021). As of now, this model has not been adapted to university athletic settings. And while student-athletes are a part of the larger student-body, their physical and mental health needs are most often supported from practitioners embedded directly within athletic departments.

Since findings from the present study indicated that student-athletes experience different patterns of symptoms compared to their non-athlete peers, it is important that efforts be made to adapt models to address this unique population. Researchers and clinicians should consider ways to adapt these models to athletic settings and use annual mental health screening tools to connect student-athletes with appropriate levels of support. For example, a clinician may use the screener to identify a student-athlete as most likely belonging to the HS class. The clinician may then consider this student-athlete as needing support services to be "stepped up," leading to this clinician reaching out to initiate individual therapy services. Alternatively, the clinician may identify a student-athlete as likely belonging to the ANX class and could connect this student-athlete with biofeedback or brief therapy support. Finally, a clinician could conduct a consultation meeting with a student-athlete likely belonging to the OE class to determine whether they may benefit from connection with additional academic supports to address feelings of overwhelmingness or are experiencing burnout and need higher levels of support. Future efforts adapting and examining the effectiveness of the stepped care treatment approach to university athletic settings could help equip athletic departments with more effective treatment planning approaches.

Finally, it is important to consider traditional barriers to treatment-seeking and willingness to engage in mental health services. A recent meta-analysis pointed to the key role that leaders, specifically coaches and athletic administrators, play in the willingness to seek mental health support (Moreland et al., 2018). These researchers suggest that attention must also be directed towards athletic leadership groups to change norms and promote mental health and well-being. They recommend that athletic departments re-allocate funding to develop sport psychological training and staffing, hire more professionals with sport background, and explore ways to increase coaches' willingness to encourage their student-athletes to seek support services. Attention to the barriers, coupled with efforts to adapt stepped care approaches, may help connect at-risk student-athletes with helpful levels of support.

TABLES

Table 1
Demographic Data

Variable	Student-Athlete Sample	Non-Athlete Sample
Age (***Median***)	20	21
Race (**%**)		
White	78.6	65.1
Black	7.3	5.8
Hispanic or Latina/o	9.1	15.2
Asian or Pacific Islander	8.3	15.0
American Indian, Alaskan Native, or Native Hawaiian	1.9	2.0
Biracial or Multiracial	4.1	4.9
Other	1.7	2.8
Biological Sex (**%**)		
Female	64.7	69.7
Male	35.3	29.9
Gender (**%**)		
Woman	63.8	68.3
Man	34.7	29.4
Trans Woman	0.1	0.1
Trans Man	0.1	0.2
Genderqueer	0.3	0.7
Another identity (please specify)	0.6	1.0
Sexual Orientation (**%**)		
Asexual	4.3	3.3
Bisexual	4.3	7.1
Gay	0.8	1.9
Lesbian	1.3	1.1

Pansexual	0.6	1.7
Queer	0.4	1.2
Questioning	1.1	1.7
Same Gender Loving	0.1	0.0
Straight/heterosexual	86.0	80.6
Another identity (please specify)	0.5	0.9

Table 2
Means and standard deviations for indicator and outcome variables, split between the student-athlete and non-athlete samples

Variable Type	Variable Name	Student-Athlete *m* (*sd*)	Non-Athlete *m* (*sd*)
Indicators	Hopeless	0.69 (0.85)	0.84 (0.87)
	Overwhelmed	1.47 (0.78)	1.56 (0.72)
	Exhausted	1.36 (0.85)	1.53 (0.75)
	Lonely	0.90 (0.89)	1.03 (0.88)
	Sad	0.99 (0.88)	1.12 (0.87)
	Depressed	0.48 (0.77)	0.64 (0.83
	Anxiety	0.85 (0.89)	1.05 (0.89)
	Anger	0.56 (0.80)	0.64 (0.82)
	Self-harm	0.10 (0.39)	0.10 (0.39)
	Suicidal Ideation	0.12 (0.41)	0.15 (0.46)
	Suicide Attempt	0.03 (0.21)	0.02 (0.17)
Outcomes	Past Therapy	0.32 (0.47)	0.42 (0.49)
	Past Psychiatry	0.09 (0.29)	0.16 (0.37)
	Past University Counseling	0.19 (0.39)	0.20 (0.40)
	Future Treatment	0.74 (0.44)	0.80 (0.40)
	Seat Belt	3.67 (0.65)	3.79 (0.56)
	Helmet – Bicycle	1.56 (1.59)	1.78 (1.68)
	Helmet – Motorcycle	3.23 (1.38)	3.35 (1.31)
	Past 30-day Alcohol	2.28 (1.70)	2.29 (1.80)
	Heavy Episodic Drinking	1.15 (1.66)	0.81 (1.46)
	Driving After Drinking	0.13 (0.33)	0.22 (0.41)
	Driving After HED	0.02 (0.12)	0.02 (0.12)
	Alcohol Consequences	1.26 (1.43)	0.98 (1.30)
	# of Sex Partners	1.70 (2.06)	1.28 (1.71)
	Condom – Oral Sex	0.32 (0.94)	0.26 (0.86)

	Condom – Vaginal Intercourse	2.32 (1.56)	1.97 (1.67)
	Condom – Anal Intercourse	1.29 (1.66)	1.14 (1.62)
	Purging	0.03 (0.18)	0.03 (0.16)
	Diet Pills	0.03 (0.17)	0.03 (0.17)
	Moderate Cardio	4.12 (2.21)	2.37 (2.01)
	Vigorous Cardio	3.77 (2.25)	1.36 (1.68)
	Weightlifting	2.92 (2.05)	1.23 (1.73)
	Sleep difficulties	0.26 (0.44)	0.33 (0.47)
	Falling Back Asleep	1.17 (1.62)	1.26 (1.71)
	Tired, Dragging, Sleepy	3.23 (2.02)	3.40 (2.10)
	Stay Awake	1.89 (1.97)	1.93 (2.04)
	Falling Asleep	1.61 (1.98)	1.78 (2.14)
	Academic Difficulties	0.42 (0.49)	0.49 (0.50)

Table 3

Correlations between indicator and outcome variables within student-athlete sample

Variable Name	1	2	3	4	5	6	7
1 Hopeless	—						
2 Overwhelmed	0.37	—					
3 Exhausted	0.4	0.65	—				
4 Lonely	0.59	0.4	0.45	—			
5 Sad	0.61	0.44	0.48	0.68	—		
6 Depressed	0.62	0.28	0.33	0.53	0.56	—	
7 Anxiety	0.52	0.43	0.45	0.5	0.56	0.56	—
8 Anger	0.48	0.29	0.32	0.43	0.48	0.52	0.51
9 Self-harm	0.26	0.1	0.13	0.21	0.21	0.32	0.22
10 Suicidal Ideation	0.34	0.11	0.14	0.27	0.26	0.43	0.26
11 Suicide Attempt	0.14	0.03	0.05	0.11	0.11	0.2	0.12
12 Past Therapy	0.24	0.16	0.19	0.24	0.25	0.29	0.29
13 Past Psychiatry	0.18	0.09	0.11	0.17	0.16	0.24	0.2
14 Past University Counseling	0.2	0.11	0.14	0.19	0.19	0.24	0.22
15 Future Treatment	0.04	0.13	0.11	0.06	0.07	0.03	0.08
16 Seat Belt	-0.05	0.01	-0.01	-0.04	-0.03	-0.07	-0.02
17 Helmet – Bicycle	-0.03	-0.03	-0.04	-0.01	-0.03	-0.01	-0.02
18 Helmet – Motorcycle	-0.04	0.05	0.03	-0.01	-0.01	-0.07	-0.01
19 Past 30-day Alcohol	0.06	0.11	0.11	0.08	0.09	0.06	0.08
20 Heavy Episodic Drinking	0	-0.04	-0.03	-0.01	-0.01	0.03	-0.01
21 Driving After Drinking	0.02	0.01	0.03	0.03	0.03	0.04	0.02
22 Driving After HED	0.01	-0.04	-0.02	0.01	0.01	0.03	0.01
23 Alcohol Consequences	0.16	0.1	0.12	0.16	0.16	0.18	0.14

24 # of Sex Partners	0.08	0.03	0.04	0.07	0.07	0.1	0.06
25 Condom – Oral Sex	-0.02	-0.1	-0.09	-0.05	-0.05	0	-0.03
26 Condom – Vaginal Intercourse	-0.06	-0.02	-0.03	-0.04	-0.06	-0.07	-0.05
27 Condom – Anal Intercourse	-0.03	-0.04	-0.07	0.01	-0.01	-0.02	-0.04
28 Purging	0.13	0.05	0.06	0.11	0.11	0.16	0.11
29 Diet Pills	0.08	0.02	0.03	0.06	0.06	0.11	0.07
30 Moderate Cardio	-0.04	-0.03	-0.06	-0.04	-0.05	-0.06	-0.04
31 Vigorous Cardio	-0.06	-0.04	-0.08	-0.06	-0.06	-0.09	-0.07
32 Weightlifting	-0.07	-0.11	-0.12	-0.09	-0.1	-0.07	-0.09
33 Sleep difficulties	0.33	0.19	0.24	0.3	0.3	0.36	0.35
34 Falling Back Asleep	0.16	0.08	0.1	0.13	0.14	0.18	0.18
35 Tired, Dragging, Sleepy	0.31	0.29	0.35	0.29	0.31	0.29	0.33
36 Stay Awake	0.21	0.16	0.2	0.17	0.19	0.21	0.23
37 Falling Asleep	0.24	0.14	0.18	0.23	0.22	0.27	0.26
38 Academic Difficulties	0.34	0.29	0.3	0.3	0.33	0.34	0.37

Table 3 cont.
Correlations between indicator and outcome variables within student-athlete sample

Variable Name	8	9	10	11	12	13	14
8 Anger	—						
9 Self-harm	0.25	—					
10 Suicidal Ideation	0.3	0.5	—				
11 Suicide Attempt	0.16	0.45	0.46	—			
12 Past Therapy	0.18	0.16	0.19	0.06	—		
13 Past Psychiatry	0.15	0.2	0.22	0.14	0.4	—	
14 Past University Counseling	0.13	0.13	0.17	0.07	0.56	0.27	—
15 Future Treatment	0.01	-0.02	-0.01	-0.05	0.23	0.12	0.18
16 Seat Belt	-0.07	-0.08	-0.08	-0.09	-0.01	-0.02	-0.01
17 Helmet – Bicycle	-0.07	0.02	-0.01	0.01	0.05	0.06	0.04
18 Helmet – Motorcycle	-0.06	-0.06	-0.07	-0.1	0.03	0.01	-0.01
19 Past 30-day Alcohol	0.09	0.06	0.06	0.03	0.11	0.08	0.08
20 Heavy Episodic Drinking	0.06	0.08	0.08	0.12	-0.02	0.04	-0.01
21 Driving After Drinking	0.06	0.05	0.05	0.06	0.03	0.04	0.03
22 Driving After HED	0.04	0.09	0.1	0.14	0.01	0.04	0.01
23 Alcohol Consequences	0.2	0.16	0.2	0.12	0.11	0.12	0.08
24 # of Sex Partners	0.11	0.09	0.11	0.08	0.1	0.09	0.07
25 Condom – Oral Sex	-0.02	0.05	0.02	0.11	-0.02	0.01	-0.02
26 Condom – Vaginal Intercourse	-0.07	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04
27 Condom – Anal Intercourse	-0.02	0.03	0.02	0.05	0.01	0.03	0.02
28 Purging	0.11	0.21	0.18	0.2	0.1	0.13	0.09
29 Diet Pills	0.11	0.14	0.14	0.18	0.05	0.08	0.03
30 Moderate Cardio	-0.04	-0.01	-0.03	-0.02	-0.04	-0.03	-0.03

31 Vigorous Cardio	-0.05	-0.02	-0.04	-0.02	-0.03	-0.03	-0.01
32 Weightlifting	-0.03	-0.02	-0.02	0.02	-0.06	-0.03	-0.04
33 Sleep difficulties	0.3	0.16	0.22	0.09	0.21	0.17	0.15
34 Falling Back Asleep	0.17	0.11	0.14	0.12	0.08	0.09	0.06
35 Tired, Dragging, Sleepy	0.26	0.13	0.17	0.06	0.16	0.12	0.11
36 Stay Awake	0.2	0.1	0.13	0.1	0.1	0.08	0.06
37 Falling Asleep	0.23	0.15	0.19	0.12	0.13	0.13	0.09
38 Academic Difficulties	0.29	0.12	0.18	0.05	0.18	0.14	0.14

Table 3 cont.

Correlations between indicator and outcome variables within student-athlete sample

Variable Name	15	16	17	18	19	20	21
15 Future Treatment	—						
16 Seat Belt	0.08	—					
17 Helmet – Bicycle	0.07	0.2	—				
18 Helmet – Motorcycle	0.13	0.37	0.41	—			
19 Past 30-day Alcohol	0.07	-0.1	-0.1	-0.04	—		
20 Heavy Episodic Drinking	-0.08	-0.13	-0.08	-0.14	0.49	—	
21 Driving After Drinking	-0.02	-0.07	-0.06	-0.12	0.23	0.18	—
22 Driving After HED	-0.05	-0.11	-0.03	-0.14	0.13	0.23	0.31
23 Alcohol Consequences	-0.03	-0.15	-0.1	-0.13	0.33	0.4	0.17
24 # of Sex Partners	-0.01	-0.12	-0.1	-0.05	0.33	0.3	0.12
25 Condom – Oral Sex	-0.04	0.01	0.08	-0.04	-0.09	0.02	-0.02
26 Condom – Vaginal Intercourse	0.03	0.07	0.08	0.08	-0.07	-0.06	-0.1
27 Condom – Anal Intercourse	0.03	0.07	0.1	0.08	-0.03	0.02	-0.04
28 Purging	-0.01	-0.06	0	-0.04	0.07	0.1	0.04
29 Diet Pills	-0.03	-0.07	-0.03	-0.07	0.05	0.1	0.07
30 Moderate Cardio	0	0.01	0.01	0.06	-0.05	-0.03	-0.05
31 Vigorous Cardio	0	0.01	0.03	0.04	-0.05	-0.02	-0.06
32 Weightlifting	-0.06	-0.01	-0.01	0.01	0	0.07	-0.02
33 Sleep difficulties	0.02	-0.04	-0.03	-0.03	0.06	0.02	0.04
34 Falling Back Asleep	-0.03	-0.04	-0.02	-0.11	0.02	0.06	0.04
35 Tired, Dragging, Sleepy	0.03	-0.05	-0.06	-0.02	0.07	0.03	0.02
36 Stay Awake	0.01	-0.03	-0.03	-0.03	0.03	0.02	0.02
37 Falling Asleep	-0.03	-0.05	-0.03	-0.08	0.06	0.07	0.03

38 Academic Difficulties	0.04	-0.03	-0.03	-0.05	0.07	0.02	0.03

Table 3 cont.

Correlations between indicator and outcome variables within student-athlete sample

Variable Name	22	23	24	25	26	27	28
22 Driving After HED	—						
23 Alcohol Consequences	0.17	—					
24 # of Sex Partners	0.12	0.41	—				
25 Condom – Oral Sex	0.07	-0.06	-0.02	—			
26 Condom – Vaginal Intercourse	-0.04	-0.15	-0.01	0.25	—		
27 Condom – Anal Intercourse	0.06	-0.02	0.11	0.4	0.58	—	
28 Purging	0.09	0.15	0.1	0.03	-0.03	0.02	—
29 Diet Pills	0.1	0.12	0.08	0.05	-0.04	0.03	0.32
30 Moderate Cardio	-0.01	-0.01	0.01	0.02	0.06	0.03	0
31 Vigorous Cardio	-0.01	0.01	0.01	0.01	0.05	0.03	0
32 Weightlifting	0.03	0.02	0.07	0.07	0.02	0.02	0
33 Sleep difficulties	0.04	0.14	0.09	0.01	-0.04	0.01	0.12
34 Falling Back Asleep	0.07	0.08	0.06	0.05	-0.04	0	0.1
35 Tired, Dragging, Sleepy	0.04	0.15	0.08	-0.05	-0.03	-0.04	0.09
36 Stay Awake	0.05	0.09	0.06	0.01	-0.04	-0.03	0.09
37 Falling Asleep	0.06	0.13	0.08	0.02	-0.04	-0.01	0.12
38 Academic Difficulties	0.02	0.14	0.08	-0.02	-0.03	0.02	0.08

Table 3 cont.

Correlations between indicator and outcome variables within student-athlete sample

Variable Name	29	30	31	32	33	34	35
29 Diet Pills	—						
30 Moderate Cardio	-0.02	—					
31 Vigorous Cardio	-0.02	0.69	—				
32 Weightlifting	0.01	0.48	0.55	—			
33 Sleep difficulties	0.09	-0.04	-0.06	-0.04	—		
34 Falling Back Asleep	0.1	0.03	0.02	0.04	0.25	—	
35 Tired, Dragging, Sleepy	0.08	0.02	0	-0.02	0.33	0.27	—
36 Stay Awake	0.07	0.03	0.01	0.02	0.18	0.26	0.46
37 Falling Asleep	0.12	-0.02	-0.03	1	0.45	0.41	0.37
38 Academic Difficulties	0.06	-0.04	-0.05	-0.06	0.35	0.12	0.28

Table 3 cont.

Correlations between indicator and outcome variables within student-athlete sample

Variable Name	36	37	38
36 Stay Awake	—		
37 Falling Asleep	0.18	—	
38 Academic Difficulties	0.19	0.19	—

Table 4

Correlations between indicator and outcome variables within non-athlete sample

Variable Name	1	2	3	4	5	6	7
1 Hopeless	—						
2 Overwhelmed	0.38	—					
3 Exhausted	0.39	0.67	—				
4 Lonely	0.58	0.39	0.41	—			
5 Sad	0.61	0.43	0.45	0.66	—		
6 Depressed	0.62	0.30	0.33	0.53	0.60	—	
7 Anxiety	0.52	0.44	0.44	0.48	0.56	0.56	—
8 Anger	0.46	0.27	0.29	0.4	0.46	0.51	0.49
9 Self-harm	0.24	0.10	0.11	0.2	0.21	0.30	0.20
10 Suicidal Ideation	0.35	0.13	0.14	0.27	0.27	0.42	0.26
11 Suicide Attempt	0.11	0.03	0.03	0.09	0.09	0.16	0.10
12 Past Therapy	0.20	0.15	0.18	0.21	0.23	0.27	0.27
13 Past Psychiatry	0.17	0.09	0.11	0.15	0.17	0.25	0.21
14 Past University Counseling	0.19	0.11	0.12	0.18	0.19	0.23	0.20
15 Future Treatment	0.02	0.10	0.10	0.04	0.06	0.04	0.08
16 Seat Belt	-0.05	-0.01	-0.01	-0.04	-0.04	-0.05	-0.02
17 Helmet – Bicycle	-0.07	-0.07	-0.06	-0.05	-0.06	-0.05	-0.05
18 Helmet – Motorcycle	-0.04	0.02	0.02	-0.01	0	-0.02	0
19 Past 30-day Alcohol	0.02	0.09	0.10	0.04	0.06	0.04	0.06
20 Heavy Episodic Drinking	0.01	-0.01	-0.02	0.01	0.02	0.02	0
21 Driving After Drinking	0	0.02	0.03	-0.01	0	0.01	0.01
22 Driving After HED	0.04	0.02	0.01	0.03	0.03	0.05	0.02
23 Alcohol Consequences	0.16	0.11	0.11	0.16	0.18	0.18	0.15

24 # of Sex Partners	0.07	0.06	0.06	0.07	0.09	0.10	0.08
25 Condom – Oral Sex	-0.02	-0.06	-0.07	-0.04	-0.05	-0.02	-0.03
26 Condom – Vaginal Intercourse	0.01	0.01	-0.01	0.04	0.01	-0.01	-0.02
27 Condom – Anal Intercourse	0.03	-0.02	-0.01	0.05	0	0.01	0
28 Purging	0.10	0.04	0.05	0.09	0.09	0.12	0.09
29 Diet Pills	0.07	0.03	0.03	0.04	0.06	0.07	0.06
30 Moderate Cardio	-0.06	-0.03	-0.05	-0.04	-0.04	-0.06	-0.04
31 Vigorous Cardio	-0.08	-0.07	-0.08	-0.06	-0.07	-0.08	-0.07
32 Weightlifting	-0.09	-0.10	-0.10	-0.08	-0.09	-0.08	-0.09
33 Sleep difficulties	0.32	0.18	0.22	0.28	0.30	0.36	0.33
34 Falling Back Asleep	0.14	0.07	0.09	0.12	0.13	0.17	0.16
35 Tired, Dragging, Sleepy	0.31	0.28	0.34	0.29	0.31	0.33	0.33
36 Stay Awake	0.19	0.15	0.18	0.15	0.18	0.21	0.22
37 Falling Asleep	0.24	0.13	0.17	0.22	0.22	0.28	0.25
38 Academic Difficulties	0.36	0.29	0.28	0.30	0.33	0.35	0.37

Table 4 cont.
Correlations between indicator and outcome variables within non-athlete sample

Variable Name	8	9	10	11	12	13	14
8 Anger	—						
9 Self-harm	0.22	—					
10 Suicidal Ideation	0.30	0.42	—				
11 Suicide Attempt	0.13	0.36	0.36	—			
12 Past Therapy	0.18	0.14	0.18	0.05	—		
13 Past Psychiatry	0.16	0.16	0.20	0.08	0.46	—	
14 Past University Counseling	0.13	0.14	0.15	0.06	0.48	0.26	—
15 Future Treatment	0	0	0	-0.03	0.24	0.14	0.15
16 Seat Belt	-0.06	-0.05	-0.05	-0.04	0	-0.01	-0.01
17 Helmet – Bicycle	-0.08	-0.02	-0.05	0	0.06	0.05	0.01
18 Helmet – Motorcycle	-0.03	0	-0.04	-0.02	0.06	0.02	0.04
19 Past 30-day Alcohol	0.05	0.03	0.03	0	0.11	0.08	0.08
20 Heavy Episodic Drinking	0.05	0.05	0.05	0.05	-0.03	0.01	-0.01
21 Driving After Drinking	0.03	-0.01	0	0	0.04	0.03	0.01
22 Driving After HED	0.05	0.02	0.05	0.04	0	0.01	0
23 Alcohol Consequences	0.19	0.17	0.20	0.10	0.10	0.10	0.09
24 # of Sex Partners	0.08	0.09	0.11	0.06	0.13	0.09	0.09
25 Condom – Oral Sex	-0.02	-0.01	-0.01	0.04	-0.06	-0.04	-0.01
26 Condom – Vaginal Intercourse	-0.04	0	-0.01	0	-0.10	-0.08	-0.01
27 Condom – Anal Intercourse	-0.04	-0.01	0.01	0.02	-0.03	-0.01	0.02
28 Purging	0.09	0.16	0.13	0.11	0.07	0.07	0.05
29 Diet Pills	0.07	0.07	0.08	0.08	0.03	0.05	0.02
30 Moderate Cardio	-0.04	-0.02	-0.03	-0.01	0	-0.01	-0.01

31 Vigorous Cardio	-0.04	-0.02	-0.04	0	-0.03	-0.03	-0.02
32 Weightlifting	-0.04	-0.03	-0.04	0.01	-0.05	-0.04	-0.05
33 Sleep difficulties	0.29	0.15	0.22	0.08	0.18	0.17	0.13
34 Falling Back Asleep	0.16	0.08	0.12	0.07	0.08	0.08	0.04
35 Tired, Dragging, Sleepy	0.27	0.14	0.19	0.06	0.17	0.14	0.11
36 Stay Awake	0.20	0.10	0.14	0.07	0.10	0.09	0.06
37 Falling Asleep	0.23	0.13	0.18	0.07	0.12	0.13	0.08
38 Academic Difficulties	0.28	0.12	0.19	0.06	0.17	0.14	0.15

Table 4 cont.

