'Legs Feed The Wolf': An evolutionary perspective on psychosocial stress, physical activity, and their associations with telomere length in NCAA student-athletes and non-athletes

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Abstract

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Psychosocial stress negatively impacts our mental and physical health, predisposing us to illness, worsened mental health, and accelerated aging. Conversely, regular physical activity, such as exercise and sports training, positively impacts our health. These opposing effects are intriguing because psychosocial stress and physical activity were inextricably linked throughout human evolution. Large populations of humans have only recently begun transitioning into more sedentary lifestyles, uncoupling psychosocial stress from physical activity. Improving our understanding of these two factors and their interactions will, in turn, improve our understanding of the mechanisms through which psychosocial stress impacts health in both modern and ancestral human populations.

My dissertation examines whether physical activity moderates the association between psychosocial stress and capillary blood telomere length in NCAA student-athletes and their non-athlete counterparts in the general student population. My first paper develops an in-depth comparison of psychosocial stress in these two groups using a suite of psychosocial stress surveys and an adapted cognitive interview protocol. Student-athletes ($N=65$) reported lower levels of current perceived stress and anxiety symptoms ($p<0.05$) but similar levels of childhood psychosocial stress, recent exposure to external stressors, and depressive symptoms compared to non-athletes ($N=57$). My second paper utilized self-report and objective measures of physical activity (i.e., accelerometry) to compare physical activity patterns in these groups. Student-athletes ($N=60$) both self-reported higher levels of physical activity and recorded higher levels of activity via accelerometry ($p>0.001$) compared to non-athletes ($N=50$). Interestingly, categorical measures of activity levels (i.e., time spent in moderate-to-vigorous physical activity) identified Rowers as the most active among student-athletes, but continuous measures of activity levels (e.g., total physical activity level) identified Track and Field athletes as the most active ($p>0.05$ for both comparisons).

My third and final paper tested whether higher physical activity weakened the association between childhood psychosocial stress and telomere length estimated from capillary blood collected on Hemaspot HF devices ($N=111$). Telomeres are DNA sequences that protect the ends of chromosomes. They shorten with cell replication, age, and oxidative stress, leading to functional decline with age and worsened health outcomes. Importantly, psychosocial stress is thought to accelerate TL shortening. My *a priori* analyses did not support a direct association between psychosocial stress, physical activity, or the interaction of these variables and telomere length. However, a *post hoc* analysis found that individuals who recorded higher total physical activity demonstrated a positive association between childhood psychosocial stress and telomere length (i.e., higher childhood stress predicted longer telomeres) while individuals who recorded lower total physical activity had a negative association (i.e., higher childhood psychosocial stress predicted shorter telomeres).

My results do not offer explicit support for the hypothesis that physical activity moderates the effects of psychosocial stress on telomere length. However, my project adds to the literature in at least several ways. It produced a novel and much-needed comparison of psychosocial stress between NCAA student-athletes and non-athletes. It illustrated and validated several data collection techniques for psychosocial stress and physical activity. Further, my telomere findings offer an exciting direction for the future exploration of psychosocial stress-physical activity interactions. Lastly, this work improves our overall understanding of NCAA student-athletes' mental and physical health and how their unique circumstances intersect with the ongoing effects of the COVID-19 pandemic.

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Paper 1 Outline:

Introduction

Intercollegiate athletics are a prominent feature of US society and culture. Nationwide, millions of fans flood stadiums and fields annually. American football and basketball's March Madness are perhaps the most notable televised events. Even sports less followed in the US, such as rowing, often bring spectators numbering in the hundreds of thousands and more viewers online for their events (HOCR). The National Collegiate Athletic Association (NCAA) reported over $1 billion in direct revenue in 2021 (Christovich, 2022; NCAA, 2022), and various local businesses – restaurants, clothing stores, etc. – set their fiscal plans around the billions of dollars exchanged during NCAA sporting events. The most highly paid state employees in 40 US states are head football coaches (USA Today). The University of Washington alone typically spends more than $130 million yearly on its athletics programs. US college sports also affect many aspects of our personal lives. Children are introduced to their families' college sports fandoms at birth, and these fandoms and related behaviors form a powerful and central part of many Americans' identity, regardless of the team's success.

Although collegiate athletics have such a strong impact on US society, the well-being and psychosocial experiences of collegiate student-athletes – the individuals at the center of these competitions – have only recently entered the agendas of major college sports organizations. Throughout their university career, student-athletes must persevere through the dual pressures of athletics and academics. They often devote more than 40 hours per week to their sport throughout much of the year (NCAA, 2015), fulfilling this commitment alongside a full course schedule where they need to maintain minimum GPAs to safeguard their scholarships and remain eligible to compete. Further, many student-athletes hold ambitions to do more in academia than simply remain eligible. Their college education is a step to becoming successful professionals and academics. In practice, many student-athletes' schedules result in greater than 80 total hours per week devoted to academic and athletic duties combined (NCAA, 2015). The limited research on student-athlete well-being suggests that these pressures exact a substantial toll on student-athletes. Approximately 33.2% report clinically significant symptoms of depression (Drew & Matthews, 2019; Wolanin et al., 2015), and about 30% report moderate to severe anxiety symptoms (Drew & Matthews, 2019). Related research suggests that student-athletes also experience behavioral health concerns such as substance misuse, eating disorders, and relationship problems at high rates (Moreland et al., 2018; Sudano & Miles, 2017). Notably, mental health symptomology and psychosocial stress appear to be higher for those participating at Division-1 institutions, women athletes, and athletes of color (Brown et al., 2021).

Given these circumstances, it is perhaps surprising that there is no standard of care or model for offering mental health support or treatment across the NCAA's member institutions. Many athletics departments rely on offsite mental health support or therapy (Drew et al., 2021; Sudano & Miles, 2017). Many student-athletes feel that NCAA member institutions are falling short despite their increased messaging to the contrary (Jayakumar & Comeaux, 2016; *McCants v. NAT. COLLEGIATE ATHLETIC ASSOCIATION*, 2017). There have been repeated calls from sports medicine, social work, and other stakeholders to improve the understanding and treatment of student-athlete health and well-being (e.g., Gill, 2008; Purcell et al., 2019; Reardon & Factor, 2012).

Unfortunately, the relative lack of systemic investment into the psychosocial well-being of student-athletes has also impacted peer-reviewed research on the topic. There is a limited body of research seeking to understand the psychosocial experiences of student-athletes and how their well-being and health compare to their peers in the general student population, and few studies examine or comment on the validity of their assessments (Reardon et al., 2019; Tahtinen et al., 2021; reviewed in more detail below). Current data on college students suggest that rates of depression and anxiety have increased consistently over the past decade (Duffy et al., 2019; Center for Collegiate Mental Health, 2017) with 15.6% of undergraduate students reporting moderate to severe levels of depression and anxiety (Auerbach et al., 2018; Eisenberg et al., 2007). Thus, the college student demographic is at increased risk for mental health crises more broadly – not only student-athletes. It is unclear exactly how engagement in US collegiate sports uniquely impacts student-athletes compared to non-athlete students. It is further unclear how they compare to non-athletes regarding life experiences preceding their tenure as athletes (e.g., childhood psychosocial stress). Better understanding how psychosocial stress is experienced and reported by student-athletes in the broader context of their university peers should enable more effective support for them as athletes and improve their academic and personal growth and health outcomes (Reardon & Factor, 2012).

It should be noted that no peer-reviewed studies have focused on how psychosocial experiences in student-athletes interact with inflammation and cellular aging. There is virtually no overlap between the psychometric assessments used in studies demonstrating psychosocial stress-biology associations in non-athlete populations and the psychosocial and mental health studies performed with NCAA student-athletes. Therefore, it is not only unclear how psychosocial stress is patterned in student-athletes compared to non-athletes, but how they may be at differential risk for the adverse effects of psychosocial stress on their biology and health.

This paper evaluates how psychosocial stress exposure in student-athletes compares to the non-athlete student population. Over the past two years, I utilized a mixed-methods approach, combining validated psychometric assessments previously associated with inflammation and cellular aging and an adapted cognitive interview protocol, to gather psychosocial stress data from student-athletes and non-athletes from the same universities. Here, I describe where these groups differ and are similar in order to guide my downstream analyses examining psychosocial stress-biology associations in student-athletes (e.g.,Paper 3) and better understand the unique risk factors they face. Additionally, given the widespread and difficult to predict impacts of the COVID-19 pandemic and its continuing effects on society, previous work may not be relevant to student-athletes' experiences over the past two years and this updated perspective would be useful for the field more generally.

Existing Research and Critiques

Three recent meta-analyses and reviews concluded that elite athletes report similar or higher mental health symptoms and psychosocial stress levels compared to non-athlete populations (Gorczynski et al., 2017; Gouttebarge et al., 2019; Tahtinen et al., 2021). However, it is unclear how well these conclusions apply to NCAA student-athletes specifically. "Elite athlete" is an inclusive term that encompasses athletes at the highest or most selective levels of competition for their sport or activity, and NCAA student-athletes represent a limited subset of this group. For example, these reviews included studies on Olympians (Drew et al., 2018) and professional athletes (Gouttebarge et al., 2015). NCAA student-athletes exist in a unique context compared to these other groups – no other groups of elite athletes face the same pressures of school and sport described above while competing in an organization with the economic and social impacts of the NCAA.

Psychometric assessments combine subjective experiences, cognitive and physiological symptoms, and socially constructed categories of unacceptable psychological-emotional traits (Kleinman, 2008). Surveys that investigate one of these factors – or even just one part of one factor – are not interchangeable and are rarely comparable without extended validation, even when they measure the same psychosocial construct. Different assessments for depressive symptoms will lead to different prevalence and symptom severity estimates (Tennyson et al., 2016). The studies included in these reviews (Gorczynski et al., 2017; Gouttebarge et al., 2019; Tahtinen et al., 2021) utilized over 30 psychometric assessments, and, unfortunately, the authors treated these assessments as more or less interchangeable in their conclusions.

Further, only five of their sources investigated US collegiate student-athletes specifically. Of these five, two (Wolanin et al., 2016; Yang et al., 2007) did not include a comparison group but stated that the rates of clinically significant depressive symptoms in their student-athlete samples (21% and 23.7%, respectively) were similar to previous studies of depressive symptoms in the general US college student population. Yang et al. (2007) compared their rates to a study that assessed depressive symptoms among students in a single undergraduate psychology course

(Kelly et al., 1999). Wolanin et al. (2016) compared the prevalence of “clinically relevant” depressive symptoms as measured by the Center for Epidemiological Study Depression Survey (CESD) to Ibrahim et al. (2013), which combined rates across multiple assessments of depressive symptomology.

The other three analyses of US collegiate student-athletes directly compared psychosocial stress in US collegiate student-athletes to US college students in the same study. However, the results were inconsistent: one demonstrated similar levels of depressive symptoms between student-athletes and non-athletes (Storch et al., 2005), one found lower symptoms in men’s baseball players compared to non-athletes (Proctor & Boan-Lenzo, 2010), and one found higher rates in men student-athletes compared to men non-athletes (Thirer et al., 1987). Notably, each of these studies used a different psychometric assessment, including: the Personality Assessment Index, CESD, Self-Rating Depression Scale, and Patient Health Questionnaire-9 (PHQ-9). Thus, it is unclear whether the similarities (or differences) in rates between student-athletes and non-athletes in these surveys are due to the rates of the underlying psychosocial constructs themselves or confounding from using different assessments. A clear consensus on how student-athlete psychosocial stress exposure compares with the general US student population is difficult, if even possible, from this literature.

In addition to these comparison concerns, only a fraction of the studies included in these reviews (~20%) reported relevant diagnostic criteria (e.g., Cronbach’s alpha for internal reliability) for their assessments, and none of these were studies that focused on US collegiate athletes. While the most popular psychometric tools are well-validated in US contexts (e.g., CESD, PHQ-9), researchers must still examine diagnostics like Cronbach’s alpha when they conduct these surveys to judge whether the assessments are performing as expected (Streiner, 2010). If the reliability or structural validity of a measure is not at acceptable levels, it should impact the study's inferences (Ali et al., 2016; Tavakol & Dennick, 2011). Such validation checks are particularly crucial when focusing on student-athletes and mental health because many psychiatric assessments (including the tools used in many of the studies above) highlight physical symptoms, such as fatigue and soreness, and may provide inaccurate scores when assessing athletes who are, in fact, simply sore from physical training (Reardon et al., 2019). It is unclear whether the authors of these studies conducted any such checks for issues that would bias symptom scores and thus the prevalence of psychosocial stress and mental health symptoms.

These concerns (the lack of direct comparisons and validity checks in published articles) limit our understanding of how NCAA student-athlete psychosocial stress compares with non-athletes. This lack of understanding, in turn, limits our ability to build predictions of how student-athlete psychosocial stress impacts their biology and health for several reasons. First, most of the assessments used in the studies focusing on US collegiate student-athletes have shown limited or no associations with biomarkers of inflammation and aging. For example, the studies in Gouttebarge et al. (2019) utilized the Depression, Anxiety, and Stress Scale (DASS-21), the PHQ-9, the General Health Questionnaire (GHQ-12), and the Beck Depression Inventory-II (BDI-II). None of these tools demonstrated significant associations in Ridout and colleagues' (2016) systematic review and meta-analysis of the association between depressive symptoms and telomere length. Second, the types of psychosocial stress may differ between student-athletes and non-athletes in subtle ways. This discrepancy is notable because different types of psychosocial stress may lead to different physiological responses that, in turn, have different long-term impacts on biology. Differences (or the lack thereof) in biomarkers between groups may be due to differences in *types* of psychosocial stress but not overall psychosocial stress (e.g., physical vs. emotional abuse). Third, the impacts of each type of stress will be critical in exploring trends and interventions in population health. The selection of assessments and interpretation of results of psychosocial stress studies require a careful eye for context and, ideally, a qualitative understanding of the shape of distress in the population in question. Such careful separation and interrogation of these ideas is currently absent from the literature.

Athlete-specific measures

Importantly, a growing proportion of the research on student-athlete well-being is focused on developing and utilizing psychometric assessments that are validated, reliable, and specific to athletes. This literature is a valuable contribution to understanding and practically managing student-athlete mental health. Accurately measuring psychosocial stress exposure and mental health symptomology is essential to advocating for, developing, and implementing appropriate and adequate interventions for student-athletes (Reardon et al., 2019). Some studies suggest that athletes have different risk factors for depression than non-athletes (Wolanin et al., 2015; Reardon et al., 2019), and there are concerns that widely used assessments like the PHQ-9 ignore important subclinical symptoms in student-athletes (Gouttebarge et al., 2021). These are essential considerations for practice-based applications, and several athlete-specific questionnaires and protocols have been developed as a result (Gouttebarge et al., 2021). The Baron Depression Screener for Athletes (BDSA) is an example of a brief, valid, and reliable psychometric assessment that focuses specifically on depressive symptoms in athletes (Reardon et al., 2019).

While these scales are incredibly valuable for investigating psychosocial stress and distress within athletes, the surveys and individual survey items are not applicable or relevant for non-athletes. For example, they often ask about the subject's emotions after successful practices and competitions. Therefore, these specific scales cannot be used to compare the prevalence or severity of clinically relevant psychiatric symptoms between student-athletes and non-athletes. However, assuming they provide a reliable measure of depressive symptoms in athletes, they may be used to validate an assessment tool for student-athletes that is used more broadly across other populations. For example, if scores on the BDSA are significantly correlated with scores on the depression subscale of the Hospital Anxiety and Depression Survey (HADS-D), then HADS-D may be capturing relevant depressive symptoms in these student-athletes. This external validation would be helpful for future analyses (e.g., Paper 3) since the HADS-D has been associated with biomarkers of inflammation and biological aging (McFarland et al., 2019; Ridout et al., 2016)

Current Study

The current study utilizes several psychometric assessments to compare psychosocial stress exposure in a sample of NCAA student-athletes to their counterparts in the general college student population (non-athletes). Some of these surveys have not been used in previous studies of collegiate student-athletes, but they have each been validated across multiple populations and languages. Importantly, they have each demonstrated significant associations with immune function and telomere length in the US. To ensure that these surveys performed as expected, I examine the internal reliability and factor structure of each survey and utilize an adapted cognitive interview protocol before conducting group comparisons. Further, I compare how student-athletes' scores on an athlete-specific measure of depression (BDSA) correspond to their depression sub-score on the HADS. This comparison is vital to determine whether the HADS, the more generalized measure previously associated with TL, provides an adequate assessment of depressive symptoms for the student-athletes in my study.

This approach allows me to accurately assess if student-athletes are uniquely stressed compared to the general college student population. As mentioned above, different types of psychosocial stress may lead to different physiological and psychological responses that, in turn, have different long-term impacts on biology and health (McLaughlin et al., 2014). For example, neglect experienced in childhood may lead to different biological outcomes than abuse. Differences (or the lack thereof) in downstream analyses may be due to differences in *types* of psychosocial stress but not overall psychosocial stress (e.g., physical vs. emotional abuse). Further, these differences may have changed throughout the past two years of the COVID-19 pandemic. Thus, the comparative and descriptive work of this paper will improve my confidence in downstream analyses (i.e., testing associations with biomarkers) and help me interpret potential differences and similarities in these biomarkers. More broadly, this analysis aims to further our understanding of mental health and well-being in student-athletes. Understanding the overlap and differences between specifically adapted measurements of mental health in student-athletes (e.g., BDSA) and more broadly comparable measures (e.g., HADS) will help us translate findings from non-athletes to athletes and vice versa. Improving mental health support for student-athletes is critical in supporting their athletic, academic, and personal growth.

Methods

COVID-19

University of Washington's (UW) Human Subjects approved my project in February 2020 (IRB ID: STUDY00009691); it was initially designed to take place in person, focusing on student-athletes and non-athletes at UW. During the subsequent COVID-19 pandemic, however, I had to redesign the data collection protocols to work within the shifting local and global guidelines for social distancing and research practices. As a result, my team and I collected much of the data remotely through online surveys, online video calls, and participant self-collection as described in "Study Protocol."

Participants

My project recruited intercollegiate student-athletes (Division-I and Division-III) from multiple schools throughout the US and students who were not competing on an NCAA team from these same schools. About half of the study participants are members of an NCAA intercollegiate team (N=65) and half are students who do not compete on an NCAA intercollegiate team (N=57).

Student-Athletes

My team recruited NCAA Division-I and Division-III student-athletes through three main strategies. First, we sent recruitment emails to the teams through a coach or team leader with the head coach's approval. Second, we provided recruitment materials to athletic trainers, who distributed them to their teams. Third, we sent recruitment materials to UW's Student-Athlete Academic Services, who distributed the materials among their student-athletes. My final sample includes student-athletes in Track and Field, Women's

Rowing, Swimming, and multiple other teams (sample N's are listed in Results). The research team explicitly sought and gained clearance from the respective heads of research and compliance officers for each Athletics Department before recruitment.

General Student Population

Non-athletes were recruited through undergraduate anthropology and biology courses across several undergraduate universities. Research team members approached a course instructor and asked permission to share recruitment materials for the study. Then, depending on the teaching modality of the course, a research team member gave a short introduction to the study and how to join over Zoom or in person. There was no verbal or "live" introduction to the study on some occasions. For these situations, instructors forwarded study information and recruitment materials directly to their course without a recruitment pitch given by a research team member.

Study Protocol

All participants were directed to an online link to complete the prescreening survey and consent form. Following this, we introduced them to the data collection protocol. To increase accessibility and participant comfort levels, and to accommodate shifting social distancing guidelines, I developed two protocols for data collection: a "Remote Data Collection" and a "Hybrid Data Collection" protocol. For either collection protocol, participants completed a prescreening survey, a series of post-study surveys, psychometric assessments, and dried blood spot (DBS) collection. Participants also had the option to wear an accelerometer to collect objective measurements of their physical activity. A small subset of participants was invited to take part in semi-structured interviews. All participants received an online gift card for completing the study and will receive part of their study data once my analysis is complete.

Prescreening

Interested individuals were directed to a confidential online screening questionnaire on REDCap where they consented to the study and provided demographic information (e.g., gender identity, racialized group identity, height, weight, age), basic information about their health (e.g., ongoing health issues), and typical levels of physical activity. They were also asked to provide information about their participation in organized and non-organized sports throughout their childhood and adolescence, their enrollment status, student-athlete status, and whether they participate in intramural activities. The research team then reached out via email, phone call, or text message (according to participant preference) to schedule their participation in the study. I included all participants at this stage if they were enrolled as an undergraduate at an NCAA member institution and were not currently experiencing COVID-19 symptoms or other acute illnesses.

Remote Data Collection

For the remote protocol, all data collection occurred remotely or with minimal (~5 minutes) in-person contact between the research team and a participant. After recruitment and initial consent, the research team either shipped participants a study kit with all the materials to complete data collection at home or scheduled a time for the participant to pick up and return the study kit to a socially-distanced campus collection site. Participants collected finger-prick DBS with a Hemaspot HF device (Spot On Sciences) according to written and video instructions on how and when to collect samples. Participants who chose to participate in the accelerometry portion of the protocol wore an accelerometer (Actigraph wGT3X-BT) for ~7 days before collecting finger-prick DBS. After DBS collection, participants returned their study kit with their sample on ice according to instructions from the research team with a prepaid shipping label. Lastly, the participants completed a series of online surveys on overall health, sports activity, detailed demographics, experiences with COVID-19, and psychosocial stress exposure.

Hybrid Data Collection

The hybrid protocol was developed as COVID-19 restrictions began to ease in Fall 2021 to offer more flexibility for participants and was approved by UW Human Subjects. Many participants chose to delay or withdraw their participation because they preferred a research team member to collect their finger-prick DBS. For this procedure, participants had one or two short appointments (~15 minutes) with the research team, depending on whether they opted to join the accelerometry portion of the study. In the first appointment, the participant was introduced to the study and asked to wear an accelerometer on their non-dominant wrist for approximately seven days. The second appointment was scheduled for at least seven days after the first. During this appointment, I collected the accelerometer and finger-prick blood in Hemaspot HF devices (Spot On Sciences). They were then asked to complete all psychometric surveys within the next 24 hours from their personal computers. If the participant opted out of the accelerometry portion of the study, they completed the finger-prick DBS collection and introduction to the online stress surveys in a single appointment. All appointments took place in the UW Biodemography Laboratory.

Psychometric assessments

Psychosocial stress is an umbrella term that includes perceived stress, stressors, and mental health diagnoses. *Perceived stress* is the individual's subjective experience of strain, negative emotions, and psychological distress (Selye, 1956), while *stressors* are potential stimuli of perceived stress exogenous to the individual (Nesse et al., 2016). *Mental health diagnoses* combine subjective experiences, cognitive and physiological symptoms interfering with daily life, and socially constructed categories of unacceptable psychological-emotional traits (Kleinman, 2008). Each of these three factors is independently associated with immune function (e.g., Ridout et al., 2016; Yang et al., 2018), so I surveyed each one to ensure I have appropriate measures for future analyses and Paper 3. Cohen's (1983) Perceived Stress Scale (PSS) assessed perceived stress over the last month. The Childhood Trauma Questionnaire – Short Form (CTQ-SF; Bernstein & Fink, 1998) evaluated childhood exposure to perceived stress and external stressors. Brugha's List of Threatening Events (Brugha & Cragg, 1990) assessed adulthood exposure to external stressors. The Hospital Anxiety and Depression Survey (HADS; Zigmond & Snaith, 1983) assessed anxiety and depression symptoms. I selected these assessments because they have repeatedly been associated with inflammation and TL (e.g., Mathur et al., 2016; Ridout et al., 2016).

I also included an athlete-specific questionnaire: the BDSA (Baron et al., 2013), which was selected over other athlete-specific measures (e.g., the Sport Mental Health Assessment Tool 1; SMHAT-1) because it measures a specific construct of symptoms (i.e., depressive) with minimal participant burden. Many other measures (including the SMHAT-1) require an extensive multi-step approach to managing and treating psychiatric symptoms.

Adapted Cognitive Interview

Cognitive interviewing is a flexible set of methods for evaluating or adapting an existing assessment to specific contexts (Willis, 2004). The goal of a cognitive interview is to explore how subjects come to their answer to a survey question and what difficulties they faced in reaching that answer. Both are necessary for ensuring the goals of a survey are being met. The most popular cognitive interviewing methods are administered verbally. I wanted a similar evaluation of my online assessments, but the logistics of performing cognitive interviews remotely would have added substantially to participant burden. The following adapted method allowed me to collect this qualitative data from all my participants.

The adapted method contained three parts. First, participants could select “Not applicable” or “Unclear item” for each survey item and were given the opportunity to explain *why* they selected that item. Second, at the end of each survey, there was an item explaining the purpose of the specific questionnaire and asking participants if they felt the survey served that purpose. For example, after the CTQ, this item read: “The goal of this survey is to assess how much stress you experienced while growing up. Do you feel that this survey accomplishes that goal? Why or why not?” This question is meant to investigate whether the survey is measuring the psychosocial construct as the construct is understood by the participant. This is adapted from longer strategies that utilize in-depth ethnographic data and qualitative interviews (Tennyson et al., 2016). Lastly, the survey asked participants if there were topics, questions, or statements that they would add to or remove from the specific survey. Including these items was meant to probe the participants' thinking and reasoning behind difficult and perhaps irrelevant survey items. This data helps highlight surveys or items that may be problematic for my sample and offers participants support for the survey when a researcher cannot be present.

Data Cleaning and Cognitive Interview Responses

Data underwent several cleaning steps to incorporate the cognitive interview answers before conducting basic tests of validity, descriptive analyses, and tests of difference between groups. First, I calculated the raw scores for each questionnaire and investigated all instances where "Unclear Item," "Not Applicable," or "Prefer not to answer" were selected as answers. When the participant provided a clear answer in the free-response section at the end of the survey, I assigned a value to "Unclear Item" as appropriate. If it was unclear how the participant wanted to respond, I removed that question from the survey for that participant. Further, I removed participants from analyses where they have not completed the relevant aspects of a survey. For example, an individual did not give a clear answer to an item in the "emotional abuse" subscale of the CTQ but fully answered the "physical abuse" subscale. I included them in comparisons of the "physical abuse" subscale but not in comparisons of the total CTQ score or the "emotional abuse" subscale. Many of the validity diagnostics and analyses described below can be performed with partial completion of a survey. For example, I can still investigate the internal reliability of the physical abuse sub-score on the CTQ if the emotional abuse sub-score is missing an item. Each instance where a clear answer was not given was recorded and analyzed in my data analysis.

Validity Diagnostics

After examining the cognitive interview responses and making coding calls on surveys as appropriate, I conducted several tests of validity for my questionnaires to ensure they performed as expected. These steps were particularly critical to include due to my use of cognitive interviews. I computed the Cronbach's alpha for the total scores of the PSS-10, Brugha's List of Threatening Events, and the BDSA and each sub-scale of the CTQ and HADS. Cronbach's alpha is a standard measure of a survey's internal consistency and reliability when the survey is measuring a single construct. A value of 0.6-0.7 is generally considered acceptable, while 0.7-0.9 is preferred. A score higher than 0.9 is often a sign of redundancy in items, and it is important to take care with inferences if such a high alpha is found (Streiner, 2010).

Additionally, I conducted a confirmatory factor analysis on the surveys with multiple dimensions: the CTQ and the HADS, to examine whether the survey items loaded on the expected factors for my sample (e.g., participants' scores on the depression items of the HADS are loading together while the anxiety items are loading together) (Bernstein et al., 2003; Hernandez et al., 2013; Zigmond & Snaith, 1983). If their hypothesized factor structure was not supported, I conducted an exploratory factor analysis to examine if an alternative factor structure may be more appropriate for my sample (Spies et al., 2019). This general approach is typically used when adapting a questionnaire in a new language or sub-population with distinct mental health risks (Saez-Flores et al., 2018; Tennyson et al., 2016).

Descriptive Statistics

After I investigated the qualitative responses to my surveys and conduct basic validation of my assessments, I summarized the descriptive statistics for my sample. First, I calculated descriptive statistics for each total score and sub-score for each psychometric assessment for the sample as a whole. Second, I calculated the basic descriptive statistics for the two subgroups based on student-athlete status. Third, I investigated correlations between the psychometric assessments with my entire sample and with student-athletes and non-athletes separately. Fourth, I calculated the descriptive statistics for student-athletes separated by sport. Lastly, I conducted a *post hoc* descriptive analysis of psychosocial stress separated by when participants completed the psychometric surveys to examine whether timing in the pandemic may have influenced their responses.