Correlations between indicator and outcome variables within non-athlete sample

Variable Name	15	16	17	18	19	20	21
15 Future Treatment	—						
16 Seat Belt	0.06	—					
17 Helmet – Bicycle	0.07	0.19	—				
18 Helmet – Motorcycle	0.09	0.31	0.44	—			
19 Past 30-day Alcohol	0.08	-0.07	-0.08	-0.03	—		
20 Heavy Episodic Drinking	-0.07	-0.14	-0.12	-0.16	0.42	—	
21 Driving After Drinking	0.01	-0.05	-0.04	-0.03	0.28	0.13	—
22 Driving After HED	-0.03	-0.08	-0.06	-0.07	0.10	0.18	0.22
23 Alcohol Consequences	-0.02	-0.13	-0.15	-0.08	0.30	0.39	0.14
24 # of Sex Partners	0.04	-0.09	-0.10	-0.05	0.32	0.25	0.09
25 Condom – Oral Sex	-0.03	0	0.06	0.02	-0.11	-0.03	-0.07
26 Condom – Vaginal Intercourse	-0.02	0.03	0	0.05	-0.07	0	-0.10
27 Condom – Anal Intercourse	0	0.03	0.04	0.05	-0.07	0	-0.09
28 Purging	-0.01	-0.03	-0.02	-0.01	0.05	0.06	0.02
29 Diet Pills	-0.01	-0.04	-0.03	-0.03	0.04	0.03	0.03
30 Moderate Cardio	0.01	0.01	0.06	0.04	0.05	0.03	-0.02
31 Vigorous Cardio	-0.03	0	0.05	0.03	0.06	0.08	0
32 Weightlifting	-0.05	-0.01	0.01	0.03	0.07	0.09	0.01
33 Sleep difficulties	0.02	-0.04	-0.05	0	0.02	0.01	0
34 Falling Back Asleep	-0.03	-0.02	0	-0.02	0	0.02	-0.02
35 Tired, Dragging, Sleepy	0.02	-0.03	-0.08	-0.01	0.04	0.01	-0.02
36 Stay Awake	0.01	-0.02	-0.05	-0.02	0	-0.02	0
37 Falling Asleep	-0.03	-0.04	-0.05	-0.02	0.02	0.05	-0.03

38 Academic Difficulties	0.03	-0.03	-0.05	0.01	0.04	0.01	0

Table 4 cont.

Correlations between indicator and outcome variables within non-athlete sample

Variable Name	22	23	24	25	26	27	28
22 Driving After HED	—						
23 Alcohol Consequences	0.13	—					
24 # of Sex Partners	0.07	0.38	—				
25 Condom – Oral Sex	-0.02	-0.07	-0.02	—			
26 Condom – Vaginal Intercourse	-0.04	-0.08	0.09	0.29	—		
27 Condom – Anal Intercourse	-0.04	-0.05	0.20	0.36	0.64	—	
28 Purging	0.03	0.13	0.08	0	-0.01	-0.01	—
29 Diet Pills	0.03	0.09	0.06	0	-0.04	-0.04	0.28
30 Moderate Cardio	0	0.01	0.03	0.03	0.03	0.05	0.02
31 Vigorous Cardio	0.01	0.05	0.06	0.05	0.04	0.07	0.04
32 Weightlifting	0.03	0.05	0.09	0.04	0.03	0.05	0.02
33 Sleep difficulties	0.03	0.14	0.07	-0.01	-0.01	0.02	0.09
34 Falling Back Asleep	0.01	0.07	0.04	0.02	-0.03	-0.03	0.07
35 Tired, Dragging, Sleepy	0.02	0.11	0.05	-0.05	-0.02	-0.02	0.08
36 Stay Awake	0.03	0.07	0.04	0	-0.02	-0.01	0.06
37 Falling Asleep	0.03	0.12	0.06	0.01	0	0.03	0.09
38 Academic Difficulties	0.03	0.14	0.07	-0.02	0.01	0.01	0.06

Table 4 cont.

Correlations between indicator and outcome variables within non-athlete sample

Variable Name	29	30	31	32	33	34	35
29 Diet Pills	—						
30 Moderate Cardio	0.02	—					
31 Vigorous Cardio	0.04	0.57	—				
32 Weightlifting	0.05	0.41	0.61	—			
33 Sleep difficulties	0.08	-0.03	-0.04	-0.04	—		
34 Falling Back Asleep	0.06	0.02	0.01	0.01	0.27	—	
35 Tired, Dragging, Sleepy	0.06	-0.05	-0.09	-0.09	0.36	0.27	—
36 Stay Awake	0.06	-0.01	-0.03	-0.04	0.18	0.23	0.43
37 Falling Asleep	0.08	-0.01	-0.02	-0.01	0.47	0.38	0.38
38 Academic Difficulties	0.05	-0.04	-0.06	-0.07	0.34	0.12	0.29

Table 4 cont.

Correlations between indicator and outcome variables within non-athlete sample

Variable Name	36	37	38
36 Stay Awake	—		
37 Falling Asleep	0.14	—	
38 Academic Difficulties	0.20	0.19	—

Table 5
Latent Class Analysis model fit statistics for student-athlete sample

	Class 1	Class 2	Class 3	Class 4	**Class 5**	Class 6	Class 7
SABIC	530041.5	361198.71	333653.99	322535.14	**317118.81**	312963.29	310308.77
Entropy	___	0.88	0.87	0.84	**0.83**	0.82	0.82
ALCP	___	0.96-0.97	0.91-0.95	0.88-0.95	**0.85-0.92**	0.82-0.93	0.80-0.93
# of Sample	___	___	___	___	___	___	___
1	25,803	12,189	7,849	3,755	**4,045**	4,954	4,356
2		13,614	6,321	7,920	**2,979**	4,139	1,211
3			11,633	6,100	**6,139**	1,586	3,675
4				8,028	**7,676**	5,462	5,098
5					**4,964**	3,972	5,045
6						5,690	3,576
7							2,842
BLRT	___	.00	.00	.00	**.00**	.00	.00

Note. *N* = 25,803. SABIC, Sample-Size Adjusted Bayesian Information Criterion; ALCP, Average Latent Class Probability; BLRT, Bootstrap Likelihood Ratio Test. Bold indicates the selected, best-fitting class.

Table 6
BCH equality tests of means across latent classes

	χ^2	*p*	Class 1 *m*	Class 2 *m*	Class 3 *m*	Class 4 *m*	Class 5 *m*
1. Past Therapy	3394.73	< .01	0.61	0.49	0.36	0.21	0.12
2. Past Psychiatry	1285.81	< .01	0.26	0.15	0.08	0.03	0.02
3. Past University Counseling	1684.32	< .01	0.39	0.28	0.2	0.11	0.07
4. Future Treatment	311.26	< .01	0.77	0.78	0.76	0.76	0.62
5. Seat Belt	102.71	< .01	3.57	3.66	3.69	3.72	3.67
6. Helmet – Bicycle	27.83	< .01	1.52	1.56	1.5	1.56	1.71
7. Helmet – Motorcycle	48.49	< .01	3.07	3.18	3.27	3.49	3.15
8. Past 30-day Alcohol	414.23	< .01	2.52	2.49	2.35	2.33	1.81
9. Heavy Episodic Drinking	42.45	< .01	1.28	1.14	1.05	1.09	1.26
10. Driving After Drinking	47.41	< .01	0.15	0.16	0.12	0.12	0.09
11. Driving After HED	39.76	< .01	0.03	0.02	0.01	0.01	0.02
12. Alcohol Consequences	858.46	< .01	1.82	1.51	1.28	1.03	0.82
13. # of Sex Partners	289.18	< .01	2.17	2.04	1.6	1.52	1.48
14. Condom – Oral Sex	70.06	< .01	0.3	0.26	0.26	0.26	0.5
15. Condom – Vaginal Intercourse	71.40	< .01	2.1	2.27	2.3	2.44	2.43
16. Condom – Anal Intercourse	7.03	.13	1.2	1.39	1.27	1.2	1.45
17. Purging	420.99	< .01	0.1	0.04	0.03	0.01	0.01
18. Diet Pills	189.82	< .01	0.07	0.04	0.02	0.01	0.02
19. Moderate Cardio	102.11	< .01	3.89	4.07	4.06	4.2	4.37
20. Vigorous Cardio	181.48	< .01	3.47	3.7	3.67	3.85	4.11
21. Weightlifting	428.61	< .01	2.68	2.87	2.66	2.91	3.5
22. Sleep difficulties	4889.83	< .01	0.6	0.35	0.31	0.12	0.05
23. Falling Back Asleep	848.07	< .01	1.8	1.28	1.26	0.91	0.83
24. Tired, Dragging, Sleepy	4470.60	< .01	4.54	3.38	3.73	2.87	1.93
25. Stay Awake	1545.91	< .01	2.8	1.99	2.12	1.59	1.19

26. Falling Asleep	2200.28	< .01	2.79	1.82	1.79	1.17	0.9
27. Academic Difficulties	6663.89	< .01	0.76	0.53	0.55	0.29	0.11

Table 7
Knowngroup Latent Class Analyses model fit indices for student-athlete and non-athlete samples

	Class Probabilities Freed	Class Probabilities Constrained	Δ
SABIC	720068.98	720453.76	384.79
Entropy	0.837	0.835	0.002

Note. SABIC, Sample-Size Adjusted Bayesian Information Criterion; Δ, change in model fit index; Bold indicates the selected, best-fitting class.

Table 8
Model fit indices of Latent Class Analyses with and without item threshold constraints for non-athlete sample

	Item Thresholds Freed	Item Thresholds Constrained	Δ
SABIC	329264.35	330094.23	829.88
Entropy	0.838	0.83	0.008

Note. SABIC, Sample-Size Adjusted Bayesian Information Criterion; Δ, change in model fit index; Bold indicates the selected, best-fitting class.

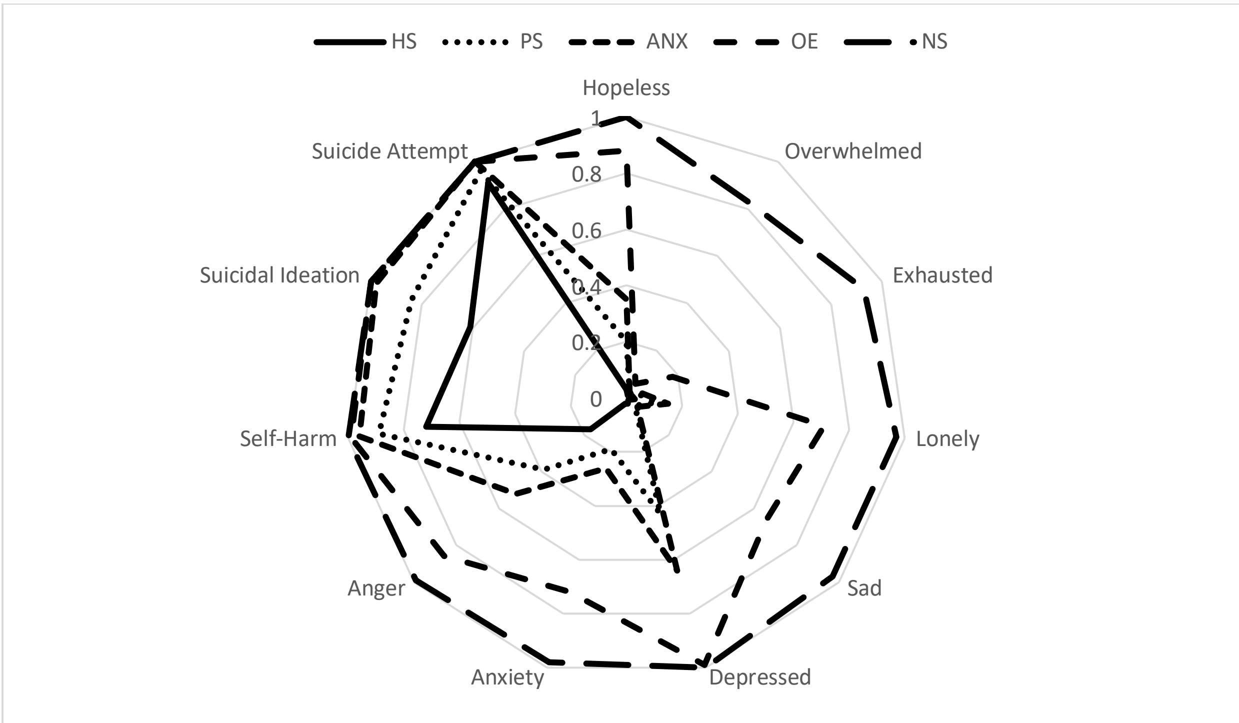

Figure 1: *Student-athlete mental health symptom latent class probabilities of endorsing "never, or not in the past year"*

Note. HS, High Symptoms Class; PS, Past Symptoms Class; ANX, Anxiety Symptoms Class; OE, Overwhelmed and Exhausted Class; NS, No Symptoms Class

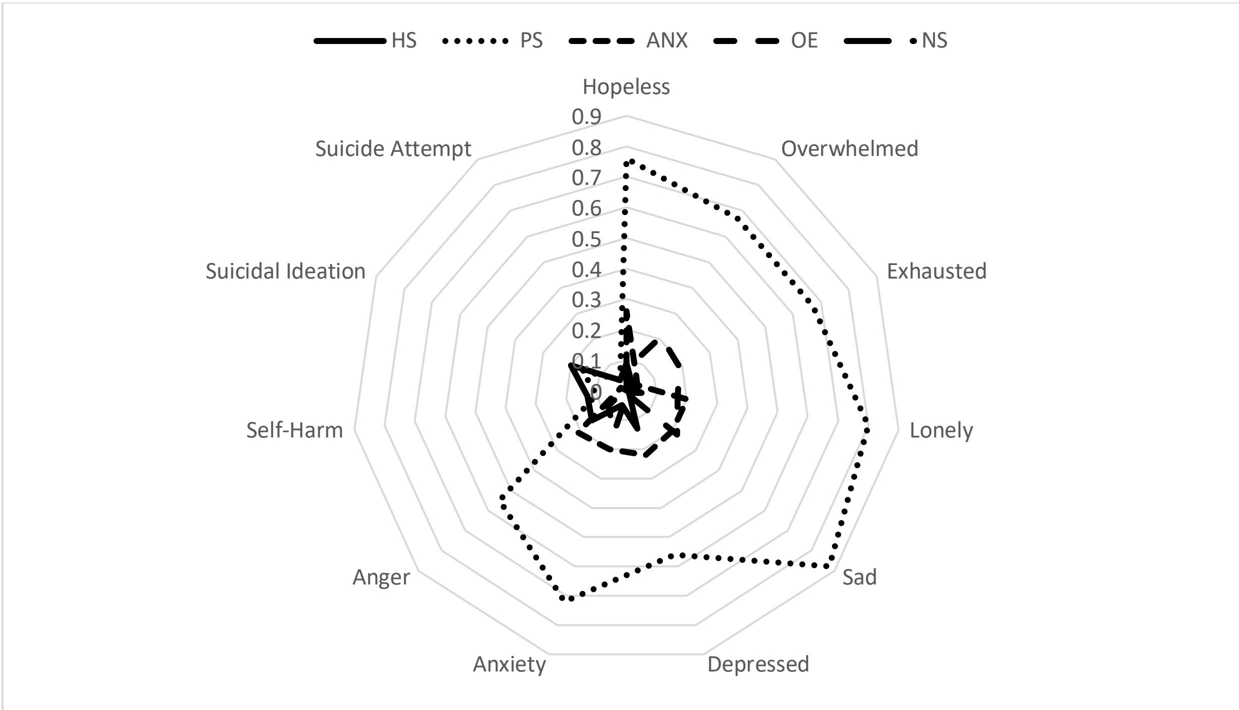

Figure 2: *Student-athlete mental health symptom latent class probabilities of endorsing "yes, in the last year"*

Note. HS, High Symptoms Class; PS, Past Symptoms Class; ANX, Anxiety Symptoms Class; OE, Overwhelmed and Exhausted Class; NS, No Symptoms Class

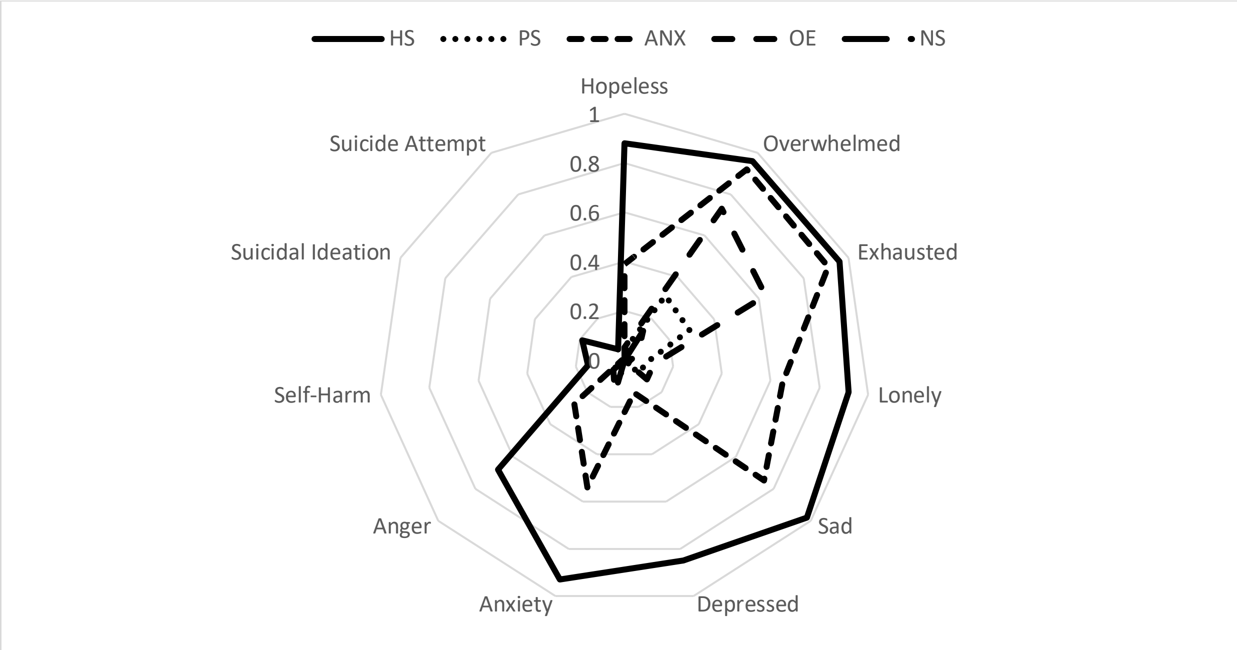

Figure 3: *Student-athlete mental health symptom latent class probabilities of endorsing "yes, in the last two weeks"*