Group Comparisons

I examined whether student-athletes and non-athletes demonstrated similar total scores and sub-scores on each survey. Based on the equivocality of previous comparisons of student-athletes and non-athletes, I did not have an *a priori* prediction regarding the direction of this difference. I used ordinary least-squares (OLS) regressions to test if there were differences in the scores for each group. First, I tested if student-athlete status is associated with psychometric scores. Then, I conducted four linear regressions with survey scores as the dependent variable, student-athlete status as the predictor variable, and several demographic variables as covariates: gender identity, racialized group identity, and age. I focused on these demographic variables because they have each been associated with different rates of specific mental health symptoms and different levels of psychosocial stress in athletes and undergraduate students (Brown et al., 2021).

Post hoc analyses on study completion date and psychosocial stress score

Data collection took place over the course of two years during the COVID-19 pandemic. During this time, many aspects of students' lives changed: courses took place remotely from March 2020 until September 2021, travel was restricted, and many other aspects of our lives were impacted. To investigate the impacts of these differences in societal and local circumstances, I conducted a *post hoc* investigation into whether psychosocial stress scores differed based on when participants completed the study. Specifically, I conducted a series of OLS regressions with survey score as the dependent variable and time as the independent variable to investigate if there are direct associations between when a participant completed the study and their psychosocial stress scores. I also conducted an additional regression model testing for differences in psychosocial stress between groups that adjusted for study completion date.

Statistical Software

I performed all statistical analyses in Stata version 17.0.

Results

Demographic Statistics

Descriptive statistics of key demographic variables are displayed in Table 1. In total, 122 participants completed the post surveys, 65 of whom were NCAA student-athletes and 57 were non-athletes. The two groups reported similar proportions in sex assigned at birth (student-athletes: 72% female; non-athletes: 79% female; two-tailed Fisher's Exact p=0.410) and gender identity (student-athletes: 71% women; non-athletes: 76% women; two-tailed Fisher's Exact p=0.435). However, the student-athlete group consists of a higher percentage of participants identifying as white (student-athletes: 82%; non-athletes 60%; two-tailed Fisher's Exact p=0.009). Non-athletes reported more ongoing chronic health problems compared to student-athletes, but not significantly so (student-athletes: 11%; non-athletes 26%; one-tailed Fisher's Exact p=0.057). These health problems mainly consisted of mental health-related conditions (e.g., depression), but also included asthma and previous injuries (see Appendix 1: Chronic Health Issue Descriptions for a full list of responses). The student-athletes participate mostly in three sports: Track and Field (N=24), Swimming (N=26), and Rowing (N=10). The student-athletes in "Other" sports were from tennis, softball, volleyball, gymnastics, and soccer (N=5). Most of the Track and Field athletes were mid- to long-distance runners (N=21) while 2 were throwers (e.g., discus, javelin) and 1 was a pole-vaulter.

Table 1. Descriptive statistics of key demographic variables for participants completing the Post Survey portion of the study.

	Whole Sample		Non-Athletes		Student-Athletes	
Variable	**N**		**N**		**N**	
Sample size	122		57		65	
General Characteristics	**Mean (SD)**		**Mean (SD)**		**Mean (SD)**	
Age (years)	21.3 (3.1)		21.7 (4.1)		21 (1.9)	
Height (cm - converted from inches)	170.6 (9.4)		167.4 (9)		173.4 (8.9)	
Weight (kg - converted from pounds)	65.9 (12.3)		64.2 (13)		67.4 (11.6)	
BMI	22.6 (3.3)		22.8 (3.7)		22.3 (2.8)	
Sex assigned at birth	**Count**	**%**	**Count**	**%**	**Count**	**%**
Female	92	75%	45	79%	47	72%
Male	30	25%	12	21%	18	28%
Intersex	.		.		.	
How would you describe yourself?	**Count**	**%**	**Count**	**%**	**Count**	**%**
Woman	86	74%	42	76%	44	71%
Man	27	23%	10	18%	17	27%
Transgender - trans femme	.		.		.	
Transgender - trans masc	.		.		.	
Genderqueer/non-conforming	3	3%	2	4%	1	2%
Prefer not to say	.		.		.	
Other	1	1%	1	2%	.	
How do you typically identify your race?	**Count**	**%**	**Count**	**%**	**Count**	**%**
American Indian/Alaska Native	.		.		.	
Hispanic or Latinx	2	2%	2	4%	.	
East Asian	4	3%	1	2%	3	5%
Southeast Asian	4	3%	2	4%	2	3%
South Asian	3	3%	3	5%	.	
Native Hawaiian or Other Pacific Islander	.		.		.	
Middle Eastern or North African	1	1%	1	2%	.	
Black or African American	1	1%		0%	1	2%
White	84	72%	33	60%	51	82%
Unknown	.		.		.	
Other	.		.		.	
Multiple	18	15%	13	24%	5	8%
Health	**Count**	**%**	**Count**	**%**	**Count**	**%**
Ongoing chronic health problem?	22	18%	15	26%	7	11%
Intramural Sports	**Count**	**%**	**Count**	**%**	**Count**	**%**
Do you participate in a recreational or intramural sports team or activity?	16	13%	9	16%	7	11%
Intercollegiate Sports	**Count**	**%**	**Count**	**%**	**Count**	**%**
Track and Field	NA		NA		24	37%
Swimming	NA		NA		26	40%
Rowing	NA		NA		10	15%
Other	NA		NA		5	8%

Cells labeled "." indicate that no participants selected that response (e.g., no participants reported "Other" for their self-identified race).

Missing Data: Student-athletes are missing 3 responses for self-identified race and gender; Non-athletes are missing 2 responses for self-identified race and gender.

Adapted Cognitive Interview

Overall, of the items left unanswered, many more were marked as “Prefer not to answer” (21 items) compared to “Unclear Item” (11 items). Out of these, none of the “Prefer not to answer” selections were explained. One Unclear Item code was followed by a clear description of the participant’s thoughts, and I was able to select an appropriate code (see Box 1 for the item and resulting coding decision). Since none of the questionnaire items were consistently answered in this way and most participants responded that the questionnaires were satisfactory (specific numbers for each survey below), none of the surveys or questionnaire items were altered based on the adapted cognitive interview. Instead, the scales and subscales with missing items were not totaled. That is, when a participant noted “Prefer Not to Answer” for one item of a survey, I did not calculate the total for that survey and did not include that survey in summary statistics or group comparisons. These responses did not differ between student-athletes and non-athletes. At most, 5 student-athletes had missing survey totals due to missing items while 4 non-athletes had missing survey totals.

Box 1. Details for the researcher coding decision of an “Unclear Item” selection with the participant’s explanation for their response.

Study ID	**1057**
Survey	Childhood Trauma Questionnaire - Short Form
Item	Question 4: “My parents were too drunk or high to take care of the family.”
Response	"Unclear Item"
Explanation	“4. My father was an alcoholic, and there were times when he was not able to take care of me/my siblings, but my mom was stable (in this sense), she just wasn't necessarily always around because she had to work.”
Item Response Options:	Never True, Rarely True, Sometimes True, Often True, Very Often True
Coding Call:	Sometimes True

Most participants reported that the surveys accomplished their intended goal (details for each survey below). However, there were some specific points that were repeatedly mentioned regarding new items or domains that could be added to each survey.

Childhood Trauma Questionnaire-Short Form

For the CTQ-SF, 10 items were marked as "Prefer not to answer", and 9 items were marked as "Unclear Item." 112 participants responded to the question asking whether the survey accomplished its goal of assessing stress experienced in childhood. Of these 112 responses, 8 reported that it did not. Two of these participants mentioned difficulties selecting answers because they grew up outside of the US. For example, one participant noted: "Not really, maybe cultural difference that made that really hard... From where I grow up people are use to being in high stress environment…" The other six negative responses mentioned that they experienced stress from parental divorce, academic and athletic pressures, and other school/social stress. These stresses were not mentioned in the survey but represented their major sources of stress growing up. In response to items to add or remove, many participants suggested that there should be items regarding pressure to succeed academically or athletically. A few participants also noted that the abuse items could be clarified. For example, one participant asked in regard to the sexual abuse items: "Sexual abuse meaning outside the family, or within the family, or either/or?" In future research, this point may need to be clarified for this population.

Hospital Anxiety and Depression Scale

For the HADS, no participants marked “Unclear Item”, but one participant responded to 5 of the 12 questions as “Prefer not to answer”. One participant provided regular responses but noted that they were confused about a few items. 72 participants answered the question about whether this survey accomplished its intended goal and only two responded that it failed. One participant responded negatively because they felt that mood and experiences are subjective. The other reported that they had mood changes recently that the questionnaire failed to assess. Specifically, the second respondent said: “No, my recent mood has been effected due to grandfathers funeral that happened this week. However these questions did not capture the mood change I had.”

In response to adding or removing items, a few participants suggested there should be more nuance in the answers (e.g., “I think that sometimes there is too big of a jump between answer options. For example, 'As much as I always could' and 'Not quite so much' seem pretty far from each other…”), there should be questions about recent changes in mood and social behavior (e.g., “Maybe ask about time spent recreationally or with friends compared to the usual amounts? Or if you're able to enjoy time with friends? Other than that I wouldn't change anything.”), and there should be a consistent scale for answers (e.g., “The ordering of the answers changed with each question, making it slightly confusing (positive to negative vs negative to positive)”). In sum, participants reported understanding what the HADS was asking, but felt that minor aspects of it could be improved.

Cohen's Perceived Stress Scale

Cohen's Perceived Stress Scale only had one item marked as "Prefer not to answer" and none as "Unclear Item." One participant reported that the survey did not accomplish its goal and responded: "I don't feel like it did, the questions are vague". 78 other participants responded that they felt the survey did accomplish its goal.

Very few participants reported issues or offered potential ways to improve the survey. Notably, a few participants reported feeling limited by the timing of the survey. For example, one participant responded: "…Currently, it's summer break for me and I don't have any classes, but I was definitely more stressed during the school year." While a strength of the survey is its reliability in assessing recent perceived stress (i.e., it asks about the past month), several participants reported that they wish they could provide context for their answers to this survey (i.e., that they are more stressed than usual or that they are less stressed than usual). Most of the specific issues raised were only reported once and appear to be more specific to the participant raising the issue, as opposed to the sample as a whole. For example, one participant mentioned: "I would add questions about specific instances of stress (ie an anxiety attack), rather than just 'in general' questions". Another participant mentioned: "Maybe add questions about the roots of stress like work, personal life, etc..." The sources or causes of stress are indeed important considerations, but they are also outside of the scope of Cohen's PSS which is specifically meant to assess perceived stress regardless of source.

Brugha’s List of Threatening Events

Brugha’s List of Threatening Events had two “Unclear Item” responses with explanations and four “Prefer not to answer” responses. One participant marked item 9 (“You were fired from your job.”) as unclear. They explained “In question 9, none of the answers applied to me. As a student I was forced to leave my campus job due to COVID, but I was not fired. I could not make income during that time, but my employer stated that students could come back once pandemic restrictions had changed”. While this specific issue was not raised by any other student, it highlights an important consideration to this item and this scale more broadly – how do some of the meanings/interpretations of this scale change with COVID? The second “Unclear Item” was Item 6: “You broke off a steady relationship.” This participant suggests improving this question that could determine how it impacts your overall psychosocial stress: “The wording is strange for question 6, because it implies only one kind of relationship stress (where the responder initiated a breakup). Breakup stress is valid and is a different type of stress if an individual is broken up with. Perhaps this question should say 'did you experience a breakup?' or add another question that asks 'Was a steady relationship broken off?'” Another participant offered a typical response to this item but added “I broke off a serious relationship because of how toxic it was.” and suggested that this brief list of questions could be improved with the ability to provide more context about the relationship to better understand its impacts.

92 participants responded to the question about whether this survey accomplished its goal and 2 answered that it did not. They suggested some important stressors should be added,

such as “being kicked out” of their housing situation and “Relative attempting suicide but not succeeding”. Future work could consider adding such questions that may be more specific to their target population.

Baron Depression Screener for Athletes

The BDSA had one “Prefer not to answer” response and two “N/A” responses. Out of the 63 participants who took the survey, only one participant said the survey did not reach its goals (i.e., “No because it is too broad and doesn’t give chance to vary.”) while the majority were positive that it did (e.g., “Yes, I think the questions asked were good!”). No participants gave specific reasoning on whether any items were unclear.

Despite the survey being designed for athletes, there were still aspects regarding training and physical exhaustion that participants believed could be improved upon. For example, one participant noted: “For appetite / tiredness, at least in [retracted sport] sometimes we practice so much it's hard to ever feel truly refreshed and it can be hard to get enough food. That's pretty normal and I wanted to clarify that.” Another responded: “Maybe add the other extreme...working out so much that your body is exhausted, but not taking rest. I tend to overwork and it makes practicing my sport very tiring”. Thus, while participants largely responded that the survey reached its goal, it could better consider the levels of exhaustion these athletes accept as part of their training.

In summary, the adapted cognitive interview demonstrated that participants largely agreed that the surveys accomplished their intended goals with only a few suggesting crucial changes to the surveys. Further, many of the changes offered by participants may be better suited for other surveys or brought up topics that were covered by another survey in the study (e.g., the PSS assesses subjective stress while Brugha's List assesses external stressors).

Cronbach's α

Most assessments demonstrated acceptable scores on measures of internal reliability (see Table 2 below for full results). Notably, the Cronbach's α for the Physical Neglect subscale of the CTQ-SF was at or below 0.60, which is typically considered the lowest value for an "acceptable" reliability (Streiner, 2010) (Total sample α = 0.542; Student-athletes α =0.47; and Non-athletes α =0.60). This indicates that the specific items within this subscale may not all be assessing the same underlying factor as intended for my sample. Investigating the item-level α's indicated poor reliability for all of the items for student-athletes (range: 0.32-0.55) compared to non-athletes (range: 0.42-0.68). Therefore, it does not appear that any specific item was driving this finding. This subscale may not be appropriate for assessing physical neglect as an isolated factor in these two groups or physical neglect as a construct may manifest differently for these groups.

Another notable finding is that the α for the Sexual Abuse subscale of the CTQ-SF was over 0.9, potentially indicating redundancy in the subscale (Total sample α = 0.97; Student-athletes α=0.95; and Non-athletes α =0.99). Investigating the item-level α's and tabulating responses across the subscale, it appears that my participants were split into two major groups regarding the sexual abuse subscale: one reporting no sexual abuse at all (the lowest score on each item) and those reporting high scores on multiple items. Specifically, this high α may be driven by two participants who reported the highest possible score on each item of the CTQ-SF's sexual abuse subscale. Importantly, one of these participants made a comment on the adapted cognitive interview portion that complements their responses. Thus, while the α is unusually high for this subscale, it may be due to participants in this sample grouping into two extremes: those with very high levels of sexual abuse while growing up and those with very little to no sexual abuse while growing up.