Note. HS, High Symptoms Class; PS, Past Symptoms Class; ANX, Anxiety Symptoms Class; OE, Overwhelmed and Exhausted Class; NS, No Symptoms Class

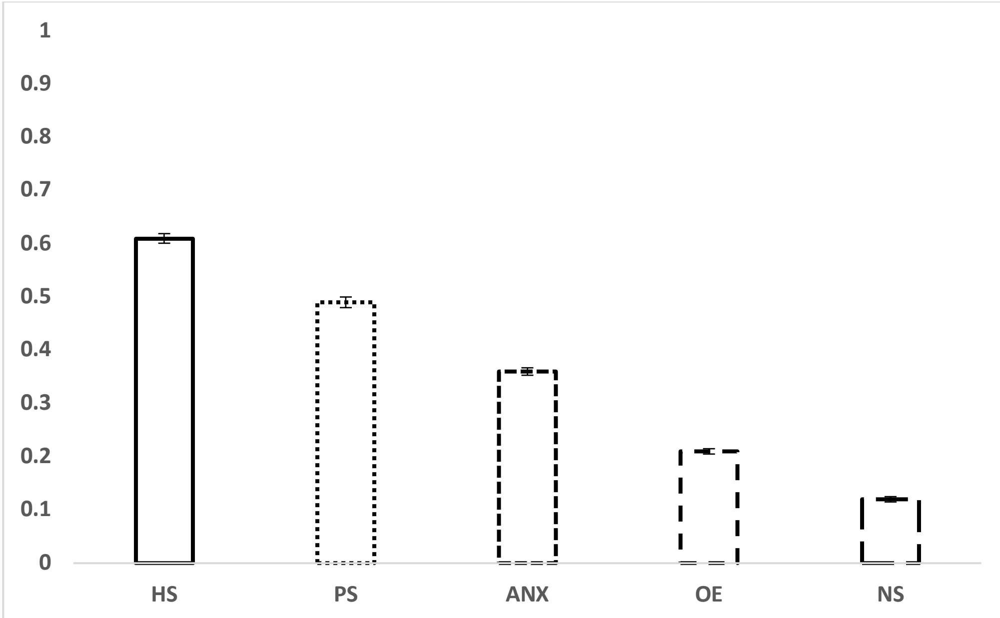

Figure 4: *Differences in likelihood of seeking past therapy services with a licensed mental health provider across classes of student-athlete mental health symptoms*

Note. HS, High Symptoms Class; PS, Past Symptoms Class; ANX, Anxiety Symptoms Class; OE, Overwhelmed and Exhausted Class; NS, No Symptoms Class

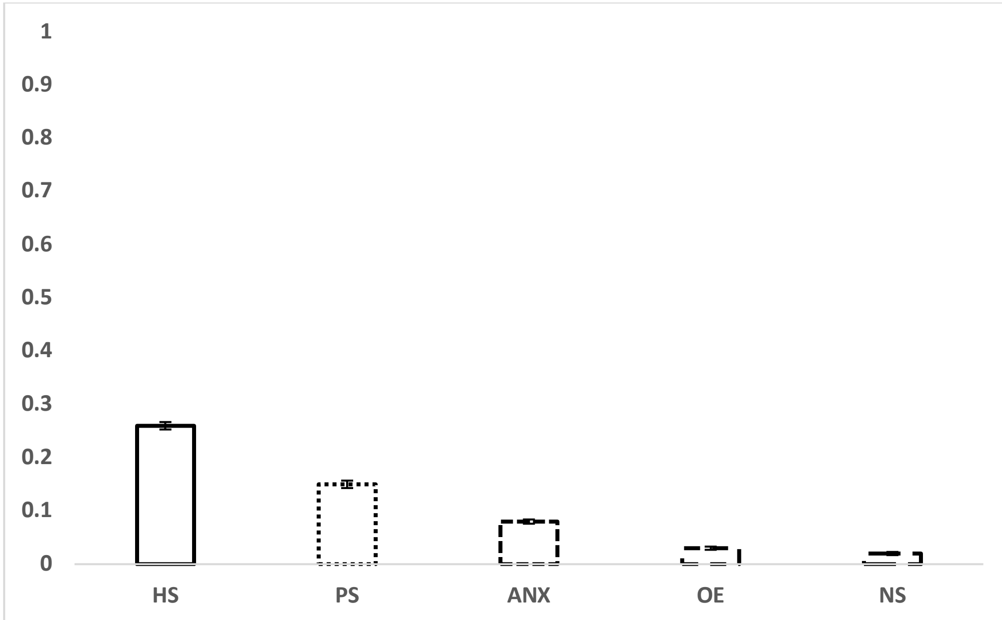

Figure 5: *Differences in likelihood of seeking past therapy services with a psychiatric provider across classes of student-athlete mental health symptoms*

Note. HS, High Symptoms Class; PS, Past Symptoms Class; ANX, Anxiety Symptoms Class; OE, Overwhelmed and Exhausted Class; NS, No Symptoms Class

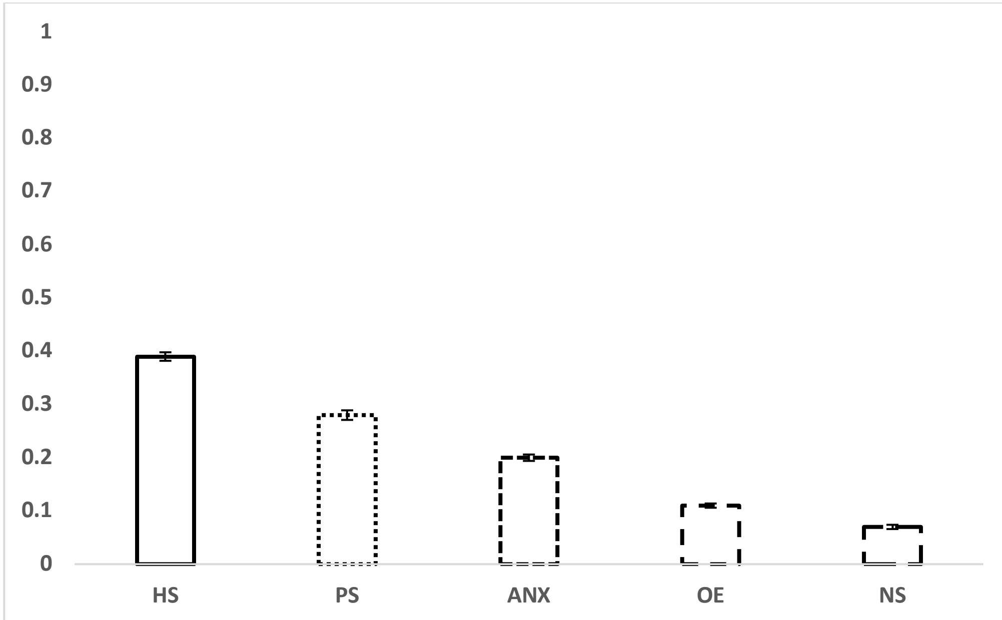

Figure 6: *Differences in likelihood of seeking past therapy services from current university counseling center across classes of student-athlete mental health symptoms*
Note. HS, High Symptoms Class; PS, Past Symptoms Class; ANX, Anxiety Symptoms Class; OE, Overwhelmed and Exhausted Class; NS, No Symptoms Class

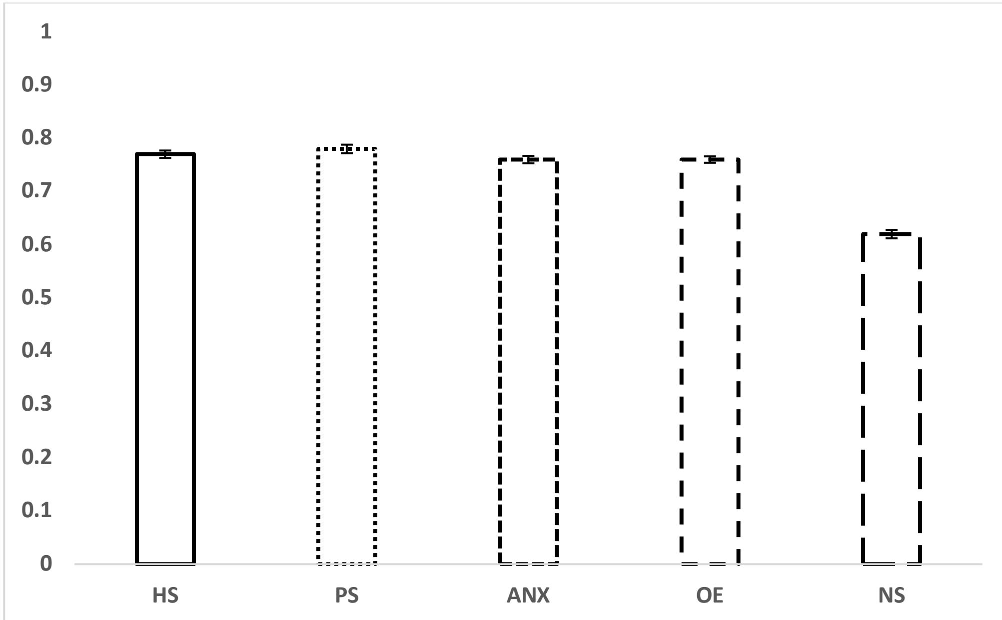

Figure 7: *Differences in likelihood of seeking future therapy services across classes of student-athlete mental health symptoms*
Note. HS, High Symptoms Class; PS, Past Symptoms Class; ANX, Anxiety Symptoms Class; OE, Overwhelmed and Exhausted Class; NS, No Symptoms Class

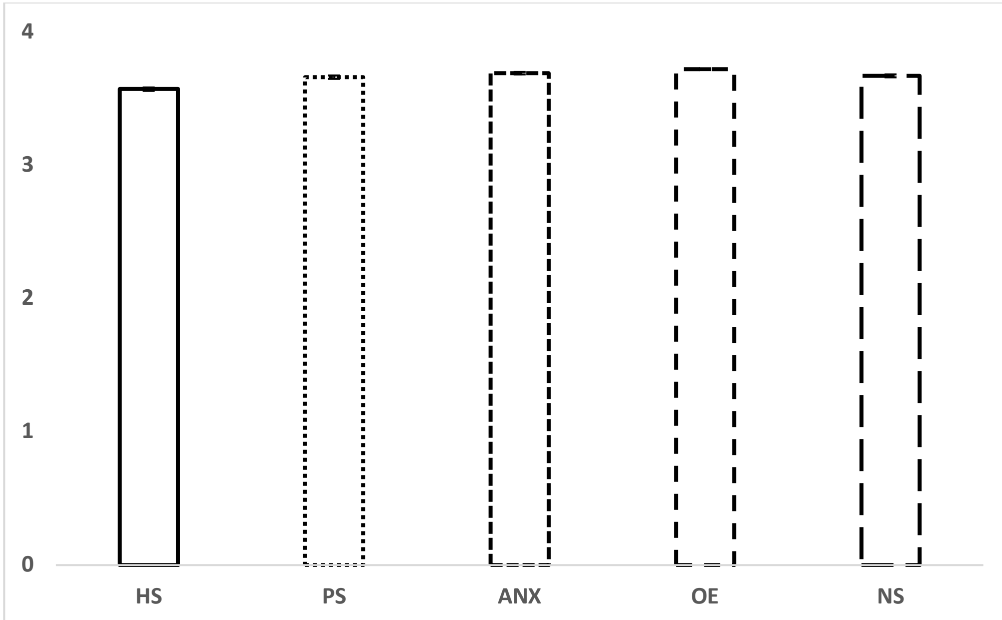

Figure 8: *Differences in endorsement of wearing a seatbelt while driving within the past year across classes of student-athlete mental health symptoms*
Note. HS, High Symptoms Class; PS, Past Symptoms Class; ANX, Anxiety Symptoms Class; OE, Overwhelmed and Exhausted Class; NS, No Symptoms Class

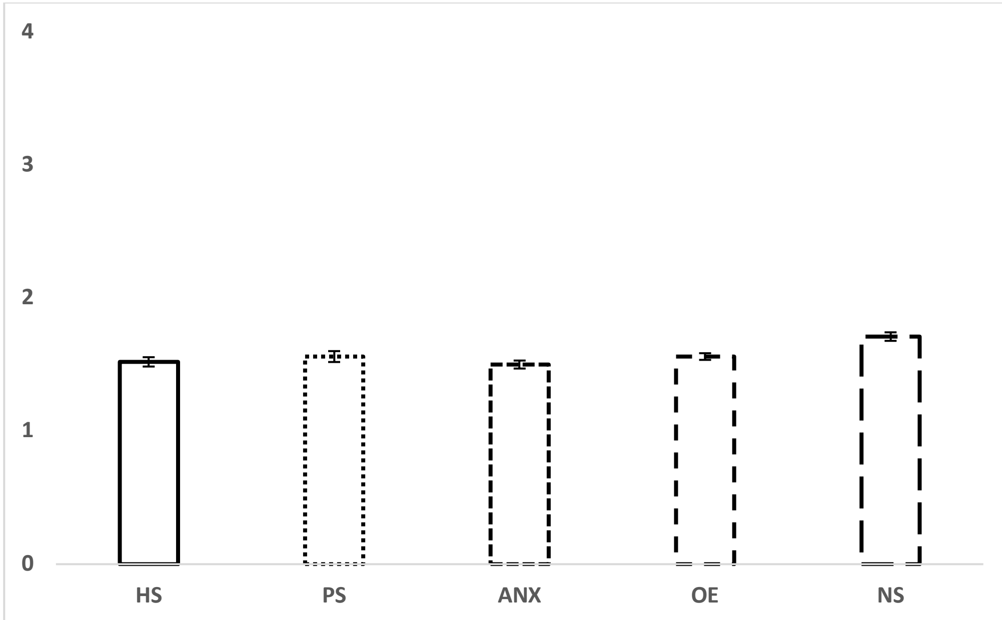

Figure 9: *Differences in endorsement of wearing a helmet while riding a bicycle within the past year across classes of student-athlete mental health symptoms*
Note. HS, High Symptoms Class; PS, Past Symptoms Class; ANX, Anxiety Symptoms Class; OE, Overwhelmed and Exhausted Class; NS, No Symptoms Class

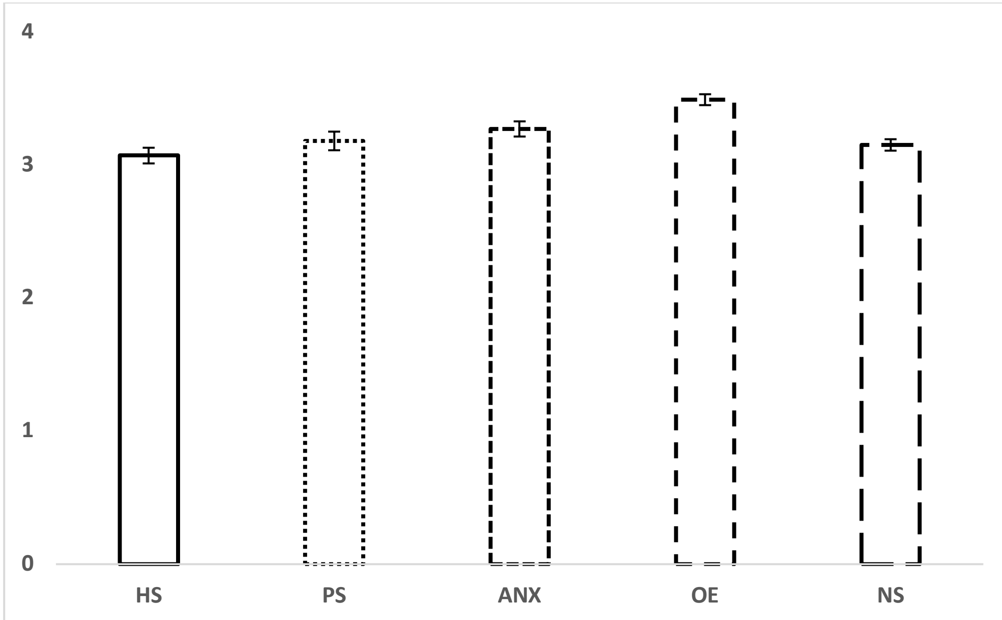

Figure 10: *Differences in endorsement of wearing a helmet while riding a motorcycle over the past year across classes of student-athlete mental health symptoms*

Note. HS, High Symptoms Class; PS, Past Symptoms Class; ANX, Anxiety Symptoms Class; OE, Overwhelmed and Exhausted Class; NS, No Symptoms Class

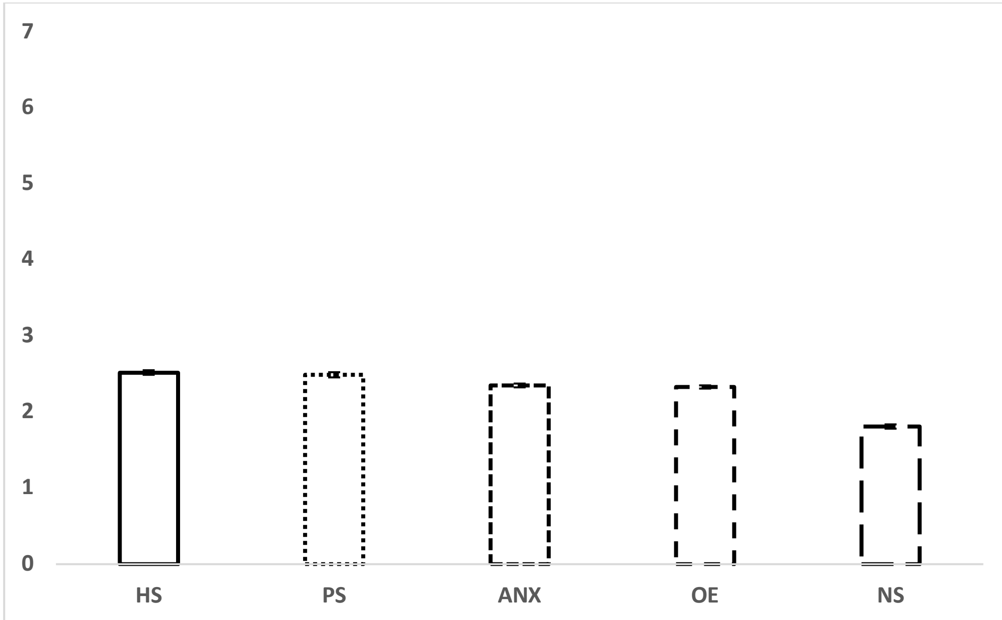

Figure 11: *Differences in endorsement of alcohol use in the past 30 days across classes of student-athlete mental health symptoms*
Note. HS, High Symptoms Class; PS, Past Symptoms Class; ANX, Anxiety Symptoms Class; OE, Overwhelmed and Exhausted Class; NS, No Symptoms Class

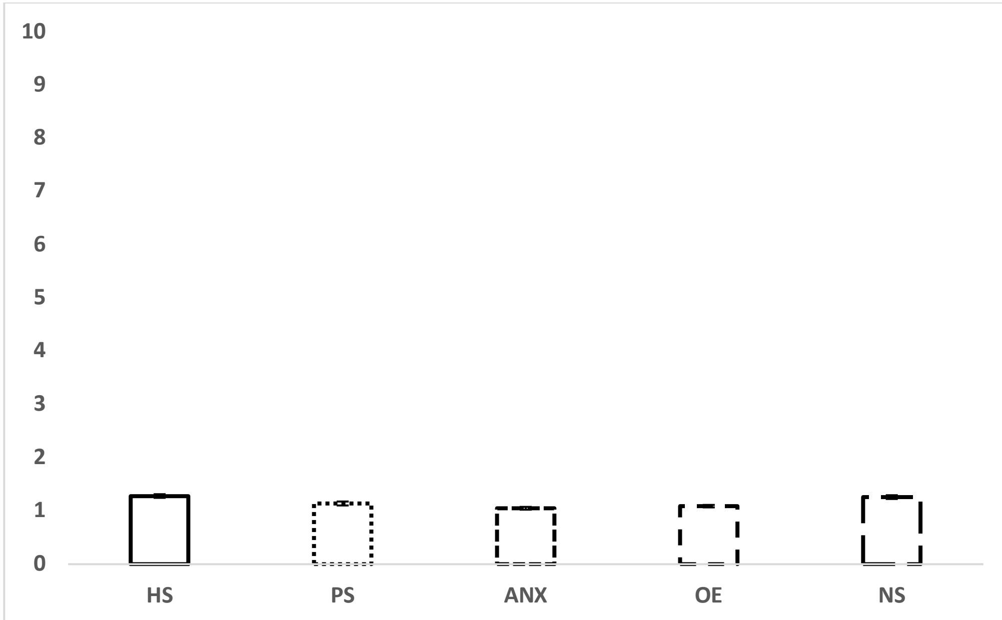

Figure 12: *Differences in endorsement of heavy episodic drinking over the past 14 days across classes of student-athlete mental health symptoms*

Note. HS, High Symptoms Class; PS, Past Symptoms Class; ANX, Anxiety Symptoms Class; OE, Overwhelmed and Exhausted Class; NS, No Symptoms Class

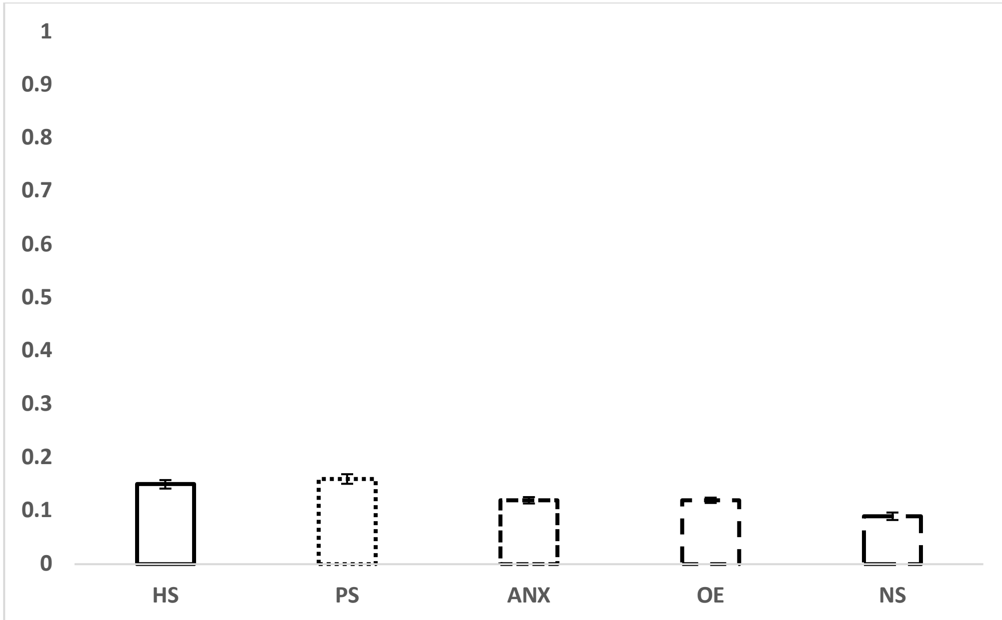

Figure 13: *Differences in likelihood of driving after consuming alcohol in the past 30 days across classes of student-athlete mental health symptoms*

Note. HS, High Symptoms Class; PS, Past Symptoms Class; ANX, Anxiety Symptoms Class; OE, Overwhelmed and Exhausted Class; NS, No Symptoms Class

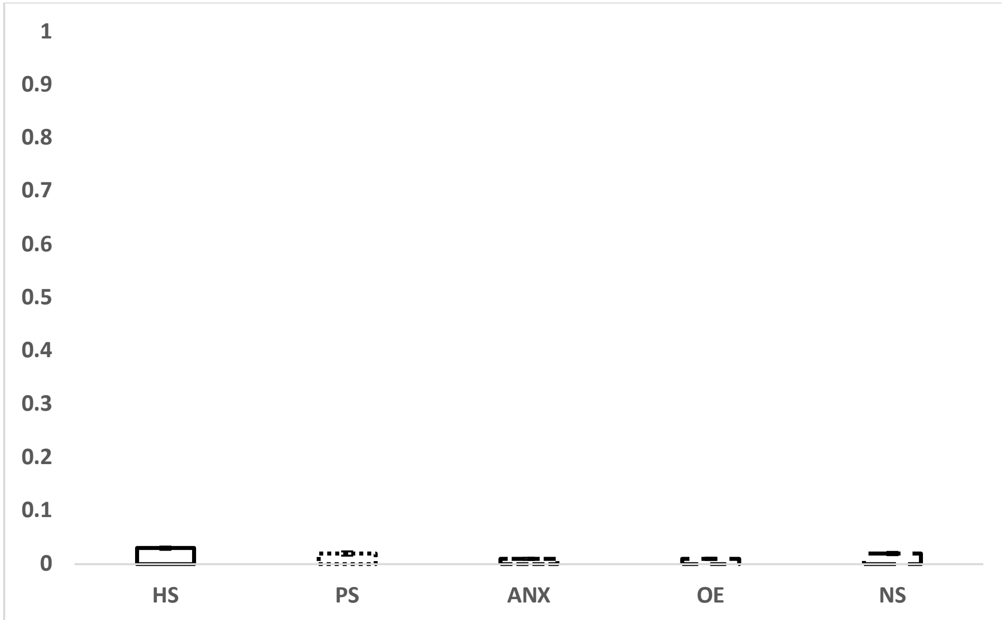

Figure 14: *Differences in likelihood of driving after heavy episodic drinking in the past 30 days across classes of student-athlete mental health symptoms*

Note. HS, High Symptoms Class; PS, Past Symptoms Class; ANX, Anxiety Symptoms Class; OE, Overwhelmed and Exhausted Class; NS, No Symptoms Class

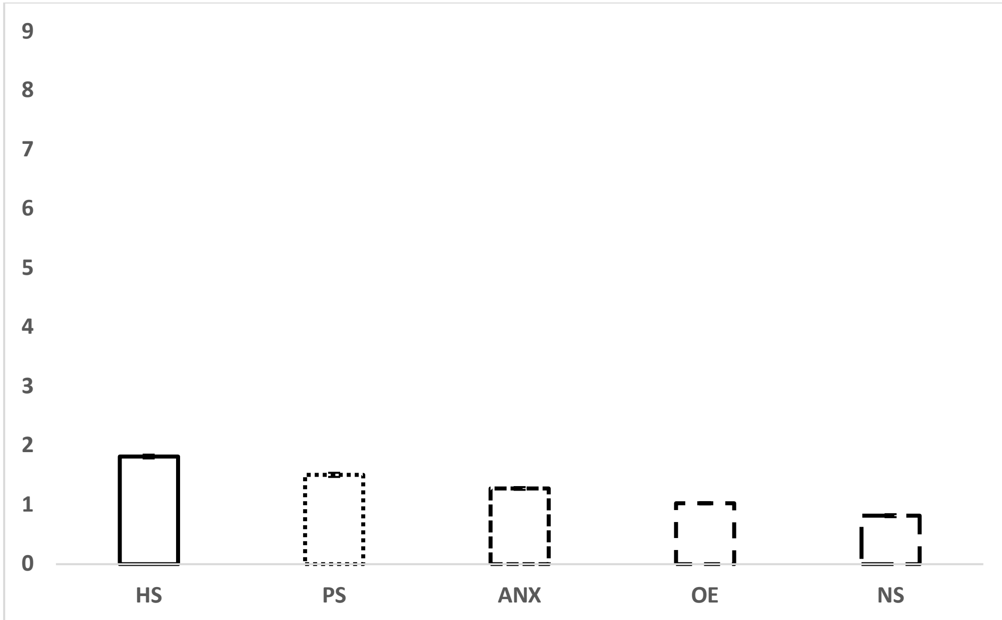

Figure 15: *Differences in endorsement of alcohol-related consequences in the past year across classes of student-athlete mental health symptoms*
Note. HS, High Symptoms Class; PS, Past Symptoms Class; ANX, Anxiety Symptoms Class; OE, Overwhelmed and Exhausted Class; NS, No Symptoms Class

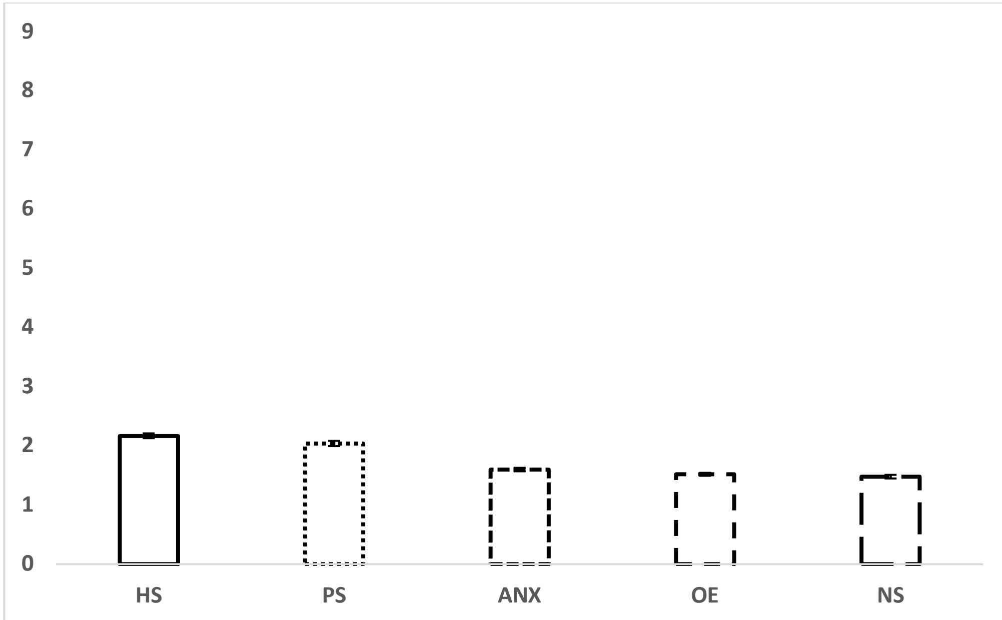

Figure 16: *Differences in endorsement of number of sexual partners in the past year across classes of student-athlete mental health symptoms*

Note. HS, High Symptoms Class; PS, Past Symptoms Class; ANX, Anxiety Symptoms Class; OE, Overwhelmed and Exhausted Class; NS, No Symptoms Class

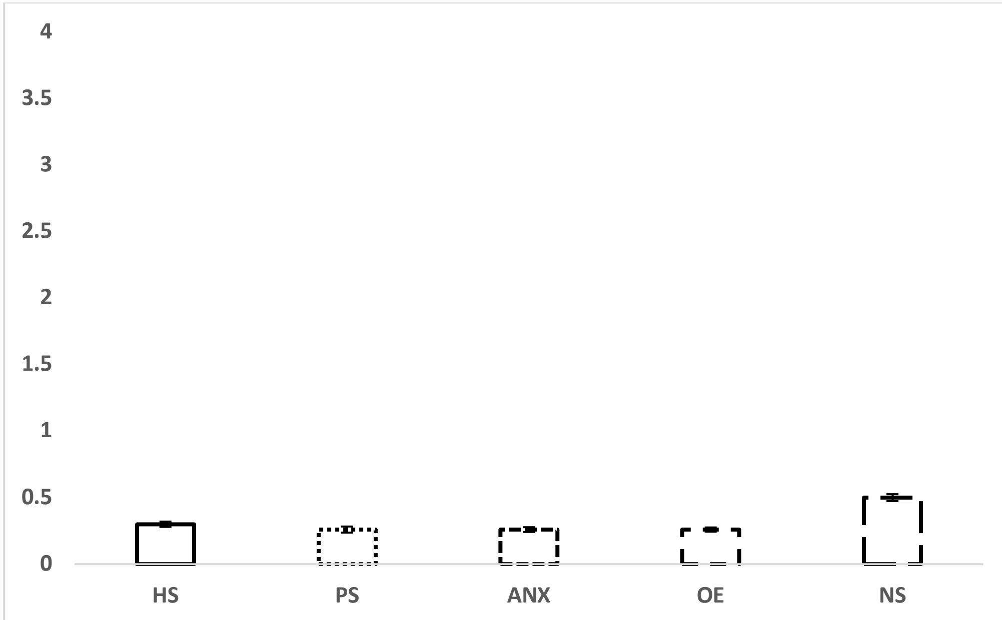

Figure 17: *Differences in endorsement of condom or other protective measures use during oral sex in the past 30 days across classes of student-athlete mental health symptoms*
Note. HS, High Symptoms Class; PS, Past Symptoms Class; ANX, Anxiety Symptoms Class; OE, Overwhelmed and Exhausted Class; NS, No Symptoms Class

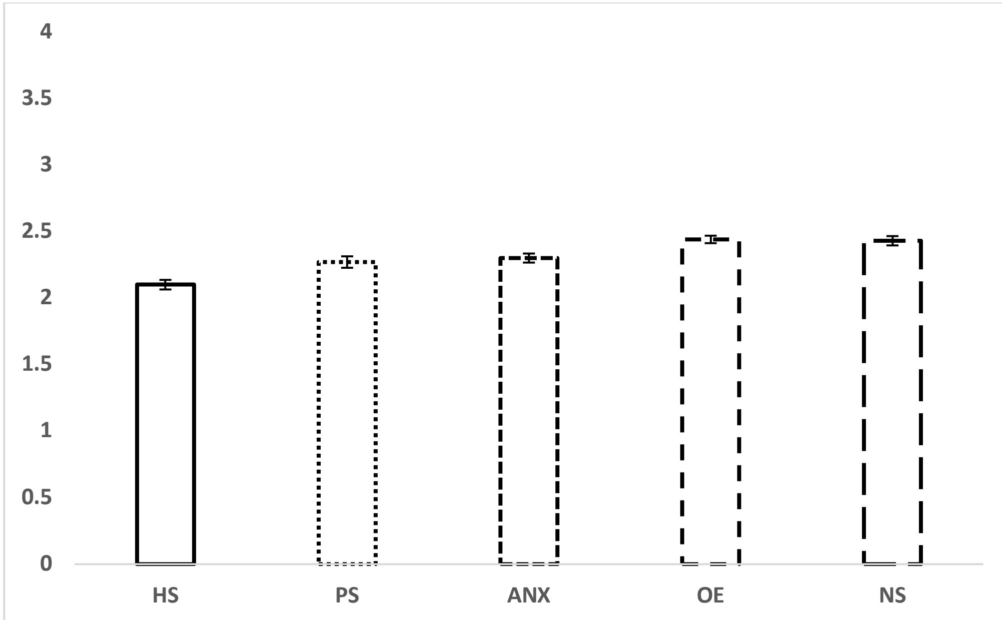

Figure 18: *Differences in endorsement of condom or other protective measures use during vaginal intercourse in the past 30 days across classes of student-athlete mental health symptoms*
Note. HS, High Symptoms Class; PS, Past Symptoms Class; ANX, Anxiety Symptoms Class; OE, Overwhelmed and Exhausted Class; NS, No Symptoms Class

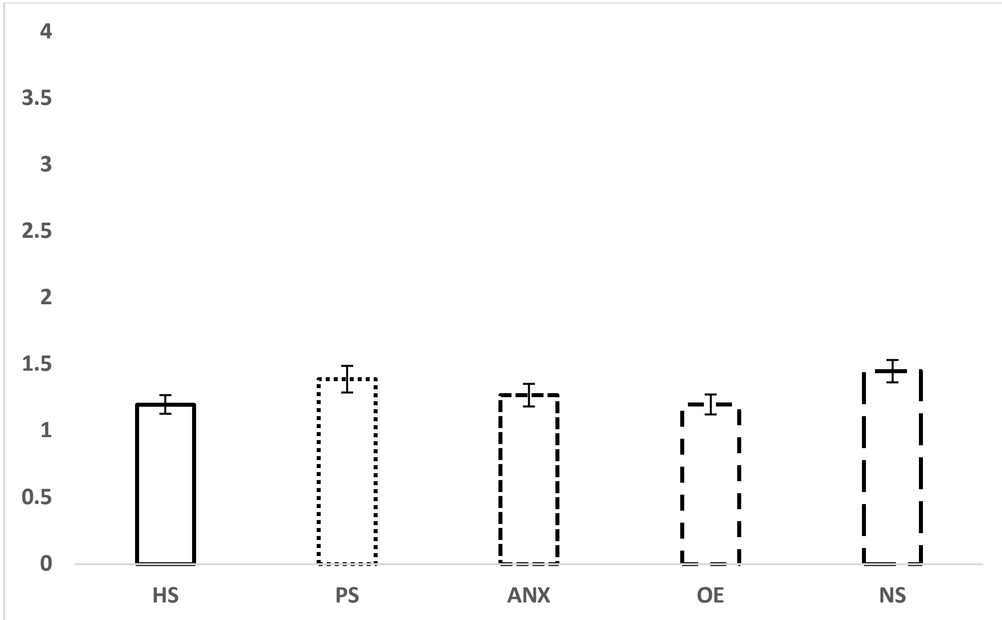

Figure 19: *Differences in endorsement of condom or other protective measures use during anal intercourse in the past 30 days across classes of student-athlete mental health symptoms*
Note. HS, High Symptoms Class; PS, Past Symptoms Class; ANX, Anxiety Symptoms Class; OE, Overwhelmed and Exhausted Class; NS, No Symptoms Class

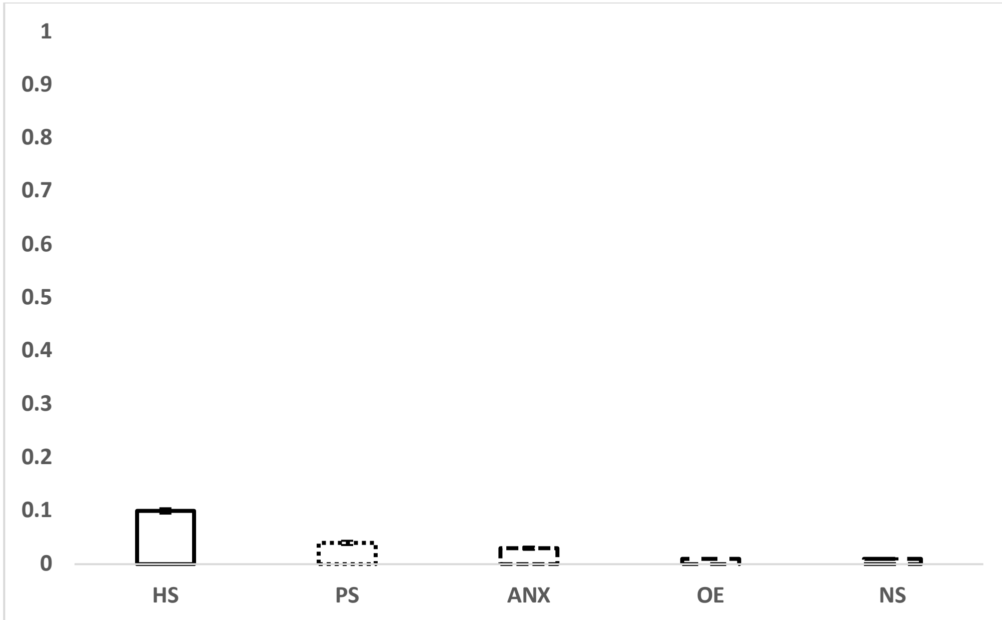

Figure 20: *Differences in likelihood of purging-related disordered eating behavior in the past 30 days across classes of student-athlete mental health symptoms*

Note. HS, High Symptoms Class; PS, Past Symptoms Class; ANX, Anxiety Symptoms Class; OE, Overwhelmed and Exhausted Class; NS, No Symptoms Class

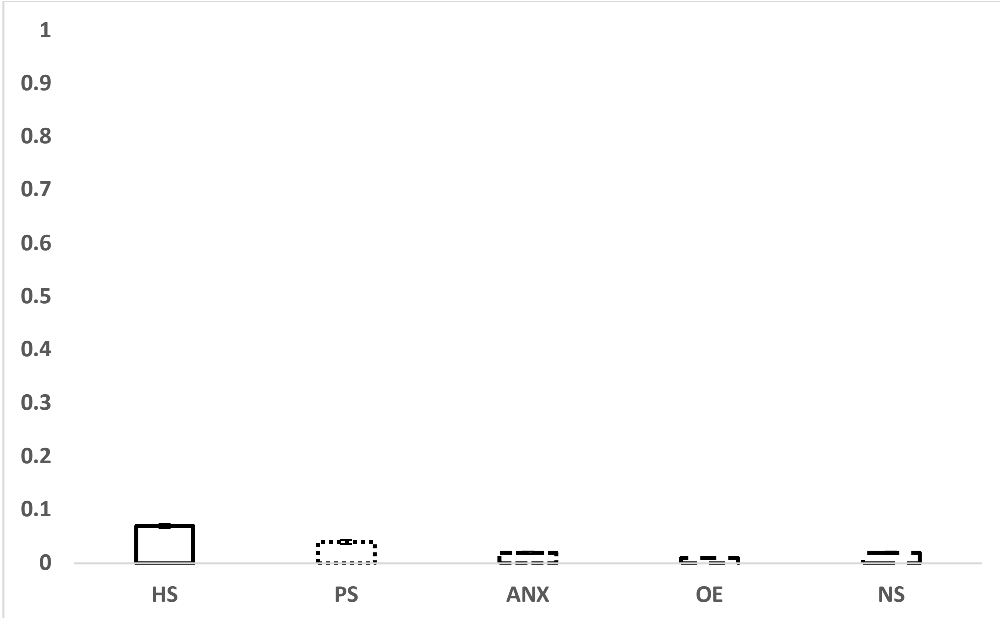

Figure 21: *Differences in likelihood of using diet pills during the past 30 days across classes of student-athlete mental health symptoms*
Note. HS, High Symptoms Class; PS, Past Symptoms Class; ANX, Anxiety Symptoms Class; OE, Overwhelmed and Exhausted Class; NS, No Symptoms Class