Table 2. Summary of the Cronbach's α for each psychometric assessment. Values of 0.6-0.7 are generally considered acceptable while 0.7-0.9 is preferred. Values higher than 0.9 may be indicative of redundancy in the scale and require further analysis.

	Whole Sample		Non-Athletes		Student-Athletes	
Variable	**α**	**95% CI**	**α**	**95% CI**	**α**	**95% CI**
Childhood Trauma Questionnaire - Short Form						
Emotional Abuse	0.86	(0.82, 0.90)	0.89	(0.84, 0.94)	0.78	(0.70, 0.86)
Physical Abuse	0.75	(0.68, 0.82)	0.80	(0.72, 0.88)	0.62	(0.49, 0.75)
Sexual Abuse	0.97	(0.96, 0.98)	0.99	(0.99, 0.99)	0.95	(0.93, 0.97)
Emotional Neglect	0.87	(0.84, 0.90)	0.87	(0.82, 0.92)	0.88	(0.84, 0.92)
Physical Neglect	0.54	(0.43, 0.65)	0.60	(0.44, 0.76)	0.47	(0.27, 0.67)
Hospital Anxiety and Depression Survey						
Anxiety Subscale	0.84	(0.80, 0.88)	0.82	(0.75, 0.89)	0.85	(0.79, 0.91)
Depression Subscale	0.81	(0.77, 0.85)	0.73	(0.63, 0.83)	0.86	(0.82, 0.90)
Single-Scale Psychometric Assessments						
Cohen's Perceived Stress Scale	0.89	(0.86, 0.92)	0.90	(0.87, 0.93)	0.86	(0.81, 0.91)
Brugha's List of Threatening Events	0.65	(0.57, 0.73)	0.69	(0.58, 0.80)	0.60	(0.46, 0.74)
Baron Depression Scale for Athletes	.		.		0.85	(0.80, 0.90)

Confirmatory Factor Analysis

I conducted a confirmatory factor analysis for both the HADS and the CTQ-SF. The original hypothesized 2-factor structure for the HADS (i.e., Depression and Anxiety; Zigmond & Snaith, 1983) was considered a "good fit" while the 5-factor structure for the CTQ-SF (Bernstein et al., 2003) failed to converge and did not calculate an estimate of goodness of fit (see Appendix 1: Confirmatory Factor Analysis Diagram to see the HADS factor structure tested). Both surveys were tested in Stata version 17.0 using its SEM diagram builder with the maximum likelihood method selected. I attempted to calculate the CTQ-SF factor analysis with Satorra-Bentler robust corrections, which is recommended due to the typical skewness of the specific items in this survey (Saez-Flores et al., 2018). The factors for HADS (i.e., Depression and Anxiety) were allowed to covary as they were originally proposed to be correlated by the original authors of the HADS. The 5-factors for the CTQ-SF were also allowed to covary because previous research indicates that they are often correlated (Bernstein et al., 2003).

The HADS model fit was assessed with two indices: the comparative fit index (CFI) and the root mean square error of approximation (RMSEA) (Saez-Flores et al., 2018). The CFI ranges between 0 and 1 with values >0.90 indicating a good model fit while values of ≤0.05 for the RMSEA indicate a good model fit and values 0.05-0.10 indicate an acceptable fit (Hu & Bentler, 2009; Steiger, 2009). The HADS indicated an acceptable fit with CFI=0.907 and RMSEA=0.079. The CTQ-SF analysis likely failed to converge due to the high number of items and factors (25 and 5, respectively) in comparison with my limited sample size (i.e., N=114 for the CTQ-SF total score). The CFA for such a complicated model typically requires a larger sample size to successfully run and test the model fit.

Exploratory Factor Analysis

Since I was unable to test (and thus unable to accept) the 5-factor structure of the CTQ-SF with a confirmatory factor analysis, I conducted an exploratory factor analysis with the total sample, only student-athletes, and only non-athletes using principal components as the extraction method (Spies et al., 2019). The loadings for these three factor analyses can be found in Table 3.

When examining the whole sample (Table 3A), EFA predicted a 6-factor structure with the original Sexual Abuse items loading together and the other original subscales spread across the other five. Notably, the Emotional Abuse and Emotional Neglect items were largely loading onto a single factor. For the student-athletes (Table 3B), EFA supported a 7-factor structure. The Sexual Abuse items loaded together again, except for one item (i.e., Item 24: “Someone molested me (took advantage of me sexually)”) which loaded with the Emotional Abuse items. The Emotional Neglect items all loaded onto a single factor while the other subscales (Emotional Abuse, Physical Abuse, and Physical Neglect) were each spread across three factors. Lastly, for the non-athletes (Table 3C), EFA supported a 5-factor structure, albeit not identical to the original 5 factors. The Emotional Abuse and Emotional Neglect items largely loaded onto a single factor while the Sexual Abuse items loaded together again. Physical Abuse and Physical Neglect were each spread across two factors.

Overall, the EFA suggests that the Sexual Abuse subscale varies largely independently of the other subscales while the Emotional Abuse and Emotional Neglect subscales are strongly correlated (i.e., when an individual reported Emotional Abuse, they were more likely to report Emotional Neglect). Physical Abuse and Physical Neglect were more varied in my sample, loading across multiple factors in different ways in each EFA. With these patterns in mind, the traditional 5-factor structure of the CTQ-SF may not reliably represent the experiences of these college students, and I should avoid splitting this survey into these subscales for analysis. While the Cronbach's α's for most of these subscales were acceptable or high, I may lose important information by focusing solely on these subscales and not the others. For example, the Physical Neglect subscale has a low Cronbach's α and these items load across many different factors in the EFA. If I do not include these items, then I may lose important opportunities for individuals to indicate relevant examples of childhood psychosocial stress. Future work should re-examine the original structure of this survey and test alternative factor structures when working with college students and NCAA student-athletes. This may help researchers define more appropriate factors that enable them to examine differences on a subscale level.

<u>Table 3.</u> Results of Exploratory Factor Analysis (EFA) of the Childhood Trauma Questionnaire-Short Form with varimax rotation. Rows are grouped by subscale and columns are grouped by factor predicted by the EFA. Bolded and shaded cells represent the strongest factor loading for each item. **3(A)** is the EFA including all participants. **3(B)** is the EFA including only the student-athletes. **3(C)** is the EFA including only the non-athletes.

A. All participants

CTQ Subscale and Item		Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
Emotional Abuse	Item 3	**0.16189**	-0.04636	-0.04491	-0.05562	-0.02844	-0.03728
	Item 8	0.09044	-0.03138	-0.04973	-0.02339	0.0683	**0.14235**
	Item 14	**0.13165**	0.01528	0.01414	-0.03762	-0.02627	0.00315
	Item 18	**0.13393**	0.04413	0.04121	-0.0852	-0.04176	-0.06449
	Item 25	**0.20417**	-0.01519	-0.06192	-0.07881	0.03412	-0.33576
Physical Abuse	Item 9	-0.08141	0.01267	0.0092	**0.56573**	-0.07621	0.09879
	Item 11	-0.04576	-0.03151	**0.32925**	-0.0266	0.06833	-0.06321
	Item 15	0.00735	0.07317	**0.27748**	-0.02427	-0.04419	-0.16273
	Item 17	-0.08282	-0.0312	**0.41537**	-0.01703	-0.07282	-0.04738
	Item 12	-0.09875	-0.03642	0.19839	0.05073	-0.00363	**0.39729**
Sexual Abuse	Item 20	-0.00378	**0.19914**	-0.05768	-0.03089	0.02168	0.02226
	Item 21	0.01262	**0.2069**	-0.02335	-0.01314	-0.07388	-0.02696
	Item 23	-0.0376	**0.20108**	-0.01151	0.0931	-0.00798	0.02377
	Item 24	-0.02323	**0.17564**	-0.00541	0.00999	0.05305	0.02493
	Item 27	-0.01225	**0.20699**	-0.02086	-0.01289	-0.01913	0.00853
Emotional Neglect	Item 5	0.08467	-0.02729	**0.14749**	0.10045	-0.02894	-0.13007
	Item 7	**0.19068**	0.01679	-0.10958	0.03225	-0.03563	-0.14558
	Item 13	**0.16221**	0.00215	-0.04905	0.02792	-0.1243	-0.05475
	Item 19	0.09824	0.00443	-0.04819	0.06656	-0.14257	**0.21933**
	Item 28	**0.16345**	-0.0119	-0.01808	-0.02918	-0.12109	0.02366
Physical Neglect	Item 1	-0.07684	-0.00852	-0.03644	0.02808	**0.53596**	0.07172
	Item 2	-0.05978	0.01806	-0.10196	-0.02703	0.02716	**0.6616**
	Item 4	-0.02613	-0.0008	-0.04386	**0.49901**	0.09853	-0.10195
	Item 6	-0.0947	-0.00831	-0.01192	-0.01128	**0.5685**	-0.02687
	Item 26	0.06708	-0.01025	-0.0299	-0.09366	**0.16726**	0.10457

B. Student-athletes

CTQ Subscale and Item		Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7
Emotional Abuse	Item 3	-0.05212	**0.19085**	-0.0166	-0.09116	0.13387	0.11109	-0.35086
	Item 8	-0.1203	-0.05076	**0.41763**	0.03232	-0.04698	0.00596	0.01741
	Item 14	-0.00855	0.09231	**0.17694**	-0.01102	-0.05391	0.0505	-0.03711
	Item 18	0.01428	0.02996	**0.29439**	-0.07468	-0.06127	0.00047	-0.1431
	Item 25	0.04659	0.10098	-0.17052	0.02843	**0.2361**	0.03464	-0.2197
Physical Abuse	Item 9	-0.01067	-0.10154	0.06215	**0.48187**	-0.01209	-0.01298	0.04168
	Item 11	-0.04289	-0.07335	0.04189	0.04532	0.04888	**0.34629**	0.20503
	Item 15	0.06415	-0.11549	0.17424	0.03769	0.07113	-0.06548	**0.20136**
	Item 17	0.07668	0.01491	0.02853	-0.04606	-0.20355	**0.4705**	-0.181
	Item 12	-0.04977	0.0696	-0.15162	-0.02598	0.12202	**0.33431**	0.06662
Sexual Abuse	Item 20	**0.42161**	0.00299	-0.19948	-0.03951	0.03442	-0.12747	0.01207
	Item 21	**0.21888**	0.02993	-0.07238	-0.03132	-0.06494	-0.00631	-0.07343
	Item 23	**0.20705**	0.00023	-0.08857	0.06001	-0.08203	0.0758	-0.0085
	Item 24	0.10272	-0.10862	**0.26741**	0.03435	-0.0527	0.05649	-0.11063
	Item 27	0	0	0	0	0	0	0
Emotional Neglect	Item 5	-0.00271	**0.14696**	-0.03615	0.13781	0.07433	-0.00723	-0.13582
	Item 7	0.04561	**0.15598**	0.05246	0.01571	-0.10378	-0.05906	-0.03053
	Item 13	0.05758	**0.2379**	-0.09271	-0.03081	-0.1062	-0.04303	0.04335
	Item 19	-0.03474	**0.2261**	-0.11876	0.01072	-0.0392	-0.0206	0.21152
	Item 28	-0.04964	**0.23448**	0.00278	-0.08677	-0.08241	-0.00484	0.14454
Physical Neglect	Item 1	-0.01963	-0.00251	-0.11119	-0.02008	**0.40471**	-0.00059	0.039
	Item 2	-0.00928	0.05694	-0.08902	-0.0326	-0.05408	0.01302	**0.62522**
	Item 4	0.01248	-0.06709	-0.01168	**0.46061**	-0.02063	-0.02934	-0.00169
	Item 6	-0.02769	-0.20526	0.16187	0.06513	**0.35385**	-0.11768	-0.02111
	Item 26	0.01166	0.00768	0.03702	-0.07701	**0.30847**	-0.06913	-0.09004

C. Non-athletes

CTQ Subscale and Item		Factor1	Factor2	Factor3	Factor4	Factor5
Emotional Abuse	Item 3	**0.1785**	-0.01901	-0.06971	-0.09696	-0.02375
	Item 8	0.05956	0.00138	-0.09851	0.08785	**0.21351**
	Item 14	**0.1161**	0.01563	0.03041	-0.00592	-0.02961
	Item 18	**0.07028**	0.04317	0.06332	0.01983	0.02558
	Item 25	**0.27409**	-0.01845	-0.02865	-0.18375	-0.38084
Physical Abuse	Item 9	-0.06731	0.00067	-0.02882	-0.02306	**0.44198**
	Item 11	0.01728	-0.04601	**0.31385**	-0.10071	-0.16923
	Item 15	-0.01373	0.05659	**0.3029**	-0.06491	-0.13996
	Item 17	-0.15751	-0.03723	**0.3396**	0.03288	0.11552
	Item 12	-0.06893	-0.01211	0.10179	0.01387	**0.32042**
Sexual Abuse	Item 20	0.01473	**0.18861**	-0.03555	-0.01541	0.00484
	Item 21	0.03218	**0.38799**	-0.0197	-0.08857	-0.0381
	Item 23	-0.01357	**0.19432**	-0.0225	0.04878	0.01736
	Item 24	-0.02587	**0.19547**	-0.03742	0.0785	0.06065
	Item 27	0	0	0	0	0
Emotional Neglect	Item 5	0.01483	-0.0271	**0.18835**	0.05416	-0.03019
	Item 7	**0.16938**	-0.00897	-0.07499	-0.00632	-0.07597
	Item 13	**0.103**	-0.02133	-0.01364	-0.00813	-0.01324
	Item 19	**0.1128**	0.03539	-0.0315	-0.07071	0.07935
	Item 28	**0.13697**	0.00477	0.03265	-0.0375	-0.08309
Physical Neglect	Item 1	-0.07072	0.00598	-0.02906	**0.45062**	0.04508
	Item 2	0.09835	0.00327	-0.14457	-0.12294	**0.21487**
	Item 4	-0.04418	0.00569	-0.05365	**0.38198**	0.00705
	Item 6	-0.08381	-0.00704	0.00424	**0.41868**	0.00138
	Item 26	0.07882	0.00075	-0.0682	0.03106	**0.13535**

Survey Scores

Descriptive statistics and the comparisons between student-athletes and non-athletes are shown in Table 4. Pairwise correlations between all psychosocial stress assessments are shown in Table 5. Briefly, student-athletes reported significantly lower levels of anxiety-related symptoms via the HADS-Anxiety scale (Figure 1) and significantly lower levels of perceived stress via Cohen's Perceived Stress Scale compared to non-athletes (Figure 2). The regression testing for differences between groups in the Emotional Abuse subscale of the CTQ-SF found a significant difference in the unadjusted model that became nonsignificant (p-value>0.05) after adding covariates (e.g., gender). There were no significant differences between groups in their scores on the other subscales of the CTQ-SF, the HADS Depression Scale, or Brugha's List of Threatening Events. Separating the survey scores across the different sports (Table 6) indicates that there is variation across sports in some of the surveys. To examine potential differences between sports in the HADS Depression scale, BDSA, and the PSS, I performed a series of simple linear regression models for which the survey score was the dependent variable and the participant's sport was the independent variable. These models were designed *post hoc* and were performed without any covariates. I found that Track and Field athletes reported lower scores on the HADS Depression scale compared to Rowers (β=-2.94; p=0.039). Further, they reported lower scores on the BDSA and the PSS compared to Swimmers (β=-2.46; p=0.018 for the BDSA; β=-4.38; p=0.023 for the PSS). There were no other significant differences in assessment scores between sports.