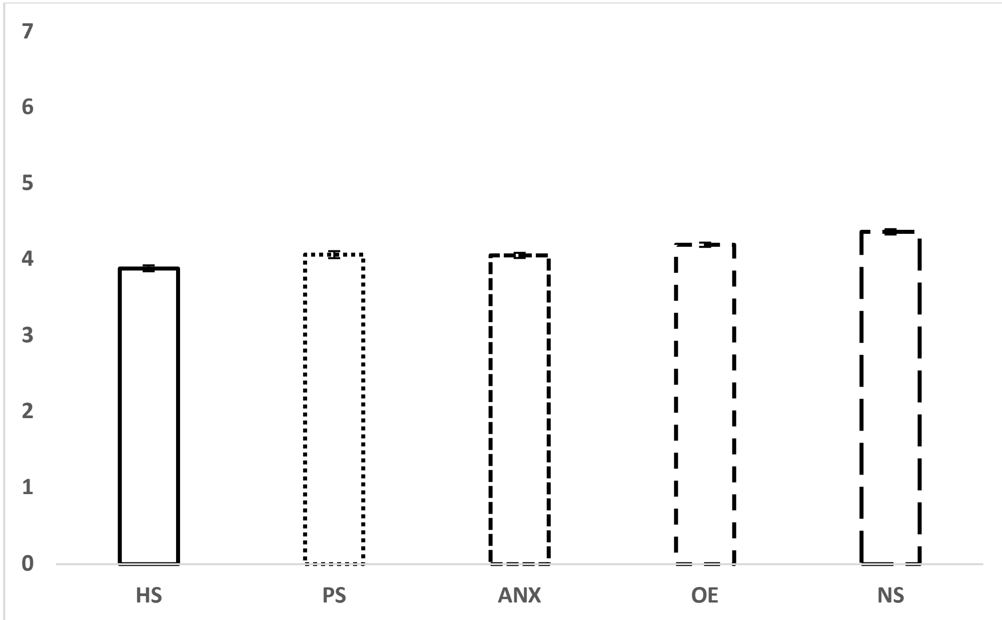

Figure 22: *Differences in endorsement of number of days engaging in moderate cardiovascular exercise in the past week across classes of student-athlete mental health symptoms*
Note. HS, High Symptoms Class; PS, Past Symptoms Class; ANX, Anxiety Symptoms Class; OE, Overwhelmed and Exhausted Class; NS, No Symptoms Class

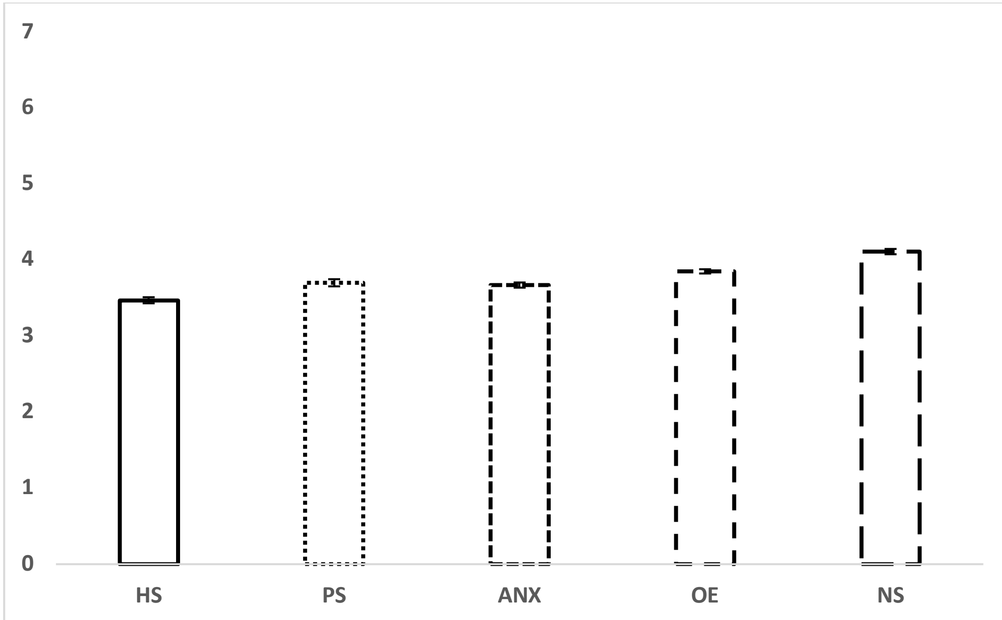

Figure 23: *Differences in endorsement of number of days engaging in vigorous cardiovascular exercise in the past week across classes of student-athlete mental health symptoms*
Note. HS, High Symptoms Class; PS, Past Symptoms Class; ANX, Anxiety Symptoms Class; OE, Overwhelmed and Exhausted Class; NS, No Symptoms Class

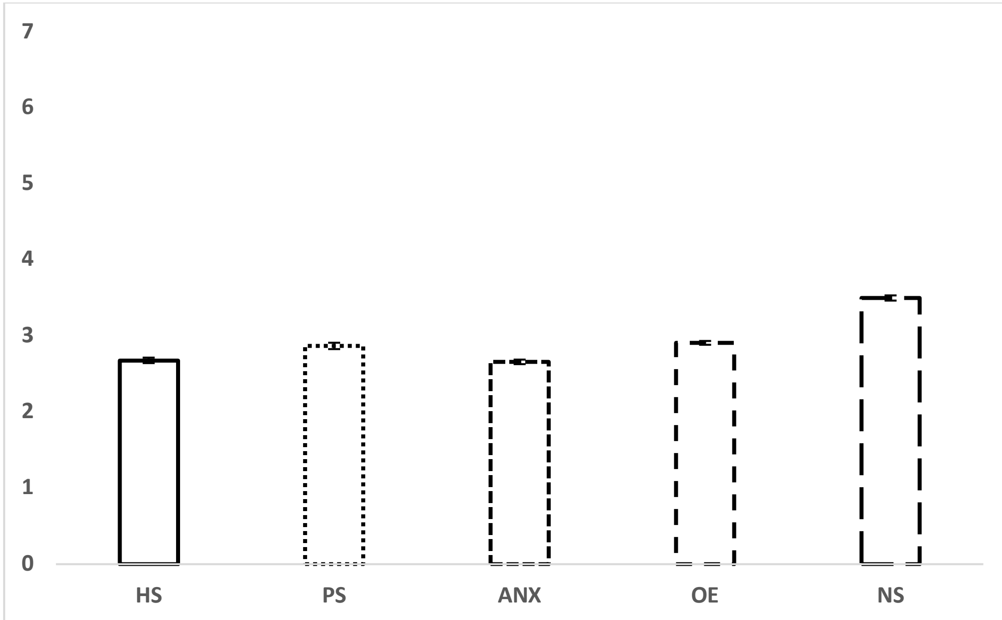

Figure 24: *Differences in endorsement of number of days engaging in weightlifting in the past week across classes of student-athlete mental health symptoms*

Note. HS, High Symptoms Class; PS, Past Symptoms Class; ANX, Anxiety Symptoms Class; OE, Overwhelmed and Exhausted Class; NS, No Symptoms Class

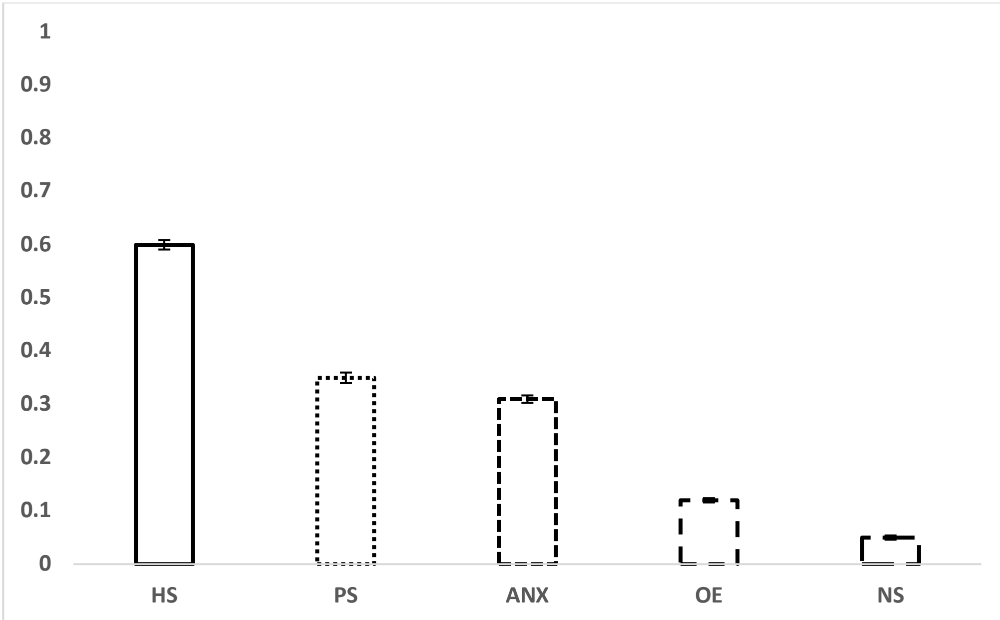

Figure 25: *Differences in likelihood of experiencing sleep difficulties in the past year across classes of student-athlete mental health symptoms*
Note. HS, High Symptoms Class; PS, Past Symptoms Class; ANX, Anxiety Symptoms Class; OE, Overwhelmed and Exhausted Class; NS, No Symptoms Class

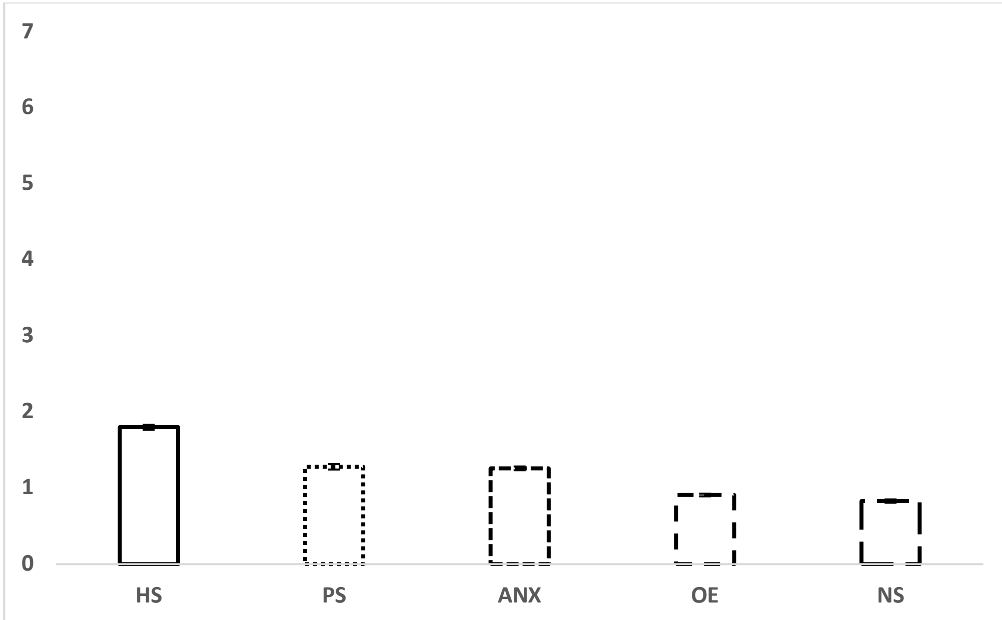

Figure 26: *Differences in endorsement of number of days in the past week experiencing trouble falling back asleep across classes of student-athlete mental health symptoms*
Note. HS, High Symptoms Class; PS, Past Symptoms Class; ANX, Anxiety Symptoms Class; OE, Overwhelmed and Exhausted Class; NS, No Symptoms Class

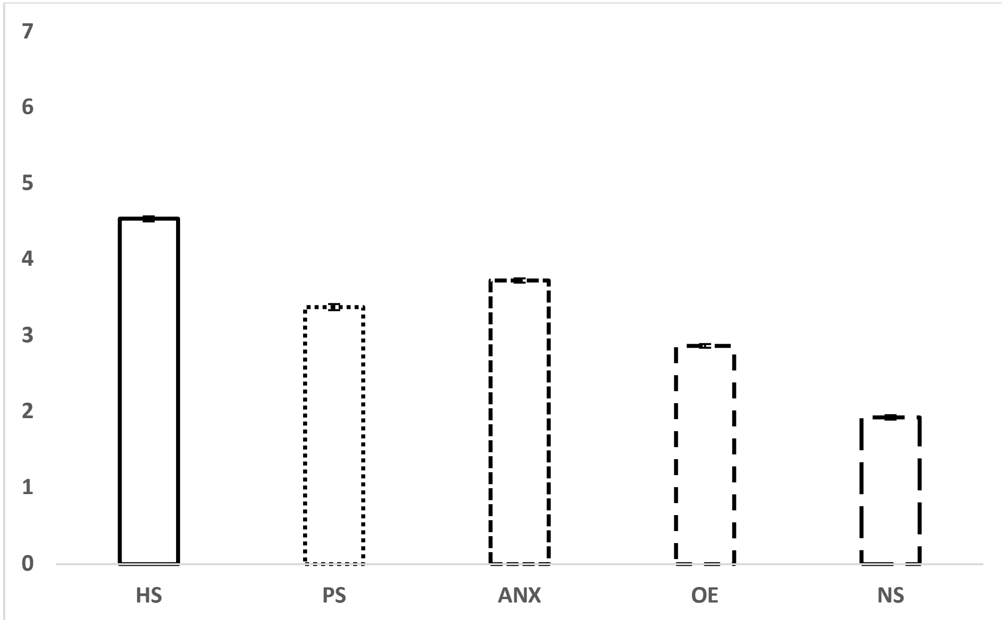

Figure 27: *Differences in endorsement of number of days in the past week experiencing feelings of tired/dragging/sleepy across classes of student-athlete mental health symptoms*
Note. HS, High Symptoms Class; PS, Past Symptoms Class; ANX, Anxiety Symptoms Class; OE, Overwhelmed and Exhausted Class; NS, No Symptoms Class

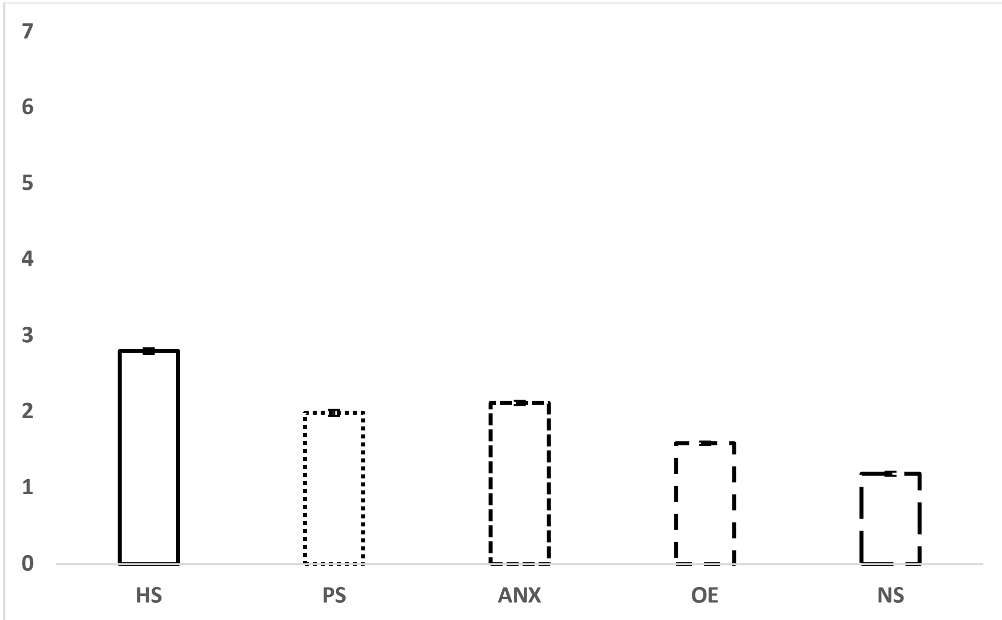

Figure 28: *Differences in endorsement of number of days in the past week experiencing trouble staying awake across classes of student-athlete mental health symptoms*
Note. HS, High Symptoms Class; PS, Past Symptoms Class; ANX, Anxiety Symptoms Class; OE, Overwhelmed and Exhausted Class; NS, No Symptoms Class

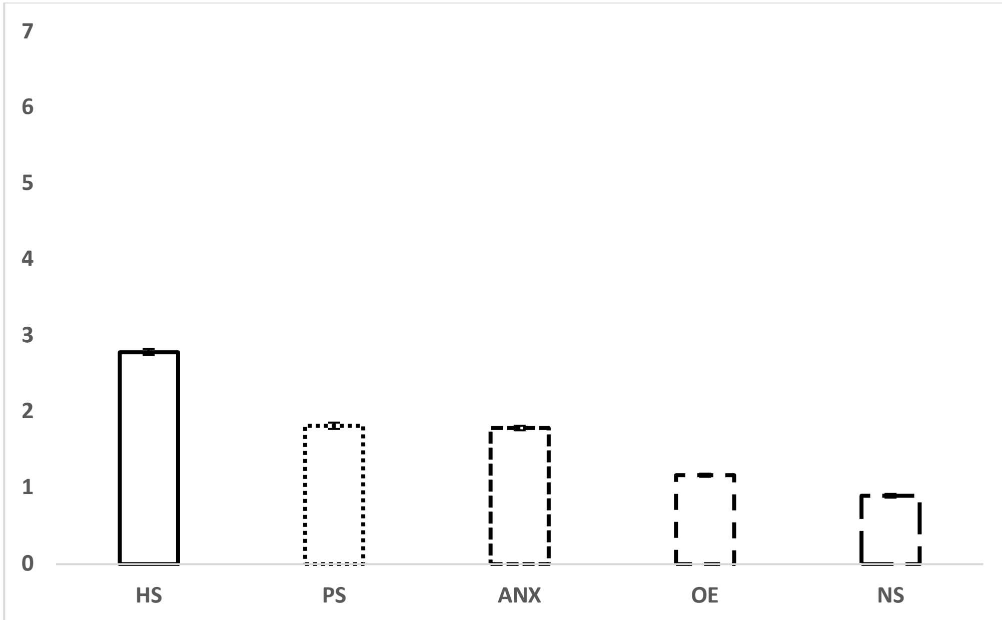

Figure 29: *Differences in endorsement of number of days in the past week experiencing trouble falling asleep across classes of student-athlete mental health symptoms*
Note. HS, High Symptoms Class; PS, Past Symptoms Class; ANX, Anxiety Symptoms Class; OE, Overwhelmed and Exhausted Class; NS, No Symptoms Class

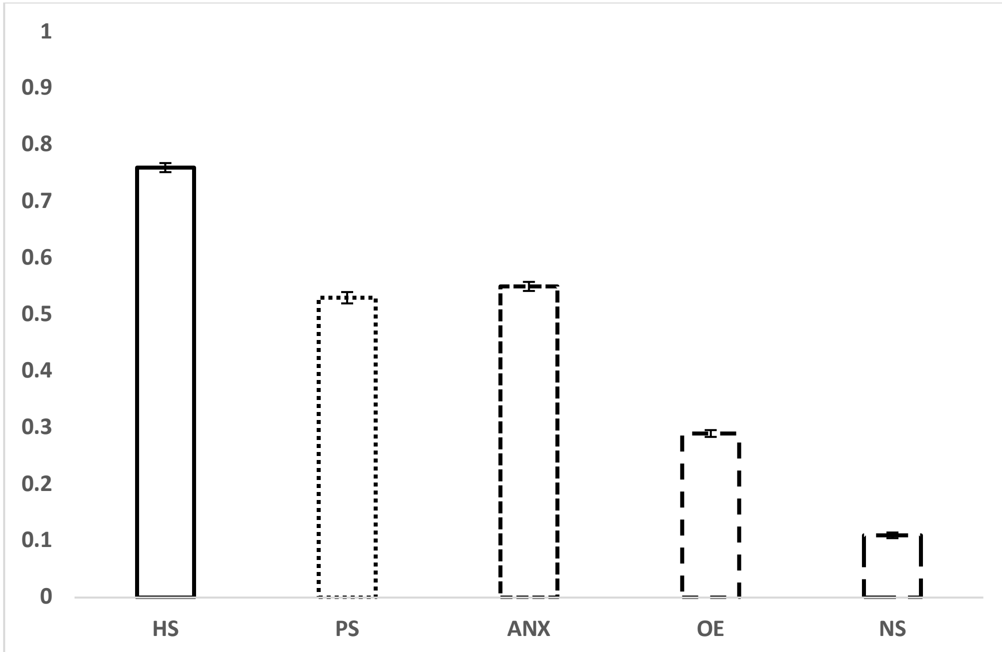

Figure 30: *Differences in likelihood of experiencing academics as difficult to handle within the past year across classes of student-athlete mental health symptoms*

Note. HS, High Symptoms Class; PS, Past Symptoms Class; ANX, Anxiety Symptoms Class; OE, Overwhelmed and Exhausted Class; NS, No Symptoms Class

REFERENCES

Alexandra, M., Maria, P., Kieran, K., Konstantinos, K., & Nikolaos, A. (2018). Psychological and situational determinants of burnout in adolescent athletes. *International Journal of Sport and Exercise Psychology, 5*, 521-536. https://doi.org/10.1080/1612197X.2017.1421680

American College Health Association (2012). *American College Health Association – National College Health Assessment II: Undergraduate Reference Group Data Report Spring 2011.* American College Health Association.