Table 4. Descriptive statistics for the psychometric assessments separated by group and regression models testing differences between groups.

	Whole Sample		Non-Athletes		Student-Athletes		Group Comparisons			
Survey	**N**	**Mean (SD)**	**N**	**Mean (SD)**	**N**	**Mean (SD)**	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Childhood Trauma Questionnaire - Short Form										
Total Score	114	33.7 (10.3)	52	35.2 (12.1)	62	32.4 (8.4)	**-3.25+**	-2.22	-1.76	-2.72
Physical Abuse	121	5.9 (2.2)	56	6.1 (2.8)	65	5.7 (1.3)	-0.52	-0.41	0.002	-0.39
Emotional Abuse	119	8.4 (4.2)	54	9.2 (5)	65	7.7 (3.3)	**-1.65***	-1.05	-0.74	**-1.50+**
Sexual Abuse	120	5.5 (2.7)	54	5.4 (2.7)	66	5.6 (2.7)	0.13	0.14	-0.03	0.24
Physical Neglect	120	6.4 (2)	56	6.5 (2.1)	64	6.3 (1.9)	-0.34	-0.17	-0.38	-0.39
Emotional Neglect	120	7.9 (3.5)	55	8.1 (3.7)	65	7.8 (3.4)	-0.36	-0.09	0.25	-0.21
Hospital Anxiety and Depression Survey										
Anxiety Subscale	118	8.5 (4.4)	54	9.4 (4.4)	64	7.7 (4.3)	**-1.82***	**-1.57+**	**-1.65+**	**-1.82***
Depression Subscale	115	3.6 (3.4)	52	4.1 (2.8)	63	3.3 (3.7)	-0.82	-0.87	-0.7	-0.77
Single-Scale Psychometric Assessments										
Cohen's Perceived Stress Scale	119	17.4 (7.1)	55	19.4 (7.2)	64	15.7 (6.6)	**-3.52****	**-2.63***	**-2.32+**	**-3.35***
Brugha's List of Threatening Events	114	2 (1.9)	53	2.3 (2.1)	61	1.8 (1.7)	-0.58	-0.44	-0.33	-0.44
Baron Depression Scale for Athletes	NA	NA	NA	NA	61	4.5 (3.6)	NA	NA	NA	NA

Group Comparisons: Values are β coefficients unless otherwise noted; + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All group comparisons are performed with OLS regressions. They each adjust for a different covariate (i.e., they are not additive). Model 1 includes no covariates. Model 2 adjusts for self-reported gender. Model 3 adjusts for self-identified race. Model 4 adjusts for age.

Table 5. Correlation matrix displaying the pairwise correlations between psychometric assessments.

	Childhood Trauma Questionnaire - Short Form						Hospital Anxiety and Depression Survey		Single-Scale Psychometric Assessments		
Variable	Total Score	Physical Abuse	Emotional Abuse	Sexual Abuse	Physical Neglect	Emotional Neglect	Anxiety Subscale	Depression Subscale	PSS	Brugha's List	BDSA
Childhood Trauma Questionnaire - Short Form											
Total Score	1	.	.	.	.	.	.	.	.	.	.
Physical Abuse	0.67*	1	.	.	.	.	.	.	.	.	.
Emotional Abuse	0.90*	0.48*	1	.	.	.	.	.	.	.	.
Sexual Abuse	0.41*	0.16	0.12	1	.	.	.	.	.	.	.
Physical Neglect	0.73*	0.32*	0.62*	0.14	1	.	.	.	.	.	.
Emotional Neglect	0.86*	0.42*	0.81*	0.07	0.60*	1	.	.	.	.	.
Hospital Anxiety and Depression Survey											
Anxiety Subscale	0.18	-0.10	0.25*	0.03	0.07	0.14	1		.	.	.
Depression Subscale	0.38*	0.06	0.45*	0.17	0.27*	0.34*	0.58*	1	.	.	.
Single-Scale Psychometric Assessments											
Cohen's Perceived Stress Scale (PSS)	0.25*	0.03	0.38*	-0.05	0.13	0.29*	0.73*	0.65*	1		
Brugha's List of Threatening Events	0.38*	0.26*	0.35*	0.09	0.34*	0.24*	0.18	0.31*	0.32*	1	
Baron Depression Scale for Athletes (BDSA)	0.49*	0.002	0.52*	0.26*	0.27*	0.36*	0.64*	0.69*	0.59*	0.39*	1

Values are Pearson's R values; * $p < 0.05$

All correlations with the BDSA only include student-athletes

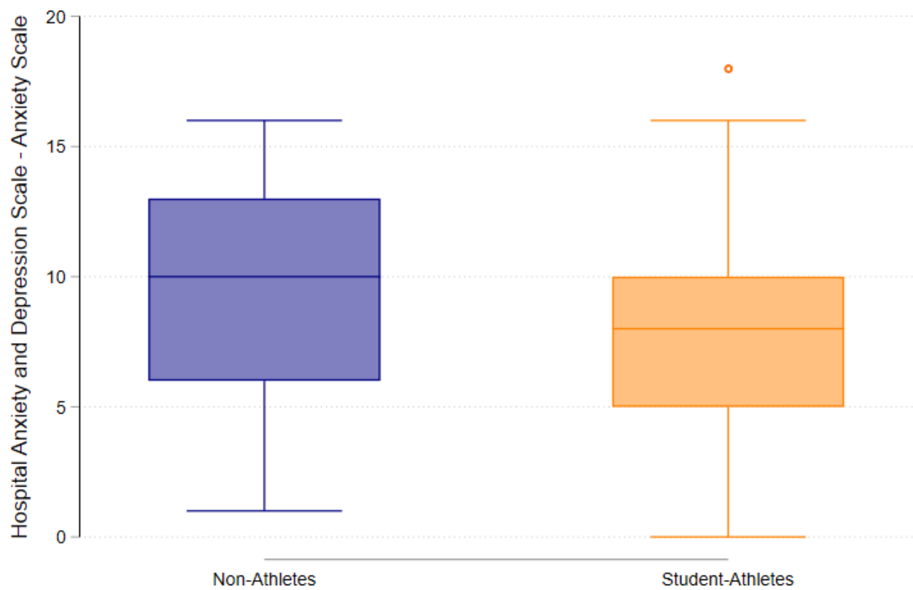


Figure 1. Box plot displaying that student-athletes reported lower scores on the Hospital Anxiety and Depression Scale – Anxiety Scale compared to non-athletes (Unadjusted β=-1.82; p=0.025)

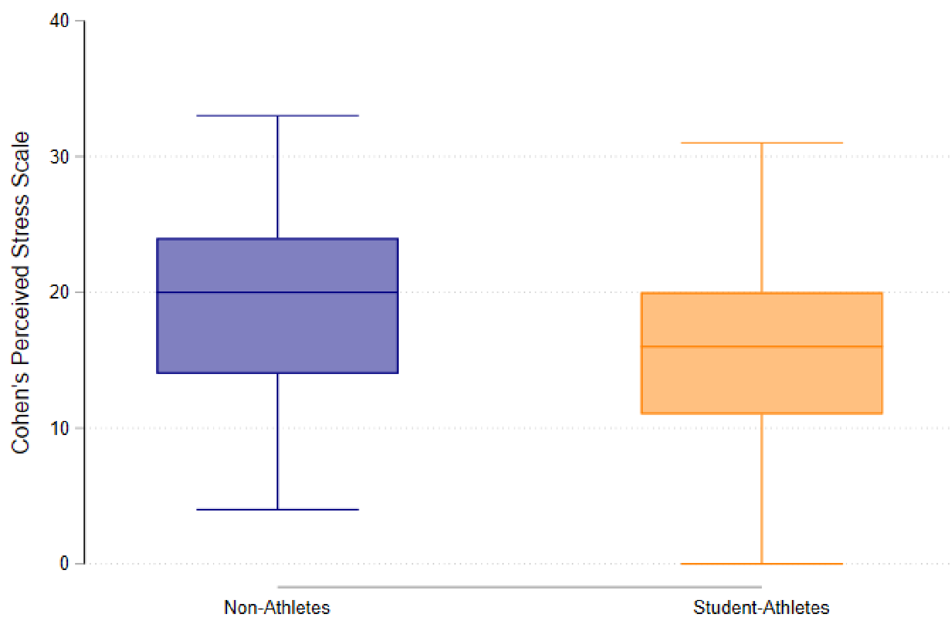


Figure 2. Box plot displaying that student-athletes reported lower scores on Cohen's Perceived Stress Scale compared to non-athletes (Unadjusted β=-3.52; p=0.006)

Table 6. Descriptive statistics for the psychometric assessments separated by sport.

	All Student-Athletes		Track and Field		Swimming		Rowing		Other	
Survey	**N**	**Mean (SD)**	**N**	**Mean (SD)**	**N**	**Mean (SD)**	**N**	**Mean (SD)**	**N**	**Mean (SD)**
Childhood Trauma Questionnaire - Short Form										
Total Score	61	32.1 (8.3)	22	30.7 (6.1)	24	33.8 (11)	10	30.8 (5.6)	5	33 (6.7)
Physical Abuse	64	5.6 (1.3)	23	5.8 (1.5)	26	5.5 (1)	10	5.5 (1.6)	5	5.8 (1.8)
Emotional Abuse	64	7.6 (3.3)	23	7.4 (3.4)	26	8 (3.6)	10	7.5 (2.8)	5	7 (2)
Sexual Abuse	65	5.6 (2.7)	24	5.1 (0.6)	26	6 (4)	10	6 (2.2)	5	5.2 (0.4)
Physical Neglect	63	6.2 (1.9)	24	6.4 (2.2)	24	6.3 (1.8)	10	5.5 (1)	5	6.2 (1.6)
Emotional Neglect	64	7.8 (3.4)	24	7.8 (4)	25	8.1 (3.4)	10	6.3 (1.9)	5	8.8 (2.5)
Hospital Anxiety and Depression Survey										
Anxiety Subscale	63	7.6 (4.3)	22	6.4 (3.9)	26	8.5 (4.6)	10	7.5 (4.2)	5	9 (4)
Depression Subscale	62	3.3 (3.7)	22	1.9 (2.5)	25	3.6 (4.1)	10	4.8 (4.4)	5	4.6 (4.2)
Single-Scale Psychometric Assessments										
Cohen's Perceived Stress Scale	63	15.7 (6.7)	23	13.2 (5)	25	17.6 (6.9)	10	16.6 (8.3)	5	16.4 (6.7)
Brugha's List of Threatening Events	60	1.8 (1.7)	21	1.4 (1.4)	24	2 (1.7)	10	2.4 (2.2)	5	1 (1.2)
Baron Depression Scale for Athletes	60	4.4 (3.5)	21	2.9 (2.2)	25	5.4 (4.4)	10	4.6 (2.8)	4	6.3 (2.9)

Baron Depression Screener for Athletes

The BDSA is a 10-item questionnaire that ranges in score from 0 to 20. The mean score for my sample is 4.5 with a standard deviation of 3.6. This survey typically uses a cutoff of 5 to indicate whether an athlete is demonstrating clinically relevant symptoms or should be forwarded to mental health support (Reardon et al., 2019). Here, 14 out of 60 student-athletes reported a score of higher than 5. Unfortunately, previous publications of the BDSA do not report their means or the proportion of athletes reporting clinically relevant symptom despite its recommended usage by experts in athlete mental health (Reardon et al., 2019). Therefore, it is difficult to know whether these rates are expected across groups, if they represent a low-risk group, or if they represent a high-risk group. Comparing participant scores on the BDSA with the HADS-Depression scale indicates a high correlation between the two (Pearson's R=0.6880, p-value<0.001). Since higher scores on the HADS-Depression scale have previously been associated with worsened health outcomes (reviewed above), it may indicate that higher scores on the BDSA are likely to be associated with similar health outcomes.

Study Completion Date and Psychosocial Stress Exposure

Data collection took place over the course of two years during the COVID-19 pandemic, so I conducted a *post hoc* analysis to examine if psychosocial stress scores differed based on when participants completed the study. Figure 3 displays when participants completed the study, separated into student-athletes and non-athletes. I conducted a series of OLS regressions with survey score as the dependent variable and time as the independent variable to investigate if there are direct associations between when a participant completed the study and their psychosocial stress scores (Table 7). These regressions showed significant associations between the date that a participant completed the study and their total score on the CTQ (β=-0.021, p=0.008) as well as their scores on the Physical Abuse, Emotional Abuse, and Emotional Neglect subscales (all p's<0.05). This β coefficient for the total CTQ score suggests that non-athletes who completed the study in 2022 scored, on average, 7.67 points lower (i.e., less stress exposure) than those who completed the survey 12 months earlier. There were no significant associations between study completion date and any of the other psychosocial stress assessments. This association is illustrated in Figure 4.