American College Health Association (2015-2019). *National College Health Assessment*. https://www.acha.org/documents/ncha/ACHA-NCHA_IIc_Paper_Survey.pdf

American College Health Association (2015). *American College Health Association – National College Health Assessment II: Undergraduate Reference Group Data Report Fall 2015.* American College Health Association.

American College Health Association (2016a). *American College Health Association – National College Health Assessment II: Undergraduate Reference Group Data Report Fall 2016.* American College Health Association.

American College Health Association (2016b). *American College Health Association – National College Health Assessment II: Undergraduate Reference Group Data Report Spring 2016.* American College Health Association.

American College Health Association (2017a). *American College Health Association – National College Health Assessment II: Undergraduate Reference Group Data Report Fall 2017.* American College Health Association.

American College Health Association (2017b). *American College Health Association – National College Health Assessment II: Undergraduate Reference Group Data Report Spring 2017.* American College Health Association.

American College Health Association (2018a). *American College Health Association – National College Health Assessment II: Undergraduate Reference Group Data Report Fall 2018.* American College Health Association.

American College Health Association (2018b). *American College Health Association – National College Health Assessment II: Undergraduate Reference Group Data Report Spring 2018*. American College Health Association.

American College Health Association (2019). *American College Health Association – National College Health Assessment II: Undergraduate Reference Group Data Report Spring 2019*. American College Health Association.

American Psychiatric Association. (2013). *Diagnostic and statistical manual of mental disorders* (5th ed.). https://doi.org/10.1176/appi.books.9780890425596

Araujo, C. G. S. (2016). The terms "athlete" and "exercisers". *American College of Cardiology*. Retrieved from http://www.acc.org/latest-in-cardiology/articles/2016/06/27/07/06/the-terms-athlete-and-exercisers

Armstron, N., Tomkinson, G. R., & Ekelund, U. (2011). Aerobic fitness and its relationship to sport, exercise training and habitual physical activity during youth. *British Journal of Sports Medicine, 45*, 849-858. https://doi.org/10.1136/bjsports-2011-090200

Arruza, J. A., Telletxea, S., Gil de Montes, L., Arribas, S., Balagué, G., Cecchini, J. A., ... Brustad, R. J. (2009). Understanding the relationship between perceived development of the competition plan and sport performance: Mediating effects of self-efficacy and state depression. *Perceptual and Motor Skills, 109*, 304-314. https://doi.org/10.2466/pms.109.1.304-314

Asparouhov, T., & Muthén, B. O. (2014). Auxiliary variables in mixture modeling: Three-step approaches using Mplus. *Structural Equation Modeling: A Multidisciplinary Journal, 21*(3), 329-341. https://doi.org/10.1080/10705511.2014.915181

Asparouhov, T., & Muthén, B. O. (2015). Residual associations in latent class and latent transition analysis. *Structural Equation Modeling: A Multidisciplinary Journal, 22*, 169-177. https://doi.org/10.1080/10705511.2014.935844

Auerbach, R. P., Mortier, P., Bruffaerts, R., Alonso, J., Benjet, C., Cuijpers, P., ... Kessler, R. C. (2018). The WHO world mental health surveys international college student project: Prevalence and distribution of mental disorders. *Journal of Abnormal Psychology, 127*(7), 623-638. https://doi.org/10.1037/abn0000362

Bailey, S. (2017). A comparison of academic and athletic performance in the NCAA. *College Student Journal, 51*(2). Retrieved from https://go.gale.com/ps/i.do?id=GALE%7CA503260888&sid=googleScholar&v=2.1&it=r&linkaccess=abs&issn=01463934&p=AONE&sw=w&userGroupName=oregon_oweb&isGeoAuthType=true

Bailey, R. J., Erekson, D. M., Cattani, K., Jensen, D., Simpson, D. M., Klundt, J., Vogeler, H. A., Schmuck, D., Worthen, V. E., Caldwell, Y., Beecher, M. E., Griner, D., & Hobbs, K. (2021). Adapting stepped care: Changes to service delivery format in the context of high demand. *Psychological Services, 19*(3), 494-501. https://doi.org/10.1037/ser0000564

Bakk, Z., & Vermunt, J. K. (2016). Robustness of stepwise latent class modeling with continuous distal outcomes. *Structural Equation Modeling: A Multidisciplinary Journal, 23*, 20-31. https://doi.org/10.1080/10705511.2014.955104

Bar-Haim, Y., Lamy, D., Pergamin, L., Bakermans, M. J., & van Ijzendoorn, M. H. (2007). Threat-related attentional bias in anxious and nonanxious individuals: A meta-analytic study. *Psychological Bulletin, 133*, 1-24. https://doi.org/10.1037/0033-2909.133.1.1

Bayes, A., Tavella, G., & Parker, G. (2021). The biology of burnout: Causes and consequences. *The World Journal of Biological Psychiatry, 22*, 686-698. https://doi.org/10.1080/15622975.2021.1907713

Bergman, L. R., & Magnusson, D. (1997). A person-oriented approach in research on developmental psychopathology. *Development and Psychopathology, 9*(2), 291-319. https://doi.org/10.1017/S095457949700206X

Berlin, K. S., Williams, N. A., & Parra, G. R. (2014). An introduction to latent variable modeling (part 1): Overview and cross-sectional latent class and latent profile analyses. *Journal of Pediatric Psychology, 39*(2), 174-187. https://doi.org/10.1093/jpepsy/jst084

Braeken, J. (2010). A boundary mixture approach to violations of conditional independence. *Psychometrika, 76*, 57-76. https://doi.org/10.1007/s11336-010-9190-4

Brauer, A. A., Athey, A. B., Ross, M. J., & Grander, M. A. (2019). Sleep and health among collegiate student athletes. *CHEST, 156*(6), 1234-1245. https://doi.org/10.1016/j.chest.2019.08.1921

Buchanan, J. L. (2012). Prevention of depression in the college student population: A review of the literature. *Archives of Psychiatric Nursing, 26*, 21-42. https://doi.org/10.1016/j.apnu.2011.03.003

Buckner, J. D., Lewis, E. M., Shah, S. M., & Walukevich, K. A. (2018). Risky sexual behavior among cannabis users: The role of protective behavioral strategies. *Addictive Behaviors, 81*, 50-54. https://doi.org/10.1016/j.addbeh.2018.01.039

Castaldelli-Maia, J. M., Gallinaro, J. G., Falcão, R. S., Gouttebarge, V., Hitchcock, M. E., Hainline, B., ... Stull, T. (2019). Mental health symptoms and disorders in elite athletes: A systematic review on cultural influencers and barriers to athletes seeking treatment. *British Journal of Sports Medicine, 53*, 707-721. https://doi.org/10.1136/bjsports-2019-100710

Celeux, G., & Soromenho, G. (1996). An entropy criterion for assessing the number of clusters in a mixture model. *Journal of Classification, 13*, 195-212.

Cham, H., Reshetnyak, E., Rosenfeld, B., & Breitbart, W. (2017). Full information maximum likelihood estimation for latent variable interactions with incomplete indicators. *Multivariate Behavioral Research, 52*, 12-30. https://doi.org/10.1080/00273171.2016.1245600

Clark, S. L., & Muthén, B. O. (2009). *Relating latent class analysis results to variables not included in the analysis*. Retrieved from https://www.statmodel.com/download/relatinglca.pdf

Clarke, T. C., Norris, T., & Schiller, J. S. (2017). Early release of selected estimates based on data from the 2016 national health interview survey. *National Center For Health Statistics*, 1-120. https://doi.org/10.1080/10705510701301834

Collins R. L., Parks G. A., & Marlatt G. A. (1985). Social determinants of alcohol consumption: The effects of social interaction and model status on the self-administration of alcohol. *Journal of Consulting and Clinical Psychology, 53*, 189–200.

Conley, C. S., Shapiro, J., Kirsch, A. C., & Durlak, J. A. (2017). A meta-analysis of indicated mental health prevention programs for at-risk higher education students. *Journal of Counseling Psychology, 64*(2), 121-140. https://doi.org/10.1037/cou0000190

Coombes, S. A., Higgins, T., Gamble, K. M., Cauraugh, J. H., & Janelle, C. M. (2009). Attentional control theory: Anxiety, emotion, and motor planning. *Journal of Anxiety Disorders, 23*, 1072-1079. https://doi.org/10.1016/j.janxdis.2009.07.009

Cornish, P. A., Berry, G., Benton, S., Barros-Gomes, P., Johnson, D., Ginsburg, R., Whelan, B., Fawcett, E., & Romano, V. (2017). Meeting the mental health needs of today's college student: Reinventing services through Stepped Care 2.0. *Psychological Services, 14*(4), 428–442. https://doi.org/10.1037/ser0000158

Cosmides, L., & Tooby, J. (2000). Evolutionary psychology and the emotions. In M. Lewis & J. M. Haviland-Jones (Eds.) *Handbook of Emotions* (2nd ed.). Guilford.

Cover, T., & Hart, P. (1967). Nearest neighbor pattern classification. *Institue of Electrical and Electronics Engineers, 13*, 21-27. https://doi.org/10.1109/TIT.1967.1053964

Cox, C. E., Ross-Stewart, L., & Foltz, B. D. (2017). Investigating the prevalence and risk factors of depression symptoms among NCAA division I collegiate athletes. *Journal of Sports Science, 5*, 14-28. https://doi.org/10.17265/2332-7839/2017.01.002

Dahlberg, L. (2022). Lonely and sad and/or sad and lonely? *International Psychogeriatrics, 34*(7), 613-616. https://doi.org/10.1017/S1041610222000308

Davis, S. R., Prince, M. A., Hallgren, K. A., Johnson, N., Stanley, L. R., & Swaim, R. C. (2019). Classes of drinking motives among American Indian youth drinkers. *Psychology of Addictive Behaviors, 33*(4), 392-400. https://doi.org/10.1037/adb0000469

DeFreese, J. D., & Smith, A. L. (2020). A person-centered exploration of athlete burnout across a competitive season. *Journal of Clinical Sport Psychology, 15*(2), 89-104. https://doi.org/10.1123/jcsp.2019-0084

DeJong, H., Fox, E., & Stein, A. (2019). Does rumination mediate the relationship between attentional control and symptoms of depression? *Journal of Behavior Therapy and Experimental Psychiatry, 63*, 28-35. https://doi.org/10.1016/j.jbtep.2018.12.007

Dolphin, L., Fitzgerald, A., & Dooley, B. (2017). Risky sex behaviours among college students: The psychosocial profile. *Early Intervention in Psychiatry, 12*, 1203-1212. https://doi.org/10.1111/eip.12526

Drew, B., & Matthews, J. (2018). The prevalence of depressive and anxiety symptoms in student-athletes and the relationship with resilience and help-seeking behavior. *Journal of Clinical Sport Psychology, 13*(3), 421-439. https://doi.org/10.1123/jcsp.2017-0043

Edwards, B., & Froehle, A. W. (2021). Examining the incidence of reporting mental health diagnosis between college student athletes and non-athlete students and the impact on academic performance. *Journal of American College Health*. https://doi.org/10.1080/07448481.2021.1874387

Edwards, B., Froehle, A. W., & Fagan, S. E. (2021). Trends in college student-athlete mental health in the National College Health Assessment (NCHA), 2011-2019. *Journal of Athletic Training*. https://doi.org/10.4085/1062-6050-586-21

Eisenberg, D., Golberstein, E., & Hunt, J. B. (2009). Mental health and academic success in college. *The B.E. Journal of Economic Analysis & Policy, 9*, 1-35.

Enders, C. K. (2010). *Applied missing data analysis*. Guilford Press.

Eysenck, M. W., Derakshan, N., Santos, R., & Calvo, M. G. (2007). Anxiety and cognitive performance: Attentional control theory. *Emotion, 7*(2), 336-353. https://doi.org/10.1037/1528-3542.7.2.336

Finch, W. H., & Bronk, K. C. (2011). Conducting confirmatory latent class analysis using Mplus. *Structural Equation Modeling, 18*, 132-151. https://doi.org/10.1080/10705511.2011.532732

Fix, E., & Hodges, J. L. (1951). Discriminatory analysis: Nonparametric discrimination consistency properties. *USAF School of Aviation Medicine*, 1-21. Retrieved from https://apps.dtic.mil/dtic/tr/fulltext/u2/a800276.pdf

Forbes, M. K., Neo, B., Nezami, O. M., Fried, E. I., Faure, K., Michelsen, B., Twose, M., & Dras, M. (2023). *Elemental psychopathology: Distilling constituent symptoms and patterns of repetition in the diagnostic criteria of the DSM-5*. PsyArXiv. https://doi.org/10.31234/osf.io/u56p2

Fullagar, H. H. K., Skorski, S., Duffield, R., Hammes, D., Coutts, A. J., & Meyer, T. (2015). Sleep and athletic performance: The effects of sleep loss on exercise performance, and physiological and cognitive responses to exercise. *Sports Medicine, 45*, 161-186. https://doi.org/10.1007/s40279-014-0260-0

Gerber, M., Jonsdottir, I. H., Lindwall, M., Ahlborg Jr., G. (2014). Physical activity in employees with differing occupational stress and mental health profiles: A latent profile analysis. *Psychology of Sport and Exercise, 15*(6), 649-658. https://doi.org/10.1016/j.psychsport.2014.07.012

Gustafsson, H., Carlin, M., Podlog, L., Stenling, A., & Lindwall, M. (2018a). Motivational profiles and burnout in elite athletes: A person-centered approach. *Psychology of Sport and Exercise, 35*, 118-125. https://doi.org/10.1016/j.psychsport.2017.11.009

Gustafsson, H., Madigan, D. J., & Lundkvist, E. (2016). Burnout in athletes. In R. Fuchs & M. Gerber (Hrsg.) *Handbuch Stressregulation und Sport*. Springer Reference Psychologie.

Gustafsson, H., Martinent, G., Isoard-Gautheur, S., Hassmén, P., & Guillet-Descas, E. (2018b). Performance based self-esteem and athlete-identity in athlete burnout: A person-centered approach. *Psychology of Sport and Exercise, 38*, 56-60. https://doi.org/10.1016/j.psychsport.2018.05.017

Hammond, T., Gialloreto, C., Kubas, H., & Davis, H. (2013). The prevalence of failure-based depression among elite athletes. *Clinical Journal of Sport Medicine, 23*(4), 273-277. https://doi.org/10.1097/JSM.0b013e318287b870

Hanin, Y.L. (1997). Emotions and athletic performance: Individual zones of optimal functioning. *European Yearbook of Sport Psychology, 1*, 29-72.

Hanin, Y. L. (2007). Emotions in sport: Current issues and perspectives. In G. Tenenbaum & R. C. Eklund (Eds.) *Handbook of sport psychology* (3rd ed., pp. 31-58). John Wiley & Sons.

Harper, S. R., & Nichols, A. H. (2008). Are they not all the same?: Racial heterogeneity amon Black male undergraduates. *Johns Hopkins University Press, 49*(3), 199-214. https://doi.org/10.1353/csd.0.0003

Härter, M. C., Conway, K. P., & Merikangas, K. R. (2003). Associations between anxiety disorders and physical illness. *European Archives of Psychiatry and Clinical Neuroscience, 253*, 313-320. https://doi.org/10.1007/s00406-003-0449-y

Hingson, R. W., Zha, W., & Weitzman, E. R., (2009). Magnitude of and trends in alcohol-related mortality and morbidity among U.S. college students ages 18-24, 1998-2005. *Journal of Studies on Alcohol and Drugs*, *Supplement*, 12-20. https://doi.org/10.15288/jsads.2009.s16.12

Hori, N., Newton, R., Nosaka, K., & Stone, M. H. (2005). Weightlifting exercises enhance athletic performance that requires high-load speed strength. *Strength and Conditioning Journal, 27*(4), 50-55.

Howard, M. C., & Hoffman, M. E. (2018). Variable-centered, person-centered, and person-specific approaches: Where theory meets the method. *Organizational Research Methods, 2*(4), 846-876. https://doi.org/10.1177/1094428117744021

Hox, J. (1998). *Multilevel modeling: When and why*. In I. Balderjahn, R. Mathar, & M. Schader (Eds.), Classification, data analysis, and data highways (pp. 147-154). Berlin, Germany: Springer.

Huang, J., Jacobs, D. F., Derevensky, J. L., Gupta, R., & Paskus, T. S. (2007). Gambling and health risk behaviors among U.S. college student-athletes: Findings from a national study. *Journal of Adolescent Health, 40*, 390-397. https://doi.org/10.1016/j.jadohealth.2006.11.146

Huang, J., Nigatu, Y. T., Smail-Crevier, R., Zhang, X., & Wang, J. (2018). Interventions for common mental health problems among university and college students: A systematic review and meta-analysis of randomized controlled trials. *Journal of Psychiatric Research, 107*, 1-10. https://doi.org/10.1016/j.jpsychires.2018.09.018

IBM Corp. Released 2017. IBM SPSS Statistics for Windows, Version 25.0. Armonk, NY: IBM Corp.

Ishaq, F. J., & Bass, J. (2019). High impact educational practices and the student athlete experience: The implementation and barriers of HIPs in the student athlete support setting. *Journal of Issues in Intercollegiate Athletics, 12*, 178-204.

Jao, N. C., Robinson, L. D., Kelly, P. J., Ciecierski, C. C., & Hitsman, B. (2019). Unhealthy behavior clustering and mental health status in United States college students. *Journal of American College Health, 67*(8), 790-800. https://doi.org/10.1080/07448481.2018.1515744

Jeffreys, H. (1961). *Theory of Probability, 3rd ed.* Oxford: Oxford University Press.

Jung, T., & Wickrama, K. A. S. (2008). An introduction to latent class growth analysis and growth mixture modeling. *Social and Personality Psychology Compass, 2*, 302-317. https://doi.org/10.1111/j.1751-9004.2007.00054.x

Khan, M. K., Khan, A., Khan, S. U., & Khan, S. (2017). Effects of anxiety on athletic performance. *Research & Investigations in Sports Medicine, 1*, 1-5.

Kilcullen, J. R., Scofield, B. E., Cummins, A. L., & Carr, B. M. (2022). Collegiate athlete mental health: Comparing treatment-seeking student-athletes and nonathletes on service utilization, clinical presentation, and outcomes. *Sport, Exercise, and Performance Psychology, 11*(2), 138-155. https://doi.org/10.1037/spy0000280

Konstam, V., Moser, D. K., De Jong, M. J. (2005). Depression and anxiety in heart failure. *Journal of Cardiac Failure, 11*(6), 455-462. https://doi.org/10.1016/j.cardfail.2005.03.006

Kosorok, M. R., & Laber, E. B. (2019). Precision medicine. *Annual Review of Statistics and Its Application, 6*, 263-286. https://doi.org/10.1146/annurev-statistics-030718-105251

Krieger, H., Young, C. M., Anthenien, A. M., & Neighbors, C. (2018). The epidemiology of binge drinking among college-aged individuals in the United States. *Alcohol Research: Current Reviews, 39*, 23-30.