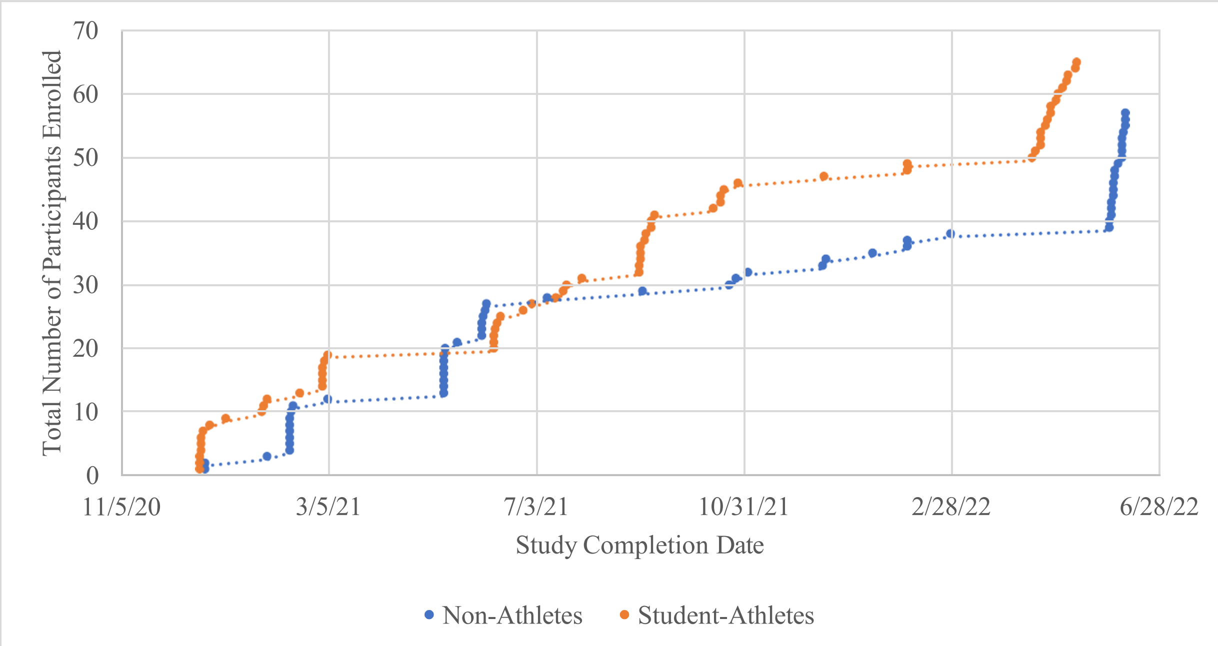
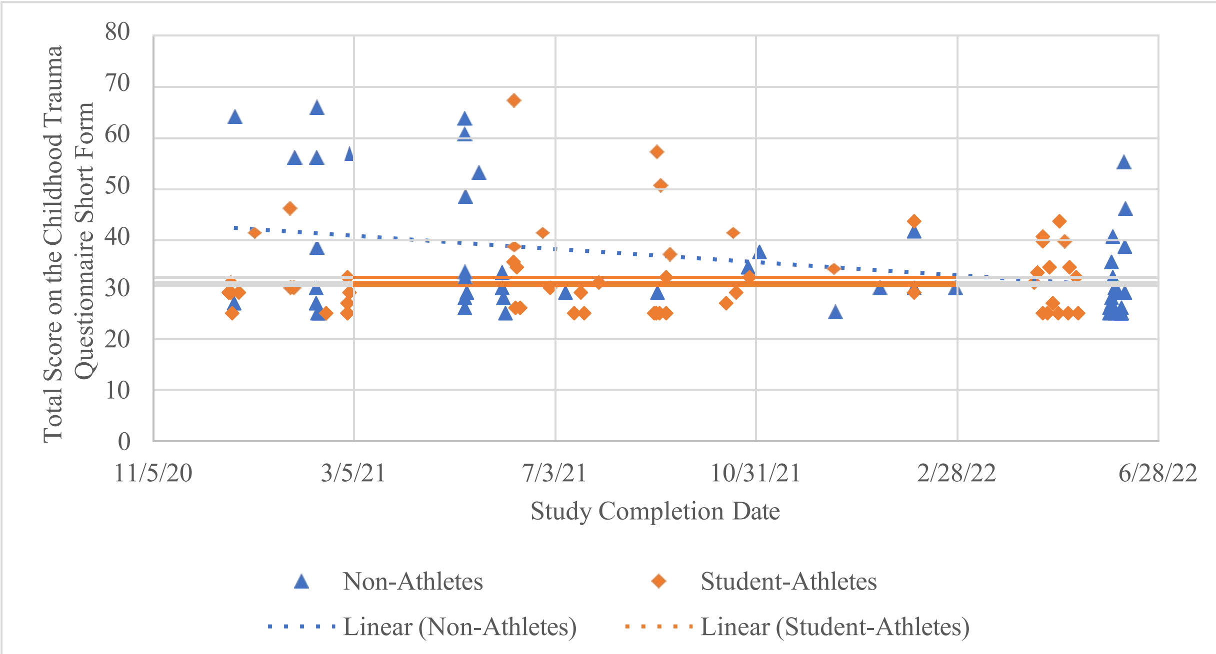


Figure 3. Graph displaying when participants completed the study. Remote Data Collection took place from November 2020 through February 2022. Hybrid Data Collection took place March 2022 through June 2022.

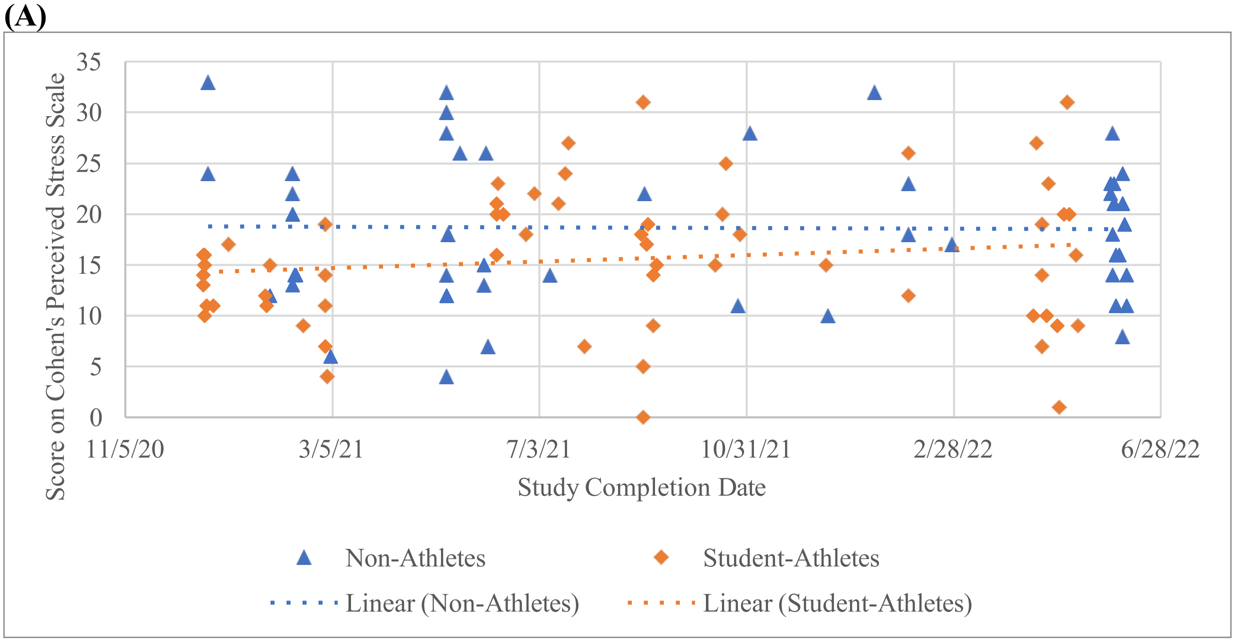
Table 7. Summary of regression models testing whether scores on psychosocial stress surveys were associated with when participants completed the study

	Whole Sample		Non-Athletes		Student-Athletes	
Survey	**N**	**β**	**N**	**β**	**N**	**β**
Childhood Trauma Questionnaire - Short Form						
Total Score	114	-0.009+	53	-0.021**	61	0.003
Physical Abuse	121	-0.002+	57	-0.005*	64	0.001
Emotional Abuse	119	-0.003	55	-0.008*	64	0.002
Sexual Abuse	120	-0.001	55	-0.002	65	0.001
Physical Neglect	120	0.000	57	-0.001	63	0.001
Emotional Neglect	120	-0.002	56	-0.006*	64	0.001
Hospital Anxiety and Depression Survey						
Anxiety Subscale	118	0.003	55	0.003	63	0.001
Depression Subscale	115	0.001	53	-0.002	62	0.005+
Single-Scale Psychometric Assessments						
Cohen's Perceived Stress Scale	119	0.003	56	-0.001	63	0.006
Brugha's List of Threatening Events	114	0.001	54	-0.001	60	0.002+
Baron Depression Scale for Athletes	NA	NA	NA	NA	61	0.002

All β's are calculated from OLS regressions with the named survey as the dependent variable and date of study completion as the independent variable. Regressions are not adjusted for any covariates. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$



(A)



(B)

Figure 4. Graphs displaying the scores on the Childhood Trauma Questionnaire-Short Form (A) and Cohen's Perceived Stress Scale (B) over the date each participant completed the study, separated by student-athletes and non-athletes. The dotted lines are the lines of best fit calculated for each group in each figure. Non-athletes who participated later in the study reported lower stress on the Childhood Trauma Questionnaire ($p=0.008$) but not on any other survey (Cohen's Perceived Stress Scale shown here as an example of no relationship; $p=0.797$). Student-athletes did not show any significant associations between completion date and scores on any of the surveys.

Discussion

Comparisons between Student-Athletes and Non-Athletes

In this study, I compared psychosocial stress exposure between a sample of NCAA student-athletes and their counterparts in the general student population (non-athletes). I found that student-athletes reported lower levels of recent perceived stress and anxiety-related symptoms when compared to non-athletes. Notably, student-athletes reported similar levels of exposure to childhood psychosocial stress, similar levels of depression-related symptoms, and similar levels of exposure to major life stressors over the past year. These results largely replicate the heterogeneous nature of the literature reviewed above, wherein some studies find similar levels (Storch et al., 2005; Wolanin et al., 2015), some higher levels (Thirer et al., 1987), and others lower levels (Proctor & Boan-Lenzo, 2010) of mental health symptoms and psychosocial stress in student-athletes compared to the general undergraduate population. It is apparent from my findings that the specific assessment tool and psychosocial construct under investigation impacts how these groups compare to one another.

It is surprising, however, that the student-athletes in my sample, specifically, reported lower levels of perceived stress and anxiety compared to non-athletes. My student-athlete sample was mainly comprised of women who compete in Track and Field, Swimming, and Rowing. Women student-athletes, in general, and athletes who compete in these sports often report higher levels of anxiety and perceived stress compared to men student-athletes and athletes in other sports (reviewed in Brown et al., 2021). Thus, we may have expected the student-athletes in my study to be more likely to show either equal or higher levels of perceived stress and anxiety when compared to non-athletes.

When separating student-athletes by sport (Table 6), Track and Field athletes reported lower depression-related symptoms than Rowers and lower depression-related symptoms and perceived stress compared to Swimmers. Thus, the differences between student-athletes and non-athletes in anxiety and stress may be driven, in part, by the relatively lower scores reported by Track and Field athletes. Given the small sample sizes for each sport (lower than 30 for each) and that many athletes were competing on the same team, my findings are likely affected by team-level factors (such as coaching staff and team culture). Moving forward, it will be important to conduct comparisons with student-athletes from a broader range of sports and larger number of teams to test this idea.

It must also be acknowledged that data collection took place during the COVID-19 pandemic which likely impacted student-athletes and non-athletes differently over the past two years. Therefore, my results may not reflect stable differences between student-athletes and non-athletes, but differences resulting from the COVID pandemic. Many social health disparities deepened, both globally and domestically, during the pandemic, highlighting the importance of support networks and access to resources in determining health and wellbeing (e.g., Hasson et al., 2021; Mukherjee, 2020; Summers-Gabr, 2020). Student-athletes may have benefited from built-in support from teammates and athletic staff that are not readily available to non-athletes. While many student-athletes may have lost opportunities for important competitions and other sports advancement during the early COVID restrictions, they likely received reliable support from their teammates, financial support for school, and, for those who remained student-athletes, maintained a continuous “purpose” in their day-to-day lives (i.e., to train and compete for their school and athletic career). Each of these factors may have contributed to student-athletes reporting lower levels of perceived stress and anxiety symptoms. Differences in support throughout the COVID pandemic could also explain why the CTQ-SF is comparable between groups. Specifically, the CTQ-SF asks about experiences that would have largely taken place before the pandemic.

With these points in mind, I began to explore how the COVID pandemic may have impacted psychosocial stress by testing the associations between when participants completed the study and their scores on the psychosocial stress surveys. Individuals who participated early in my study did so while more restrictive social-distancing measures were in place. For example, courses were conducted remotely, and they had less access to public spaces. If COVID-related pressures increased participants' scores on these stress surveys, we'd expect them to be higher for my participants who completed the study earlier (i.e., in 2021 vs 2022). Surprisingly, only CTQ-SF scores were associated with when participants completed the study and it was only significant in non-athletes. The CTQ-SF is meant to assess psychosocial stress while growing up and ideally participants' scores are independent of current circumstances. However, current psychosocial stress may impact recall of previous experiences, causing individuals to report having higher levels of childhood stress when their current levels of stress are high. One interpretation of these findings, then, is that non-athletes were impacted more strongly by COVID-19 measures early in the study, causing them to report higher levels of stress while growing up. However, these same individuals did not report higher levels of any other measurements of psychosocial stress. Therefore, another likely interpretation is simply that my team recruited individuals with higher levels of childhood stress earlier in the study by chance.

Fortunately, I have several other questionnaires and sources of data I can use to better understand the group differences in perceived stress and anxiety-related symptoms. First, participants completed several questionnaires on their thoughts and experiences with the

COVID-19 pandemic. Investigating how COVID-related disruptions are associated with scores on stress surveys should help determine whether these associations between survey completion date and CTQ-SF scores are spurious or indicate an effect of recall bias. Second, I have several survey instruments asking student-athletes about their team's culture, why they selected their specific school, and their motivations for their competing in their sport. Investigating these may help disentangle whether student-athlete stress is lower due to greater social support and connectedness in their sports. Broadly, investigating these differences in my sample should do more than just highlight where one group is more or less stressed than the other. These analyses may point to important features that protected student-athletes throughout the COVID-19 pandemic and may serve as important protective factors for their mental health and wellbeing in the future. It may also highlight strategies that can be implemented to help non-athletes.