Kroenke, K., Spitzer, R. L., & Williams, J. B. W. (2001). The PHQ-9: Validity of a brief depression severity measure. *Journal of General Internal Medicine, 16*(9), 606-613. https://doi.org/10.1046/j.1525-1497.2001.016009606.x

Kroshus, E. (2016). Variability in institutional screening practices related to collegiate student-athlete mental health. *Journal of Athletic Training, 51*(5), 389-397. https://doi.org/10.4085/1062-6050-51.5.07

Kushki, A., Drumm, E., Mobarak, M. P., Tanel, N., Dupuis, A., Chau, T., ... Anagnostou, E. (2013). Investigating the autonomic nervous system response to anxiety in children with autism spectrum disorders. *PLoS ONE, 8*(4), 1-8. https://doi.org/10.1371/journal.pone.0059730

Lattie, E. G., Adkins, E. C., Winquist, N., Stiles-Shields, C., Wafford, Q. E., & Graham, A. K. (2019). Digital mental health interventions for depression, anxiety, and enhancement of psychological well-being among college students: Systematic review. *Journal of Medical Research, 21*(7), 1-19. https://doi.org/10.2196/12869

Li, H., Moreland, J. J., Peek-Asa, C., & Yang, J. (2017). Preseason anxiety and depressive symptoms and prospective injury risk in collegiate athletes. *The American Journal of Sports Medicine, 45*(9), 2148-2155. https://doi.org/10.1177/0363546517702847

Lipson, S. K., Lattie, E. G., & Eisenberg, D. (2019). Increased rates of mental health service utilization by U.S. college students: 10-year population-level trends (2007-2017). *Psychiatric Services, 70*, 60-63. https://doi.org/10.1176/appi.ps.201800332

Llera, S. J., & Newman, M. G. (2010). Effects of worry on physiological and subjective reactivity to emotional stimuli in generalized anxiety disorder and nonanxious control participants. *Emotions, 10*(5), 640-650. https://doi.org/10.1037/a0019351

Looby, A., & Earleywine, M. (2007). Negative consequences associated with dependence in daily cannabis users. *Substance Abuse Treatment, Prevention, and Policy, 2*(3), 1-7. https://doi.org/10.1186/1747-597X-2-3

Mancine, R. P., Gusfa, D. W., Moshrefi, A., Kennedy, S. F. (2020). Prevalence of disordered eating in athletes categorized by emphasis on leanness and activity type – a systematic review. *Journal of Eating Disorders, 8*, 47. https://doi.org/10.1186/s40337-020-00323-2

Marks, I. M., & Nesse, R. M. (1994). Fear and fitness: An evolutionary analysis of anxiety disorders. *Ethology and Sociobiology, 15*, 247-261.

Martin, E. A., Unfried, A., Kim, S., & Beckham, G. K. (2021). Changes in university club athletes' and non-athlete students' stress and perceived gains across a semester. *Recreational Sports Journal, 45*, 4-16. https://doi.org/10.1177/1558866120982593

Martinent, G., Louvet, B., Decret, J. (2020). Longitudinal trajectories of athlete burnout among young table tennis players: A 3-wave study. *Journal of Sport and Health Science, 9*, 367-375. https://doi.org/10.1016/j.jshs.2016.09.003

Maslach, C., & Jackson S. E. (1981). The measurement of experienced burnout. *Journal of Occupational Behaviour, 2*, 99-113.

McFadden, T., Fortier, M., Sweet, S. N., & Tomasone, J. R. (2020). Physical activity participation and mental health profiles in Canadian medical students: Latent profile analysis using continuous latent profile indicators. *Psychology, Health & Medicine,* 1-13. https://doi.org/10.1080/13548506.2020.1757131

McLachlan, G., & Peel, D. (2000). *Finite mixture modeling*. New York, NY: Wiley

Miech, R. A., Johnston, L. D., O'Malley, P. M., Bachman, J. G., & Schulenberg, J. E. (2016). Monitoring the Future national survey results on drug use, 1975–2015: Volume I, Secondary school students. Ann Arbor: Institute for Social Research, The University of Michigan. Available at https://monitoringthefuture.org/pubs.html#monographs

Moreland, J. J., Coxe, K. A., & Yang, J. (2017). Collegiate athletes' mental health services utilization: A systematic review of conceptualizations, operationalizations, facilitators, and barriers. *Journal of Sport and Health Science, 7*, 58-69. https://doi.org/10.1016/j.jshs.2017.04.009

Moulds, M. L., Kandris, E., Starr, S., Wong, A. C. M. (2007). The relationship between rumination, avoidance and depression in a non-clinical sample. *Behaviour Research and Therapy, 45*, 251-261. https://doi.org/10.1016/j.brat.2006.03.003

Muthén, B. O. (2001). Latent variable mixture modeling. In G. A. Marcoulides, & R. E. Schumacker (Eds.), *New developments and techniques in structural equation modeling* (pp. 1–33). Lawrence Erlbaum Associates.

Muthén, B. O., & Muthén L. K. (2000). Integrating person-centered and variable-centered analyses: Growth mixture modeling with latent trajectory classes. *Alcoholism: Clinical and Experimental Research, 24*, 882-891.

Muthén, L. K. & Muthén, B. O. (1998-2017). *Mplus User's Guide, Eighth Edition*. Los Angeles, CA: Muthén & Muthén

National Collegiate Athletic Association (2016, January). *Results from the 2015 GOALS study of the student-athlete experience*. NCAA Convention, San Antonio, TX, United States.

https://www.ncaa.org/sites/default/files/GOALS_convention_slidebank_jan2016_public.pdf

National Collegiate Athletic Association (2018). *NCAA national study on substance use habits of college student-athletes*. National Collegiate Athletic Association. https://www.ncaa.org/sites/default/files/2017RES_Substance_Use_Executive_Summary_FINAL_20180611.pdf

National Collegiate Athletic Association (2020a). *2020-21 NCAA division I manual*. National Collegiate Athletic Association. https://www.ncaapublications.com/productdownloads/D121.pdf

National Collegiate Athletic Association (2020b). *2020-21 NCAA division III manual*. National Collegiate Athletic Association. https://www.ncaapublications.com/productdownloads/D321.pdf

National Collegiate Athletic Association (2023). *Staying on track to graduate*. Retrieved from https://www.ncaa.org/sports/2021/2/10/student-athletes-current-staying-track-graduate

Srivastava, D. B. (2019). *Scalise says student athletes face structural isolation on campus*. Retrieved from https://www.thecrimson.com/article/2019/10/30/athletes-isolated-on-campus/

National Institute on Alcohol Abuse and Alcoholism. (2015). *College Drinking* [Fact Sheet]. Retrieved from https://pubs.niaaa.nih.gov/publications/collegefactsheet/Collegefactsheet.pdf

Newman, M. G., & Llera, S. J. (2011). A novel theory of experiential avoidance in generalized anxiety disorder: A review and synthesis of research supporting a contrast avoidance model of worry. *Clinical Psychology Review, 31*, 371-382. https://doi.org/10.1016/j.cpr.2011.01.008

Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A monte carlo simulation study. *Structural Equation Modeling: A Multidisciplinary Journal, 14*, 535-569. https://doi.org/10.1080/10705510701575396

Oswalt, S. B., Lederer, A. M., Chestnut-Steich, K., Day, C., Halbritter, A., & Ortiz, D. (2020). Trends in college students' mental health diagnoses and utilization of services, 2009-2015. *Journal of American College Health, 68*, 41-51. https://doi.org/10.1080/07448481.2018.1515748

Patrick, M. E., Terry-McElrath, Y. M., Evans-Polce, R. J., & Schulenberg, J. E. (2020). Negative alcohol-related consequences experienced by young adults in the past 12 months: Differences by college attendance, living situation, binge drinking, and sex. *Addictive Behaviors, 105*, 1-9. https://doi.org/10.1016/j.addbeh.2020.106320

Petersen, K. J., Qualter, P., & Humphrey, N. (2019). The application of latent class analysis for investigating population child mental health: A systematic review. *Frontiers in Psychology, 10*, 1-16. https://doi.org/10.3389/fpsyg.2019.01214

Petrie, T. A., & Russell, R. K. (1995). Academic and psychosocial antecedents of academic performance for minority and nonminority college football players. *Journal of Counseling & Development, 73*, 615-620.

Pijpers, J. R., Oudejans, R. D., Holsheimer, F., & Bakker, F. C. (2003). Anxiety-performance relationships in climbing: A process-oriented approach. *Psychology of Sport and Exercise, 4*, 283-304.

Podlog, L. (2016). Sport injury. In R. J. Schinke, K. R. McGannon, & B. Smith (Eds.) *Routledge International Handbook of Sport Psychology* (1st ed.). Routledge.

Reich, A. L., Milroy, J. J., Wyrick, D. L., & Hebard, S. P. (2021). A social ecological framework: Counselors' role in improving student-athletes' help-seeking behaviors. *Journal of College Counseling, 24*, 81-96. https://doi.org/10.1002/jocc.12178

Reinhardt, M., Horváth, Z., Morgan, A., Kökönyei, G. (2020). Well-being profiles in adolescence: Psychometric properties and latent profile analysis of the mental health continuum model – a methodological study. *Health and Quality of Life Outcomes, 18*, 1-10. https://doi.org/10.1186/s12955-020-01332-0

Rexroat, M. (2014). *NCAA national study of substance use habits of college student-athletes*. Retrieved from the National Collegiate Athletic Association website: https://www.ncaa.org/sites/default/files/ Substance%20Use%20Final%20Report_FINAL.pdf

Rice, S. M., Purcell, R., De Silva, S., Mawren, D., McGorry, P. D., & Parker, A. G. (2016). The mental health of elite athletes: A narrative systematic review. *Sports Medicine, 46*, 1333-1353. https://doi.org/10.1007/s40279-016-0492-2

Sapolsky, R. M. (2004). *Why zebras don't get ulcers* (3rd ed.). New York, NY: Holt Paperbacks

Sawatzky, R., Russell, L. B., Sajobi, T. T., Lix, L. M., Kopec, J., & Zumbo, B. D. (2018). The use of latent variable models to identify invariant items in test construction. *Quality of Life Research, 27*, 1745-1755. https://doi.org/10.1007/s11136-017-1680-8

Sclove, S. L. (1987). Application of model-selection criteria to some problems in multivariate analysis. *Psychometrika, 52*, 333-343.

Sheehan, R. B., Herring, M. P., & Campbell, M. J. (2018). Associations between motivation and mental health in sport: A test of the hierarchical model of intrinsic and extrinsic motivation. *Frontiers in Psychology, 9*(707), 1-10. https://doi.org/10.3389/fpsyg.2018.00707

Sinha, P., Calfee, C. S., & Delucchi, K. L. (2021). Practitioner's guide to latent class analysis: Methodological considerations and common pitfalls. *Critical Care Medicine, 49*, e63-e79. https://doi.org/10.1097/CCM.0000000000004710

Spitzer, R. L., Kroenke, K., & Williams, J. B. W. (2006). A brief measure for assessing generalized anxiety disorder: The GAD-7. *Archives of Internal Medicince, 166*(10), 1092-1097. https://doi.org/10.1001/archinte.166.10.1092

Spurk, D., Hirschi, A., Wang, M., Valero, D., & Kauffeld, S. (2020). Latent profile analysis: A review and "how to" guide of its application withing vocational behavior research. *Journal of Vocational Behavior, 120*, 1-21. https://doi.org/10.1016/j.jvb.2020.103445

Suris, J. C., Michaud, P. A., Akre, C., & Sawyer, S. M. (2008). Health risk behaviors in adolescents with chronic conditions. *Pediatrics, 122*(5), 1113-1118. https://doi.org/10.1542/peds.2008-1479

Swanholm, E., Vosvick, M., & Chng, C. (2009). Pessimism, trauma, risky sex: Covariates of depression in college students. *American Journal of Health Behavior, 33*(3), 309-318.

Tein, J. Y., Coxe, S., & Cham, H. (2013). Statistical power to detect the correct number of classes in latent profile analysis. *Structural Equation Modeling, 20*, 640-657. https://doi.org/10.1080/10705511.2013.824781

Weinberg, R. S., & Hunt, V. V. (1976). The interrelationships between anxiety, motor performance, and electromyography. *Journal of Motor Behavior, 8*(3), 219-224.

Woody, M. L., Owens, M., Burkhouse, K. L., & Gibb, B. E. (2015). Selective attention toward angry faces and risk for major depressive disorder in women: Converging evidence from retrospective and prospective analyses. *Clinical Psychological Science, 4*(2), 206-215. https://doi.org/10.1177/2167702615581580

World Health Organization (2018). *Global status report on alcohol and health 2018: Executive summary*. World Health Organization.

Yaroslavsky, I., Allard, E. S., & Sanchez-Lopez, A. (2019). Can't look away: Attention control deficits predict rumination, depression symptoms and depressive affect in daily life. *Journal of Affective Disorders, 245*, 1061-1069. https://doi.org/10.1016/j.jad.2018.11.036

Zamboanga, B. L., Merrill, E. J., Olthuis, J. V., Martin, J. L., Jarrell, J. T., Cannon, M., Meca, A., Milroy, J. J., & Wyrick, D. L. (2022). A national study on drinking game behaviors and related consequences among NCAA student-athletes: Racial/ethnic and sex differences. *Journal of Studies on Alcohol and Drugs, 83*, 74-84. https://doi.org/10.15288/jsad.2022.83.74

Zeiger, J. S., Silvers, W. S., Fleegler, E. M., & Zeiger, R. S. (2019). Cannabis use in active athletes: Behaviors related to subjective effects. *PLoS ONE, 14*(6), 1-16. https://doi.org/10.1371/journal.pone.0218998

APPENDIX A

Demographics Items

Variable	Item	Response Options
Age	How old are you?	_________ years
Sex	What sex were you assigned at birth, such as on an original birth certificate?	Female, Male
Gender	Which term do you use to describe your gender identity?	Woman, Man, Trans Woman, Trans Man, Genderqueer, Another identity (please specify)
Race	How do you usually describe yourself? (Mark all that apply)	White, Black, Hispanic or Latino/a, Asian or Pacific Islander, American Indian/Alaska Native/Native Hawaiian, Biracial or Multiracial, Other
Sexual Orientation	What term best describes your sexual orientation?	Asexual, Bisexual, Gay, Lesbian, Pansexual, Queer, Questioning, Same Gender Loving, Straight/heterosexual, Another identity (please specify)
School Year	What is your year in school?	1st year undergraduate, 2nd year undergraduate, 3rd year undergraduate, 4th year undergraduate, 5th year undergraduate, Graduate or

		professional, Not seeking a degree, Other
Athletic Affiliation	Within the last 12 months, have you participated in organized college athletics at any of the following level?	Varsity (No/Yes), Club sports (No/Yes), Intramurals (No/Yes)

APPENDIX B

Mental Health Indicators

Have you ever...

Item	Response Options				
Felt things were hopeless	No, never	No, not in the last 12 months	Yes, in the last 12 months	Yes, in the last 30 days	Yes, in the last 2 weeks
Felt overwhelmed by all you had to do	No, never	No, not in the last 12 months	Yes, in the last 12 months	Yes, in the last 30 days	Yes, in the last 2 weeks
Felt exhausted (not by physical activity)	No, never	No, not in the last 12 months	Yes, in the last 12 months	Yes, in the last 30 days	Yes, in the last 2 weeks
Felt very lonely	No, never	No, not in the last 12 months	Yes, in the last 12 months	Yes, in the last 30 days	Yes, in the last 2 weeks
Felt very sad	No, never	No, not in the last 12 months	Yes, in the last 12 months	Yes, in the last 30 days	Yes, in the last 2 weeks
Felt so depressed that it was difficult to function	No, never	No, not in the last 12 months	Yes, in the last 12 months	Yes, in the last 30 days	Yes, in the last 2 weeks
Felt overwhelming anxiety	No, never	No, not in the last 12 months	Yes, in the last 12 months	Yes, in the last 30 days	Yes, in the last 2 weeks
Felt overwhelming anger	No, never	No, not in the last 12 months	Yes, in the last 12 months	Yes, in the last 30 days	Yes, in the last 2 weeks
Intentionally cut, burned, bruised, or otherwise injured yourself	No, never	No, not in the last 12 months	Yes, in the last 12 months	Yes, in the last 30 days	Yes, in the last 2 weeks
Seriously considered suicide	No, never	No, not in the last 12 months	Yes, in the last 12 months	Yes, in the last 30 days	Yes, in the last 2 weeks
Attempted suicide	No, never	No, not in the last 12 months	Yes, in the last 12 months	Yes, in the last 30 days	Yes, in the last 2 weeks

APPENDIX C

Health Risk Behavior Items

Substance Use

Within the last 30 days, on how many days did you use...

Item	Response Options							
Alcohol	Never used	Have used, but not in last 30 days	1-2 days	3-5 days	6-9 days	10-19 days	20-29 days	Used daily
Cannabis								

Over the last two weeks, how many times have you had five or more drinks of alcohol at a sitting?

N/A, don't drink
None
1 time
2 times
3 times
4 times
5 times
6 times
7 times
8 times
9 times
10 or more times

Within the last 30 days, did you...

Item	Response Options

Drive after drinking any alcohol at all	N/A, don't drive	N/A, don't drink	No	Yes
Drive after drinking five or more drinks of alcohol	N/A, don't drive	N/A, don't drink	No	Yes

Within the last 12 months, have you experienced any of the following when drinking alcohol?

Item	**Response Options**		
Did something you later regretted	N/A, don't drink	No	Yes
Forgot where you were or what you did	N/A, don't drink	No	Yes
Got in trouble with the police	N/A, don't drink	No	Yes
Someone had sex with me without my consent	N/A, don't drink	No	Yes
Had sex with someone without their consent	N/A, don't drink	No	Yes
Had unprotected sex	N/A, don't drink	No	Yes
Physically injured yourself	N/A, don't drink	No	Yes
Physically injured another person	N/A, don't drink	No	Yes
Seriously considered suicide	N/A, don't drink	No	Yes

Risky Sex

Within the last 12 months, with how many partners have you had oral sex, vaginal intercourse, or anal intercourse? ____________________________________ number of partners.

Within the last 30 days, how often did you or your partner(s) use a condom or other protective barrier (e.g., male condom, female condom, dam, glove) during...

Item	**Response options**						
Oral sex?	N/A, never did this	Have not done this sexual activity during the last 30 days	Never	Rarely	Sometimes	Most of the time	Always

	sexual activity						
Vaginal Intercourse?	N/A, never did this sexual activity	Have not done this sexual activity during the last 30 days	Never	Rarely	Sometimes	Most of the time	Always
Anal Intercourse?	N/A, never did this sexual activity	Have not done this sexual activity during the last 30 days	Never	Rarely	Sometimes	Most of the time	Always

Disordered Eating

Within the last 30 days, did you do any of the following?

Item	Response Options	
Vomit or take laxatives to lose weight	No	Yes
Take diet pills to lose weight	No	Yes

Risky Driving/Riding

Within the last 12 months, how often did you...

Item	Response Options					
Wear a seatbelt when you rode in the car?	N/A, did not do this activity withing the last 12 months	Never	Rarely	Sometimes	Most of the time	Always

Wear a helmet when you rode a bicycle?	N/A, did not do this activity withing the last 12 months	Never	Rarely	Sometimes	Most of the time	Always
Wear a helmet when you rode a motorcycle?	N/A, did not do this activity withing the last 12 months	Never	Rarely	Sometimes	Most of the time	Always

APPENDIX D

Help-Seeking Behavior Items

Item	Response Options	
Have you ever received psychological or mental health services from a counselor/therapist/psychologist?	No	Yes
Have you ever received psychological or mental health services from a psychiatrist?	No	Yes
Have you ever received psychological or mental health services from your current college/university's Counseling or health services?	No	Yes
If in the future you were having a personal problem that was really bothering you, would you consider seeking help from a mental health professional?	No	Yes

APPENDIX E

Performance-Related Outcomes

Exercise

On how many of the past 7 days did you...

Items								
Do moderate-intensity cardio or aerobic exercise (cause a noticeable increase in heart rate, such as a brisk walk) for at least 30 minutes?	0 days	1 day	2 days	3 days	4 days	5 days	6 days	7 days
Do vigorous-intensity cardio or aerobic exercise (caused large increases in breathing or heart rate, such as jogging) for at least 20 minutes?	0 days	1 day	2 days	3 days	4 days	5 days	6 days	7 days
Do 8-10 strength training exercises (such as weight machines) for 8-12 repetitions each?	0 days	1 day	2 days	3 days	4 days	5 days	6 days	7 days

Sleep

Within the last 12 months, have sleep difficulties been traumatic or very difficult for you to handle?

Response Options	
No	Yes

In the past 7 days, how often have you...

Items	**Response Options**

Awakened too early in the morning and couldn't get back to sleep?	0 days	1 day	2 days	3 days	4 days	5 days	6 days	7 days
Felt tired, dragged out, or sleepy during the day?	0 days	1 day	2 days	3 days	4 days	5 days	6 days	7 days
Gone to bed because you just could not stay awake any longer?	0 days	1 day	2 days	3 days	4 days	5 days	6 days	7 days
Had an extremely hard time falling asleep?	0 days	1 day	2 days	3 days	4 days	5 days	6 days	7 days

Academics

Within the last 12 months, have academics been traumatic or very difficult for you to handle?