Performance of Psychometric Assessments

Alongside these comparisons, I tested the internal reliability of these surveys, performed factor analysis where applicable, and implemented an adapted cognitive interview protocol to ensure that the surveys included in my study were assessing psychosocial stress as expected. All of these surveys demonstrated acceptable and preferred levels of internal reliability across both groups with the exception of the Physical Abuse and Physical Neglect subscales of the CTQ-SF. Notably, the Sexual Abuse subscale demonstrated extremely high internal reliability (>0.95) for all groups. These reliability findings were replicated via the factor analyses with the HADS and the CTQ-SF. The HADS demonstrated an acceptable fit with its original 2-factor structure while exploratory factor analysis suggested alternatives to the CTQ-SF's original 5-factor structure. Despite the fact that the CTQ-SF was structured differently between groups, an overwhelming majority of my participants reported that the CTQ-SF and all other surveys properly assessed their targeted psychosocial stress construct. For context, over 100 participants finished each of the surveys, providing over 6,000 opportunities for participants to mark items as “Unclear Item” or “Prefer not to answer.” However, only 31 items received these responses. The overall high Cronbach’s alpha scores along with the positive cognitive interviews for each survey offer converging evidence that these measures are behaving appropriately for my sample.

The deviations noted in these validity diagnostics (i.e., variable factor structure for the CTQ-SF and weak reliability for Physical Abuse and Physical Neglect) may be due to the conditions needed for student-athletes to reach their elite level of competition. These individuals required a high level of nutrition, reliable access to training facilities (particularly for Rowing and Swimming), and, likely, a degree of financial stability in their family or broader networks in order to develop the physical and mental characteristics needed to compete on an intercollegiate level. Therefore, some of the constructs measured by the CTQ-SF may not group together as it does with other groups in the US that haven’t undergone such a selective process.

Specifically, the low alphas for student-athletes’ responses to the Physical Abuse and Physical Neglect subscales of the CTQ-SF suggest that the items/experiences noted in these scales were less likely to co-occur. For example, the Physical Neglect subscale asks for participants to respond how often the following was true while growing up: “I didn’t have enough to eat”, “I knew that someone was there to take care of me and protect me”, “My parents were too drunk or high to take care of the family”, “I had to wear dirty clothes”, and “There was someone to take me to the doctor if I needed it”. It may be that student-athletes in the sports sampled here would not have had the support or time needed to train or improve in their sport if these five items correlated strongly. That is, if you do not have enough to eat and you don’t have someone to take care of you, you may not have the access and energy needed to properly train. Thus, we may be more likely to see student-athletes with low levels of Physical Neglect or with discordant scores on these items compared to non-athletes. The reliability of the Physical Neglect subscale does appear to be more sensitive to local contexts than the other subscales (Spies et al., 2019). Conversely, the other scales on the CTQ-SF, such as Emotional and Sexual Abuse, assess exposures that have a long and damaging history in youth and NCAA sports.

While I conducted a range of traditional methods to test the validity of my measures, it was still very useful to include the adapted cognitive interview protocol. This protocol offered every participant the opportunity to contextualize to their answers and highlight concerns or questions they had with the specific surveys. Many participants suggested ways of specializing questionnaires to students or athletes and adding specific questions regarding their own responses to stress or contexts around the stress. While these suggestions often go past the goal of the specific questionnaires (i.e., suggesting the PSS should ask about sources of stress), it is important to consider these wants when interpreting participants' answers. Offering the opportunity for participants to respond with questions even after answering provides me the opportunity to learn more about their reasoning and thought process. Also, it offered chances for participants to report less frequent stresses (e.g., one of participant's house burned down in a forest fire) that are impactful for them and give them a space to better express themselves. This feedback will also be invaluable to improving these surveys and analyses for future projects with student-athletes.

Future Research

This paper aimed to further our understanding of mental health and well-being in student-athletes by comparing their psychosocial stress exposure to non-athletes. Importantly, I used the same set of psychometric instruments for both groups and collected both samples simultaneously. Overall, the psychosocial stress of these groups was similar, but student-athletes reported lower levels of current perceived stress and anxiety-related symptoms.

In the wake of these results, I have at least several follow-up analyses planned to better understand the nature and etiologies of these differences. First, I will conduct a full analysis of semi-structured interviews conducted with 20 of my participants, which offered participants the opportunity to discuss how COVID was impacting their lives and stress at length. Second, I will investigate associations between stress scores and participants' responses to multiple surveys on COVID-related disruptions. Third, I will investigate how student-athletes responded to questions of team culture and their athletic motivations to examine the role of their teams and athlete-centric resources in their experience of psychosocial stress during the COVID-19 pandemic. Importantly, following up on these three analyses will provide more insight into whether the differences between student-athletes and non-athletes in this study is related to the pandemic or are broader, more stable differences in these groups. In regards to my future biomarker work this sample (including Paper 3), this paper supports the use of these surveys in assessing the associations between psychosocial stress and biology in student-athletes and non-athletes. I will draw upon this analysis to plan these downstream analyses (i.e., testing associations with inflammation) and help me interpret future results.

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Paper 2: **A comparison of physical activity in collegiate student-athletes and non-athletes**

Paper 2 Outline:

Introduction

The biological consequences of physical activity are a longstanding topic of interest within Biological Anthropology (e.g., Leonard, 2001; Neel, 1962). Humans and our ancestors evolved in environments that required high levels of physical activity, and only recently have large groups begun transitioning to more sedentary lifestyles (Antón et al., 2002). Many populations still engage in high levels of physical activity daily (e.g., the Hadza, Raichlen et al., 2017). However, we are still discovering exactly how our bodies address the many challenges of physical activity, such as increased energetic expenditure, and how these adaptations moderate our responses to other ecological challenges, such as pathogen exposure and psychosocial stress (Chow et al., 2022; Ocobock, 2020 Neel, 1962). Critically, it is unclear if and how the various facets of physical activity (e.g., time spent in moderate-to-vigorous physical activity, total daily amount, activity intensity, etc.) distinctly impact human bodies (Brady et al., 2022).

Regular exercise and increased leisure time physical activity are clearly associated with a reduced risk of cardiovascular disease, mental illness, cognitive decline, and all-cause mortality in industrialized populations (Arem et al., 2015; Jee et al., 2018; Paluch et al., 2022; Raichlen & Alexander, 2017; Silverman & Deuster, 2014; Wang et al., 2021). These benefits are typically attributed to increased time spent in moderate-to-vigorous physical activity (MVPA), but some studies suggest that *any* increase in physical activity leads to health benefits in these groups (O'Donovan et al., 2017). Further, subsistence populations who demonstrate high levels of overall physical activity (e.g., the Hadza and the Tsimané) also show low rates of chronic diseases associated with inactivity (Kaplan et al., 2017; Raichlen et al., 2017). The associations between physical activity and health outcomes are not necessarily monotonic, however. The benefits of physical activity appear to follow an inverted U-shape where individuals experience increasing health benefits as their activity increases, up to a certain point. After this point, they experience diminishing returns (Merghani et al., 2016; Schnohr et al., 2015). Additionally, surpassing the "optimum" levels of physical activity can lead to adverse health effects, not only reduced benefits (Meeusen et al., 2013; Sargent et al., 2014; Schnohr et al., 2021). Not all physical activity is associated with health benefits. For example, multiple high-powered studies have demonstrated that increased occupational physical activity is associated with adverse health after adjusting for covariates such as health behaviors, socioeconomic status, and even self-reported job type (Coenen et al., 2018; Holtermann et al., 2021; Lee et al., 2021; but see Gomez et al., 2022). Two explanations for these adverse effects are that occupational physical activity often takes place at lower intensities for long periods of time without adequate recovery time and that employees have less control over when or how much they are active (Holtermann et al., 2018).

My dissertation examines how physical activity is associated with telomere length and, further, if physical activity moderates the relationship between psychosocial stress and telomere length in a sample of NCAA student-athletes and university students not competing on an NCAA team. Given the complex relationships between different physical activities and biological outcomes noted above, it is crucial for me to assess and describe multiple aspects of my sample's physical activity before conducting downstream analyses. While it may appear obvious that student-athletes engage in more MVPA than non-athletes, how they compare in other facets of their physical activity (e.g., time spent in light intensity, overall activity levels) is less clear. Importantly, these other facets of their physical activity may have impacts on their biology that is independent of, interacts with, or even opposes the beneficial effects of MVPA. Student-athletes train primarily to improve their performance rather than their health and have limited agency in the timing, intensity, and volume of their physical activity (Maffetone & Laursen, 2016). These factors may lead them to excessively high physical activity levels and inadequate recovery time, putting them at greater risk for sustaining a variety of physical injuries and other negative health outcomes (Vetter & Symonds, 2010; Yang et al., 2012). Conversely, non-athletes are more likely to train to improve their health or aesthetic reasons and are probably less active than World Health Organization (WHO) and National Institutes of Health (NIH) recommendations (Kwan et al., 2012; López-Valenciano et al., 2021).

This paper, therefore, combines self-report and objective measures of physical activity to create a detailed description and comparison of physical activity in these groups to be used in downstream analyses. Specifically, this analysis will help enable me to disentangle what facets of activity are helpful, what facets may be hurtful, and, importantly for my research (Paper 3), how various facets of activity impact our responses to other challenges like psychosocial stress.

Measuring Physical Activity

Physical activity is typically assessed either through self-report surveys or objective tracking via a wearable monitor. Each method has strengths and limitations, which researchers must weigh according to their research goals. The current consensus is that combining both methods allows researchers to build a more holistic understanding of participants' activity patterns (Falck et al., 2021).

Self-Reported Physical Activity

Self-report measures of physical activity can scale from a single question to intensive journaling and daily reporting, each step incurring a different level of participant burden and varying costs and benefits to researchers (Prince et al., 2008, 2020). Single questions or short surveys on physical activity are non-invasive and offer little participant burden (Sylvia et al., 2014). Journaling can either be easy or difficult depending on the frequency and depth of reporting – daily records result in more participant burden than a recall of the past week (Taylor-Piliae et al., 2006). For researchers, surveys require little to no funding or dedicated infrastructure, are often straightforward (at least seemingly) to operationalize for analysis, and can be collected quickly as part of a battery of surveys (Warren et al., 2010).

Unfortunately, while self-report surveys often demonstrate acceptable test-retest reliability, many fail to show strong validity against objective measures of physical activity (Silsbury et al., 2015). Self-reported physical activity is prone to errors in recall, desirability bias, and differences in subjective valuation of activity (e.g., what is 'intense' exercise?) (Prince et al., 2008; Sylvia et al., 2014; Warren et al., 2010). Systematic reviews of studies comparing self-reported and direct measures of physical activity find substantial discrepancies with both under- and over-reporting physical activity (Adamo et al., 2009; Prince et al., 2008). These issues appear to impact some measures more than others. For example, if the researchers' goal is simply to build broad categories of exercise in the elderly, like defining groups as "no exercise," "1-3 hours of exercise", and "more than 3 hours," then brief one or two question measures such as the Stanford Brief Activity survey may be reliable when compared to objective metrics and observational data (Taylor-Piliae et al., 2006). If the goal is to explore activity in more active young adults and uncover nuanced relationships with biology, recall issues and differences in subjective valuation may contribute substantial noise and bias (Sylvia et al., 2014). Daily journals and responses can help alleviate some of these issues: collecting data daily or recording exercise as it happens will reduce recall bias and provides additional context for the research team (Taylor-Piliae et al., 2006). Unfortunately, these measurements introduce a substantial participant burden and have numerous issues with participant compliance. A broad consensus exists among physical activity researchers that successfully examining the effects of physical activity requires data that is richer than what can be provided solely via self-report measures. The past two decades have seen a push toward more objective metrics of physical activity and related behaviors (Prince et al., 2008, 2020).

Objective Measures of Physical Activity

Objective measures of physical activity address many of the issues associated with self-reports by removing recall bias or subjective interpretation of "intensity" through wearable technology such as accelerometers. In theory, every participant is measured by the same monitor and, thus, the same metric. Accelerometers are wearable devices that capture changes in acceleration of the body segment to which they are attached and provide detailed information, such as movement direction and duration (Gao et al., 2021). These records are often reduced to create summary variables of an individual's physical activity, such as time spent in moderate-to-vigorous physical activity (MVPA), for statistical analysis (Migueles et al., 2022). Objective measures like these are often more strongly related to health measures than questionnaires (Menai et al., 2017; Sabia et al., 2015).

Accelerometers, however, introduce their own potential sources of bias. The specific methods researchers select for their study have substantive impacts on their outcomes and determine their comparability with other studies (Brady et al., 2022; Migueles et al., 2017; 2022). Unfortunately, many studies fail to report on key methodological decisions, making it difficult to accurately compare data between studies and interpret how methodological decisions influenced their findings and conclusions. Further, the most common approach to operationalizing physical activity is transforming the continuous physical activity data into categories (e.g., time spent in MVPA). This strategy reduces statistical power by obscuring meaningful variability, may violate statistical assumptions, and misrepresents the continuous nature of physical activity (Migueles, Aadland, et al., 2022; O'Donovan et al., 2017). Fortunately, newer techniques that address these shortcomings are gaining in popularity, diversifying and improving the tool kit for physical activity research (Gao et al., 2021; Migueles, Aadland, et al., 2022; Rosenberger et al., 2019).

Assessing Activity in Student-Athletes

NCAA student-athletes are at increased risk of engaging in physical activity at levels that compromise their health and training (Meeusen et al., 2013). Many specialists worry that even light activity accumulated throughout the day, such as walking between classes across campus, can meaningfully hamper their recovery times and hurt their overall health (Driller et al., 2017). Despite this, only one peer-reviewed study has objectively assessed daily activity patterns in student-athletes, and it excluded sports-related activity (Driller et al., 2017). Research on athletes' physical activity, particularly objectively measured activity, has almost exclusively been done in training or competition and with only one sport at a time (Gómez-Carmona et al., 2020). There is no published, objective assessment of how sports-related and daily living activity patterns compare across sports. Thus, there is little understanding of how athletes' activity accumulates throughout the day and how it differs across sports.