Response Options	
No	Yes

APPENDIX F

SPSS Syntax for Cleaning, Computing, and Recoding Variables

```
Comment ID variable and sysmis.
DATASET ACTIVATE DataSet1.
COMPUTE ID=$CASENUM.
EXECUTE.

recode RNQ47 (-9 = sysmis) (1=1) (2=2) (3=3).
execute.

VALUE LABELS RNQ47
1 'Male'
2 'Female'
3 'Non-Binary'.
execute.

recode all (sysmis=-999).
execute.

ALTER TYPE NQ46(f8).

Recode NQ46 (18=1) (19=1) (20=1) (21=1) (22=1) (23=1) (24=1) (25=1)
(26=2) (27=2) (28=2) (29=2) (30=2) (31=2) (32=2) (33=2) (34=2) (35=2) (36=2) (37=2)
(38=2) (39=2) (40=2) (41=2) (42=2) (43=2) (44=2) (45=2) (46=2) (47=2) (48=2) (49=2)
(50=3) (51=3) (52=3) (53=3) (54=3) (55=3) (56=3) (57=3) (58=3) (59=3) (60=3) (61=3)
(62=3) (63=3) (64=3) (65=3) (66=3) (67=3) (68=3) (69=3) (70=3) (71=3) (72=3) (73=3)
(74=3) (77=3) (78=3) (79=3) (80=3) (81=3) (87=3) (88=3) (89=3) (90=3) (93=3) (94=3)
(96=3) (97=3) (98=3) (sysmis=-999) into agegrp.
execute.

recode agegrp (sysmis=-999).
execute.

Comment Recoding mental health indicators.
RECODE NQ30A to NQ30K (1=0) (2=1) (3=2) (4=3) (5=4).
execute.

Value labels NQ30A to NQ30K
0 'No, never'
1 'No, not in the last 12 months'
2 'Yes, in the last 2 weeks'
3 'Yes, in the last 30 days'
4 'Yes, in the last 12 months'.
execute.

RECODE NQ30A to NQ30K (0=0) (1=0) (2=2) (3=2) (4=1) into MHSX1 to MHSX11.
execute.
```

Value labels MHSX1 to MHSX11
0 'Never or not in the last year'
1 'Yes, Within the last Year'
2 'Yes, Within the last 30 days'.
execute.

Comment Recoding MH history co-variates.
RECODE NQ31A1 to NQ31B7 (1=0) (2=1) (3=2) (4=3) (5=4) (6=5).
execute.

Value labels NQ31A1 to NQ31B7
0 'No'
1 'Yes, no tx'
2 'Yes, medication'
3 'Yes, psychotherapy'
4 'Yes, medication & therapy'
5 'Yes, other tx'.
execute.

RECODE NQ31A1 to NQ31B7 (0=0) (1=1) (2=1) (3=1) (4=1) (5=1) (6=1) into DxHx1 to DxHx15.
execute.

Value labels DxHx1 to DxHx15
0 'No'
1 'Yes, diagnosed and/or treated'.
execute.

COMPUTE Dx3 = (Dxhx1+Dxhx3+Dxhx4+Dxhx5+Dxhx7+Dxhx8+Dxhx9+Dxhx10+Dxhx11+ Dxhx12+Dxhx13+Dxhx14+Dxhx15).
execute.

Recode Dx3 (0=0) (1=1) (2=1) (3=1) (4=1) (5=1) (6=1) (7=1) (8=1) (9=1)
(10=1) (11=1) (12=1) (13=1).
execute.

Value labels Dx3
0 'No'
1 'Yes, Diagnosed and/or Treated'.
execute.

RECODE NQ18A (1=0) (2=1).
execute.

Value labels NQ18A
0 'No'

1 'Yes'.
execute.

Comment recode other meds Qs.
RECODE NQ18B to NQ18E (1=0) (2=1).
execute.

Value labels NQ18B to NQ18E
0 'No'
1 'Yes'.
execute.

Comment Recoding outcomes.

Comment help seeking.
RECODE NQ34A to NQ34B (1=0) (2=1).
execute.

Value labels NQ34A to NQ34B
0 'No'
1 'Yes'.
execute.

Recode NQ35 (1=0) (2=1).
Recode NQ36 (1=0) (2=1).
execute.

Value labels NQ35 to NQ36
0 'No'
1 'Yes'.
execute.

Comment Performance outcomes.

Comment Academic Performance.
RECODE NQ33A (1=0) (2=1).
execute.

Value labels NQ33A
0 'No'
1 'Yes'.
execute.

RECODE NQ45A1 to NQ45D4 (1=0) (2=1) (3=2) (4=3) (5=4) (6=5).
execute.

Value labels NQ45A1 to NQ45D4
0 'This did not happen to me/not applicable'
1 'I have experienced this issue but my academics have not been affected'
2 'Received a lower grade on an exam or important project'
3 'Received a lower grade in the course'
4 'Received an incomplete or dropped the course'
5 'Significant disruption in thesis, dissertation, research, or practicum work'.
execute.

Comment exercise performance.
RECODE NQ29A to NQ29C (1=0) (2=1) (3=2) (4=3) (5=4) (6=5) (7=6) (8=7).
execute.

Value labels NQ29A to NQ29C
0 '0 days'
1 '1 day'
2 '2 days'
3 '3 days'
4 '4 days'
5 '5 days'
6 '6 days'
7 '7 days'.
execute.

Comment sleep.
RECODE NQ33K (1=0) (2=1).
execute.

Value labels NQ33K
0 'No'
1 'Yes'.
execute.

RECODE NQ44A to NQ44D (1=0) (2=1) (3=2) (4=3) (5=4) (6=5) (7=6) (8=7).
execute.

Value labels NQ44A to NQ44D
0 '0 days'
1 '1 day'
2 '2 days'
3 '3 days'
4 '4 days'
5 '5 days'
6 '6 days'
7 '7 days'.
execute.

```
Comment health risk behaviors.

Comment Substance Use.
RECODE NQ8A5 to NQ8A6 (1=0) (2=1) (3=2) (4=3) (5=4) (6=5) (7=6) (8=7).
execute.

Value labels NQ8A5 to NQ8A6
0 'Never used'
1 'Have used, but not in last 30 days'
2 '1-2 days'
3 '3-5 days'
4 '6-9 days'
5 '10-19 days'
6 '20-29 days'
7 'Used daily'.
execute.

RECODE NQ13 (1=sysmis) (2=0) (3=1) (4=2) (5=3) (6=4) (7=5) (8=6) (9=7) (10=8) (11=9)
(12=10) into hed.
execute.

Value labels hed
0 'None'
1 '1 time'
2 '2 times'
3 '3 times'
4 '4 times'
5 '5 times'
6 '6 times'
7 '7 times'
8 '8 times'
9 '9 times'
10 '10 or more times'.
execute.

RECODE NQ14A to NQ14B (1=sysmis) (2=sysmis) (3=0) (4=1) into dui1 to dui2.
execute.

Value labels dui1 to dui2
0 'No'
1 'Yes'.
execute.

RECODE NQ16A to NQ16I (1=sysmis) (2=0) (3=1) into conseq1 to conseq9.
execute.
```

```
Value labels conseq1 to conseq9
0 'No'
1 'Yes'.
execute.

Comment Safety in car/bike/motorcycle.
RECODE NQ4A to NQ4D (1=sysmis) (2=0) (3=1) (4=2) (5=3) (6=4) into safe1 to safe4.
execute.

Value labels safe1 to safe4
0 'Never'
1 'Rarely'
2 'Sometimes'
3 'Most of the time'
4 'Always'.
execute.

Comment risky sex.
If (NQ19 ge 10) NQ19 = 9.
execute.

Value labels NQ19
0 '0 partners'
1 '1 partner'
2 '2 partners'
3 '3 partners'
4 '4 partners'
5 '5 partners'
6 '6 partners'
7 '7 partners'
8 '8 partners'
9 '9 or more partners'.
execute.

RECODE NQ22A to NQ22C (1=sysmis) (2=sysmis) (3=0) (4=1) (5=2) (6=3) (7=4) into
condom1 to condom3.
execute.

Value labels condom1 to condom3
0 'Never'
1 'Rarely'
2 'Sometimes'
3 'Most of the time'
4 'Always'.
execute.
```

```
Comment disordered eating behaviors.
RECODE NQ38C to NQ38D (1=0) (2=1).
execute.

Value labels NQ38C to NQ38D
0 'No'
1 'Yes'.
execute.

Comment recode athletics participation.
RECODE NQ64A to NQ64C (1=0) (2=1).
execute.

Value labels NQ64A to NQ64C
0 'No'
1 'Yes'.
execute.

COMMENT Count outcomes.
Compute totconseq = sum(conseq1 to conseq9).
execute.
```

APPENDIX G

Mplus Code for Model Comparisons – Class Probabilities

Class Probabilities Constrained Between Student-Athletes and Non-Athletes

DATA:

FILE is Davis_ACHA_CombineAUX123022.csv;

VARIABLE:

NAMES ARE

ID NQ64A NQ64B NQ64C NQ46 agegrp RNQ47A RNQ47B RNQ47C

RNQ48 NQ54A NQ54B NQ54C NQ54D NQ54E NQ54F

NQ54G NQ51 NQ55 PAREQ RNQ47 size MHSX1 MHSX2

MHSX3 MHSX4 MHSX5 MHSX6 MHSX7 MHSX8 MHSX9

MHSX10 MHSX11 Dx1 Dx2 Dx3 NQ18A NQ34A NQ34B NQ35

NQ36 safe1 safe2 safe3 safe4 NQ8A5 NQ8A6 hed dui1 dui2

conseq1 conseq2 conseq3 conseq4 conseq5 conseq6 conseq7

conseq8 conseq9 NQ19 condom1 condom2 condom3 NQ38C

NQ38D NQ29A NQ29B NQ29C NQ33K NQ44A NQ44B NQ44C

NQ44D NQ33A NQ45A1 NQ45A3 NQ45B4

NQ45B7 NQ45C6 NQ45D4 totconseq;

MISSING = all(-999);

USEVARIABLES ARE

MHSX1 MHSX2 MHSX3 MHSX4 MHSX5 MHSX6

MHSX7 MHSX8 MHSX9 MHSX10 MHSX11

Dx1 Dx2 Dx3 agegrp RNQ47A;

CATEGORICAL ARE MHSX1 MHSX2 MHSX3 MHSX4 MHSX5 MHSX6

MHSX7 MHSX8 MHSX9 MHSX10 MHSX11;

CLASSES = g (2) c (5);

KNOWNCLASS = g (NQ64A = 0 NQ64A = 1);

ANALYSIS:

TYPE = MIXTURE;

PROCESSORS = 20;

MODEL:

%OVERALL%

c on Dx1 Dx2 Dx3 agegrp RNQ47A;

OUTPUT: tech4 tech7 tech11 tech14;

Class Probabilities Freed Between Student-Athletes and Non-Athletes

DATA:

FILE is Davis_ACHA_CombineAUX123022.csv;

Variable:

NAMES ARE

ID NQ64A NQ64B NQ64C NQ46 agegrp RNQ47A RNQ47B RNQ47C

RNQ48 NQ54A NQ54B NQ54C NQ54D NQ54E NQ54F

NQ54G NQ51 NQ55 PAREQ RNQ47 size MHSX1 MHSX2

MHSX3 MHSX4 MHSX5 MHSX6 MHSX7 MHSX8 MHSX9

MHSX10 MHSX11 Dx1 Dx2 Dx3 NQ18A NQ34A NQ34B NQ35

NQ36 safe1 safe2 safe3 safe4 NQ8A5 NQ8A6 hed dui1 dui2

conseq1 conseq2 conseq3 conseq4 conseq5 conseq6 conseq7

conseq8 conseq9 NQ19 condom1 condom2 condom3 NQ38C

NQ38D NQ29A NQ29B NQ29C NQ33K NQ44A NQ44B NQ44C

NQ44D NQ33A NQ45A1 NQ45A3 NQ45B4

NQ45B7 NQ45C6 NQ45D4 totconseq;

MISSING = all(-999);

USEVARIABLES ARE

MHSX1 MHSX2 MHSX3 MHSX4 MHSX5 MHSX6

MHSX7 MHSX8 MHSX9 MHSX10 MHSX11

```
Dx1 Dx2 Dx3 agegrp RNQ47A;

CATEGORICAL ARE MHSX1 MHSX2 MHSX3 MHSX4 MHSX5 MHSX6
MHSX7 MHSX8 MHSX9 MHSX10 MHSX11;

CLASSES = g (2) c (5);
KNOWNCLASS = g (NQ64A = 0 NQ64A = 1);

ANALYSIS:
TYPE = MIXTURE;
PROCESSORS = 20;

MODEL:
%OVERALL%
c on Dx1 Dx2 Dx3 agegrp RNQ47A;
c on g;

OUTPUT: tech4 tech7 tech11 tech14;
```

APPENDIX H

Mplus Code for Model Comparisons – Thresholds

Non-Athlete Item Thresholds Constrained to Equal Student-Athletes

```
DATA:
FILE is Davis_ACHA_CombineAUX123022.csv;

VARIABLE:
NAMES ARE
ID NQ64A NQ64B NQ64C NQ46 agegrp RNQ47A RNQ47B RNQ47C
RNQ48 NQ54A NQ54B NQ54C NQ54D NQ54E NQ54F
NQ54G NQ51 NQ55 PAREQ RNQ47 size MHSX1 MHSX2
MHSX3 MHSX4 MHSX5 MHSX6 MHSX7 MHSX8 MHSX9
MHSX10 MHSX11 Dx1 Dx2 Dx3 NQ18A NQ34A NQ34B NQ35
NQ36 safe1 safe2 safe3 safe4 NQ8A5 NQ8A6 hed dui1 dui2
conseq1 conseq2 conseq3 conseq4 conseq5 conseq6 conseq7
conseq8 conseq9 NQ19 condom1 condom2 condom3 NQ38C
NQ38D NQ29A NQ29B NQ29C NQ33K NQ44A NQ44B NQ44C
NQ44D NQ33A NQ45A1 NQ45A3 NQ45B4
NQ45B7 NQ45C6 NQ45D4 totconseq;

MISSING = all(-999);

USEVARIABLES ARE
MHSX1 MHSX2 MHSX3 MHSX4 MHSX5 MHSX6
MHSX7 MHSX8 MHSX9 MHSX10 MHSX11
```

```
Dx1 Dx2 Dx3 agegrp RNQ47A;

CATEGORICAL ARE MHSX1 MHSX2 MHSX3 MHSX4 MHSX5 MHSX6
MHSX7 MHSX8 MHSX9 MHSX10 MHSX11;

USEOBSERVATIONS (NQ64A eq 0);

CLASSES = c (5);

ANALYSIS:
TYPE = MIXTURE;
PROCESSORS = 20;

MODEL:
%OVERALL%
c on Dx1 Dx2 Dx3 agegrp RNQ47A;

%c#1%
  [MHSX1$1@-3.573];
  [MHSX1$2@-2.013];
  [MHSX2$1@-4.398];
  [MHSX2$2@-3.287];
  [MHSX3$1@-4.044];
```

[MHSX3$2@-3.276];

[MHSX4$1@-3.454];

[MHSX4$2@-2.484];

[MHSX5$1@-4.897];

[MHSX5$2@-4.082];

[MHSX6$1@-3.681];

[MHSX6$2@-1.717];

[MHSX7$1@-3.665];

[MHSX7$2@-2.572];

[MHSX8$1@-1.579];

[MHSX8$2@-0.746];

[MHSX9$1@0.941];

[MHSX9$2@1.726];

[MHSX10$1@0.457];

[MHSX10$2@1.488];

[MHSX11$1@2.313];

[MHSX11$2@3.030];

%c#2%

[MHSX1$1@-1.350];

[MHSX1$2@3.280];

[MHSX2$1@-3.788];

[MHSX2$2@0.783];

```
  [MHSX3$1@-3.114];
  [MHSX3$2@0.881];
  [MHSX4$1@-2.112];
  [MHSX4$2@2.347];
  [MHSX5$1@-3.324];
  [MHSX5$2@2.441];
  [MHSX6$1@-0.285];
  [MHSX6$2@4.430];
  [MHSX7$1@-1.439];
  [MHSX7$2@2.384];
  [MHSX8$1@-0.438];
  [MHSX8$2@2.799];
  [MHSX9$1@2.090];
  [MHSX9$2@4.467];
  [MHSX10$1@1.638];
  [MHSX10$2@5.147];
  [MHSX11$1@3.223];
  [MHSX11$2@6.929];

%c#3%
  [MHSX1$1@-0.639];
  [MHSX1$2@0.458];
  [MHSX2$1@-3.693];
```

```
  [MHSX2$2@-2.455];
  [MHSX3$1@-2.902];
  [MHSX3$2@-2.250];
  [MHSX4$1@-1.721];
  [MHSX4$2@-0.619];
  [MHSX5$1@-2.926];
  [MHSX5$2@-1.108];
  [MHSX6$1@0.571];
  [MHSX6$2@1.824];
  [MHSX7$1@-1.067];
  [MHSX7$2@-0.173];
  [MHSX8$1@0.048];
  [MHSX8$2@0.981];
  [MHSX9$1@3.260];
  [MHSX9$2@4.408];
  [MHSX10$1@3.685];
  [MHSX10$2@5.959];
  [MHSX11$1@6.442];
  [MHSX11$2@6.571];
%c#4%
  [MHSX1$1@1.960];
  [MHSX1$2@2.946];
  [MHSX2$1@-2.717];
```

```
  [MHSX2$2@-0.970];
  [MHSX3$1@-1.552];
  [MHSX3$2@-0.565];
  [MHSX4$1@0.889];
  [MHSX4$2@1.991];
  [MHSX5$1@0.658];
  [MHSX5$2@1.993];
  [MHSX6$1@4.520];
  [MHSX6$2@5.699];
  [MHSX7$1@0.923];
  [MHSX7$2@1.755];
  [MHSX8$1@1.794];
  [MHSX8$2@2.757];
  [MHSX9$1@4.885];
  [MHSX9$2@5.833];
  [MHSX10$1@7.426];
  [MHSX10$2@7.835];
  [MHSX11$1@15.000];
  [MHSX11$2@15.001];

%c#5%
  [MHSX1$1@5.741];
  [MHSX1$2@5.784];
```

```
  [MHSX2$1@1.484];
  [MHSX2$2@1.771];
  [MHSX3$1@2.608];
  [MHSX3$2@2.788];
  [MHSX4$1@3.575];
  [MHSX4$2@3.807];
  [MHSX5$1@3.430];
  [MHSX5$2@3.743];
  [MHSX6$1@5.266];
  [MHSX6$2@5.267];
  [MHSX7$1@4.008];
  [MHSX7$2@4.129];
  [MHSX8$1@4.245];
  [MHSX8$2@4.512];
  [MHSX9$1@6.213];
  [MHSX9$2@6.372];
  [MHSX10$1@5.955];
  [MHSX10$2@6.234];
  [MHSX11$1@6.355];
  [MHSX11$2@6.642];

OUTPUT: tech4 tech7 tech11 tech14;
```

Non-Athlete Item Thresholds Freely Estimated

```
DATA:

FILE is Davis_ACHA_CombineAUX123022.csv;


VARIABLE:

NAMES ARE

ID NQ64A NQ64B NQ64C NQ46 agegrp RNQ47A RNQ47B RNQ47C

RNQ48 NQ54A NQ54B NQ54C NQ54D NQ54E NQ54F

NQ54G NQ51 NQ55 PAREQ RNQ47 size MHSX1 MHSX2

MHSX3 MHSX4 MHSX5 MHSX6 MHSX7 MHSX8 MHSX9

MHSX10 MHSX11 Dx1 Dx2 Dx3 NQ18A NQ34A NQ34B NQ35

NQ36 safe1 safe2 safe3 safe4 NQ8A5 NQ8A6 hed dui1 dui2

conseq1 conseq2 conseq3 conseq4 conseq5 conseq6 conseq7

conseq8 conseq9 NQ19 condom1 condom2 condom3 NQ38C

NQ38D NQ29A NQ29B NQ29C NQ33K NQ44A NQ44B NQ44C

NQ44D NQ33A NQ45A1 NQ45A3 NQ45B4

NQ45B7 NQ45C6 NQ45D4 totconseq;


MISSING = all(-999);


USEVARIABLES ARE

MHSX1 MHSX2 MHSX3 MHSX4 MHSX5 MHSX6

MHSX7 MHSX8 MHSX9 MHSX10 MHSX11
```

Dx1 Dx2 Dx3 agegrp RNQ47A;

CATEGORICAL ARE MHSX1 MHSX2 MHSX3 MHSX4 MHSX5 MHSX6

MHSX7 MHSX8 MHSX9 MHSX10 MHSX11;

USEOBSERVATIONS (NQ64A eq 0);

CLASSES = c (5);

ANALYSIS:

TYPE = MIXTURE;

PROCESSORS = 20;

MODEL:

%OVERALL%

c on Dx1 Dx2 Dx3 agegrp RNQ47A;

OUTPUT: tech4 tech7 tech11 tech14;