A substantial barrier to such comparisons is that some sports preclude using wrist-worn accelerometers (e.g., swimming, American football). In these circumstances, accelerometry fails to record much of the athlete's training-related activity, and they would appear less active than members of other sports. They may even appear less active than non-athletes, depending on how much these athletes rest and recover between training sessions (Driller et al., 2017). Further, there is some concern that differences in sports-typical movement patterns (e.g., running vs. rowing) may bias accelerometers to report one sport as more "intense" than another.

Ideally, a combination of self-report and objective measurement may help circumvent these obstacles. Student-athletes build their lives around training and competition schedules, so their self-reported time and intensity of training or competition is likely highly accurate. Therefore, it may be possible to utilize this self-reported data in tandem with objective data to examine or correct for biases in wear time and sports type. For example, when examining swimmers, I can investigate whether combining objectively measured time in MVPA and self-reported training time makes their activity profiles appear more similar to other athletes. For sports that rely upon different movements (e.g., runners and rowers), I can check that the accelerometer's most active times of day correspond to the times when athletes report training or competing. For example, I will investigate if a rower's activity is exceptionally high during a regatta. I can also test if a self-reported "intense" training session is concordant with a greater number of accelerations. Convergent evidence across these contexts may increase confidence that accelerometry assesses activity across sports comparably.

As noted previously, there is no published comparison of activity levels across student-athletes in different sports and only one published comparison of student-athletes and non-athletes. It is therefore difficult to predict all the potential issues that may arise. Conducting a mixed methods protocol permits additional flexibility to investigate potential measurement disagreements and biases as they arise.

Current Study

This paper is focused on understanding how physical activity is patterned in my sample before conducting downstream analyses. Specifically, I will utilize both self-report and objective data to assess and compare the physical activity of young adults engaged in NCAA athletics and those in the general university student population. For self-report measures, I asked participants to describe their engagement in sports and related activities during their youth, their typical activity levels as adults, and their activity during the study. For objective measures, I asked them to wear an Actigraph wGT3X-BT (Pensacola, FL, USA) on their non-dominant wrist for seven days to track their movement. I will operationalize the accelerometry data in several ways by calculating time spent at different activity intensities (e.g., MVPA), their Average Acceleration (AvAcc) throughout the study, and the intensity gradient (IG) of their activity. I will focus mainly on describing and comparing the means and variation in these variables across groups and between sports.

Methods

COVID-19

University of Washington's (UW) Human Subjects approved my project in February 2020 (IRB ID: STUDY00009691); it was initially designed to take place in person, focusing on student-athletes and non-athletes at UW. During the subsequent COVID-19 pandemic, however, I had to redesign my project to collect data within the shifting local and global guidelines for social distancing and research practices. As a result, my team and I collected much of the data remotely through online surveys, online video calls, and participant self-collection as described in "Study Protocol." Study items, such as the Hemaspot HF and the Actigraph (both described below), were provided to participants mostly through socially-distanced meetings and shipping.

Participants

My team and I recruited intercollegiate student-athletes (Division-I and Division-III) from multiple schools throughout the US and students from these same schools who were not competing on an NCAA team. About half of the participants in my initial sample are members of an NCAA intercollegiate team (N=60), and half are students who do not compete on an NCAA intercollegiate team (N=50).

Student-Athletes

My team recruited NCAA Division-I and Division-III student-athletes through three main strategies. First, we sent recruitment emails to the teams through a coach or team leader with the head coach's approval. Second, we provided recruitment materials to athletic trainers, who distributed them to their teams. Third, we sent recruitment materials to

UW's Student-Athlete Academic Services, who distributed the materials among their student-athletes. My final sample includes student-athletes in Track and Field, Women's Rowing, Swimming, and multiple other teams (sample N's are listed in Results). The research team explicitly sought and gained clearance from the respective heads of research and compliance officers for each Athletics Department before recruitment.

General Student Population

Non-athletes were recruited through undergraduate anthropology and biology courses across several undergraduate universities. Research team members approached a course instructor and asked permission to share recruitment materials for the study. Then, depending on the teaching modality of the course, a research team member gave a short introduction to the study and how to join over Zoom or in person. There was no verbal or "live" introduction to the study on some occasions. For these situations, instructors forwarded study information and recruitment materials directly to their course without a recruitment pitch given by a research team member.

Study Protocol

All participants were directed to an online link to complete the prescreening survey and consent form. Following this, we introduced them to the data collection protocol. To increase accessibility and participant comfort levels, and to accommodate shifting social distancing guidelines, I developed two protocols for data collection: a "Remote Data Collection" and a "Hybrid Data Collection" protocol. For either collection protocol, participants completed a prescreening survey, a series of post-study surveys, psychometric assessments, and dried blood spot (DBS) collection. Participants also had the option to wear an accelerometer to collect objective measurements of their physical activity. A small subset of participants was invited to take part in semi-structured interviews. All participants received an online gift card for completing the study and will receive part of their study data once my analysis is complete.

Prescreening

Interested individuals were directed to a confidential online screening questionnaire on REDCap where they consented to the study and provided demographic information (e.g., gender identity, racialized group identity, height, weight, age), basic information about their health (e.g., ongoing health issues), and typical levels of physical activity. They were also asked to provide information about their participation in organized and non-organized sports throughout their childhood and adolescence, their enrollment status, student-athlete status, and whether they participate in intramural activities. The research team then reached out via email, phone call, or text message (according to participant preference) to schedule their participation in the study. I included all participants at this stage if they were enrolled as an undergraduate at an NCAA member institution and were not currently experiencing COVID-19 symptoms or other acute illnesses.

Remote Data Collection

For the remote protocol, all data collection occurred remotely or with minimal (~5 minutes) in-person contact between the research team and a participant. After recruitment and initial consent, the research team either shipped participants a study kit with all the materials to complete data collection at home or scheduled a time for the participant to pick up and return the study kit to a socially-distanced campus collection site. Participants collected finger-prick DBS with a Hemaspot HF device (Spot On Sciences) according to written and video instructions on how and when to collect samples. Participants who chose to participate in the accelerometry portion of the protocol wore an accelerometer (Actigraph wGT3X-BT; described in detail below) for ~7 days before collecting finger-prick DBS. After DBS collection, participants returned their study kit with their sample on ice according to instructions from the research team with a prepaid shipping label. Lastly, the participants completed a series of online surveys on overall health, sports activity, detailed demographics, experiences with COVID-19, and psychosocial stress exposure.

Hybrid Data Collection

The hybrid protocol was developed as COVID-19 restrictions began to ease in Fall 2021 to offer more flexibility for participants and was approved by UW Human Subjects. Many participants chose to delay or withdraw their participation because they preferred a research team member to collect their finger-prick DBS. For this procedure, participants had one or two short appointments (~15 minutes) with the research team, depending on whether they opted to join the accelerometry portion of the study. In the first appointment, the participant was introduced to the study and asked to wear an accelerometer on their non-dominant wrist for approximately seven days. The second appointment was scheduled for at least seven days after the first. During this appointment, I collected the accelerometer and finger-prick blood in Hemaspot HF devices (Spot On Sciences). They were then asked to complete all psychometric surveys within the next 24 hours from their personal computers. If the participant opted out of the accelerometry portion of the study, they completed the finger-prick DBS collection and introduction to the online stress surveys in a single appointment. All appointments took place in the UW Biodemography Laboratory.

Self-Report Measures of Physical Activity

Participants responded to surveys on their physical activity in both the prescreening and post surveys. Briefly, they answered questions regarding their participation in sports in childhood and adolescence, their current levels of activity, their activity in the past week, and whether their activity has changed with the COVID-19 pandemic. (See Appendix 2 for a complete list of questions.)

Prescreening Surveys

In the prescreening, participants answered if they participated in organized or "not organized" sports or activities growing up, which sports/activities they participated in, and which ages they regularly participated in these activities. The focus on sports in childhood is meant to help recall and provide specific points of comparison between groups. Further, organized sports are the predominant source of physical activity for US children (Koorts et al., 2019). For their current/adulthood levels of physical activity, they were asked if they exercise regularly and, if so, how many hours they had exercised in the past seven days, specifically. They were also asked if they participate in intramural sports or on an intercollegiate sports team, what sport/activity they are a part of, and how many hours they participate each week. Members of the track and field team were asked questions regarding their event and weekly mileage. All other student-athletes were asked about their position/event. Since more participants completed the prescreening than the post survey, the sample sizes for these surveys are larger than for the post surveys or accelerometry data. As noted above, no participants were excluded from the study at this stage by the research team.

Post Surveys

At the end of the study, participants were asked to focus on their physical activity in the past week. If they were partaking in the Actigraph portion, this period aligned with their time wearing the Actigraph. If they did not wear an Actigraph, they were asked to refer to the past seven days. Specifically, they were asked to approximate how many hours they spent exercising or training for a sport over the last seven days and what types of exercise they performed. Then, they were asked to compare this to how much and what kinds of exercise or training they have been engaging in throughout the COVID pandemic and what they engaged in before COVID. They also indicated whether they had engaged in an intense workout in the past 48 hours. Lastly, they were given an open-ended question "Is there anything else noteworthy about your physical activity from the past week that you think we should know? (e.g., 'I hurt my ankle, so I did not run as much as normal'; 'I had more free time, so I ran more than normal,' etc.)".

Objective measures of Physical Activity

Migueles et al. (2017) outlined a list of criteria that accelerometry-based studies should include to improve transparency and comparability across studies. I cover the main points below, but a more detailed discussion of these criteria and how my study addresses them is found in the Appendix 2.

Data Collection

Objective measures of physical activity were assessed via Actigraph wGT3X-BT (Actigraph LLC, Pensacola, FL, USA). I selected this device because it is the most commonly used research-grade accelerometer and can export raw data to third-party programs for data processing and analysis (Migueles et al., 2019; Wijndaele et al., 2015). Participants were asked to wear the Actigraph on their non-dominant wrist for seven days with the sampling frequency set at 90 Hz. Placing the accelerometer on the non-dominant wrist improves participant compliance, reduces noise compared to the dominant wrist, and has become common practice for population-based studies of accelerometry (e.g., Doherty et al., 2017; Menai et al., 2017). 90 Hz was selected as the sampling frequency to compromise between maximizing collection frequency and compatibility with data filtering and processing programs, as many programs function best in multiples of 30 Hz; (Migueles et al., 2017). I defined "non-wear time" for any interval where no movement is recorded for 60 continuous minutes (Doherty et al., 2017; Migueles et al., 2017).

I conducted my analyses with the following set of criteria for the definition of a "valid" day and week (i.e., days and weeks that are included in my analyses). I included days with 16+ hours of recorded wear time and participants with 4+ valid days of measurement (Migueles et al., 2019). Older recommendations suggested that 10+ hours of wear-time was required to accurately assess time spent in different activity levels (e.g., MVPA) and a large proportion of older studies utilize this criterion (Migueles et al., 2017). Newer recommendations, however, suggest that 16+ hours provide a more accurate assessment of activity levels and help avoid wear-time related biases in activity assessment (Migueles et al., 2022). I used the default filtering setting for the Actigraph wGT3X-BT as opposed to the Low Frequency Extension (these are the only two options). These filters define and remove "non-human movements" to lessen noise and detect human movements with more precision. For example, these are meant to remove accelerations coming from the vibrations associated with riding in a car. While the specifics of the default filtering setting are proprietary information (and unavailable to researchers), it is known that the Low Frequency Extension can bias data in more active participants (see Appendix 2 for more details). I assessed physical activity with 1-second epochs since I expect that student-athletes regularly engage in short bursts of activity (Migueles et al., 2017).

Raw acceleration data was exported from Actilife, the proprietary Actigraph software, to R and processed with the GGIR package (https://cran.r-project.org/), an open-source R-package specially developed for analyzing raw accelerometry data (Migueles et al., 2019). GGIR processes acceleration signals using local gravity as a reference, so accelerations are expressed in milligravitational units (m*g*) instead of the proprietary "counts" calculated by Actilife. Using open-source resources such as the GGIR package and m*g* helps improve the transparency, consistency, and comparability of different study methodologies (Migueles, Molina-Garcia, et al., 2022).

Data Operationalization

The accelerometry data was operationalized in several ways. Before any analysis, I visually inspected each participant's graph of weekly recorded behavior to ensure it began and ended at the correct time and date for each participant and that any reported non-wear times from the participant are correctly marked. Any anomalies (e.g., extended non-wear times) were noted. Then, each 1-second epoch where the participant was deemed "awake" (see "Sleep" below for more details) was assigned a category of activity intensity as follows: sedentary (< 35 m*g*), light (35–99.9 m*g*), and MVPA (> 100 m*g*) based on the average acceleration (m*g*) recorded during that epoch. I then calculated the number of 1-second epochs individuals spent on average per day in each category for the group comparisons. No single recommended set of intensity thresholds exists for assessing activity intensity across all ages and demographics because most cut-points are based on specific actions, such as running on a treadmill, in a specific demographic, such as children aged 5-10 years old (Migueles et al., 2017). However, Hildebrand et al. (2014) used indirect calorimetry from young adults performing over a dozen "daily activities" to define a series of cut points with the Actigraph GT3X+ worn on the non-dominant wrist. These are the most widely recommended for continuous physical activity monitoring in young adults (Migueles et al., 2017) and were the cut-points used in these analyses.

To overcome the issues with categorizing physical activity (more detail in Appendix 2), I also calculated Average Acceleration (AvAcc) and the physical activity Intensity Gradient (IG) for each participant. Other advanced methods of operationalizing accelerometry data have been developed over the past few years, but AvAcc and IG are the only two with demonstrated associations with health outcomes in young adults (Backes et al., 2022). AvAcc is calculated by the GGIR R-package. First, it averages the raw accelerations across all 1-second epochs during a valid 24-hour period when the accelerometer was being worn and the participant was awake. Next, it averages this value across all valid days of activity recording (i.e., 16+ hours of wear time). The final value is expressed in m*g* and provided a single metric for the total volume of daily activity in this study (Dygrýn et al., 2021).

The IG is a single, continuous value that represents the amount of time that a person spends across all intensity levels (Migueles, Aadland, et al., 2022; Rowlands et al., 2018). It is based on the finding that a negative curvilinear relationship exists between physical activity intensity and the time an individual spends at that intensity (Rowlands et al., 2018). That is, over a 24-hour period, the vast majority of 1-second epochs will have low levels of recorded acceleration (e.g., the equivalent of sitting or typing on a computer; 0-25 m*g*) and the number of epochs recorded at each increasing level of intensity (e.g., a comfortable walk to a jog; 25-200 m*g*) drops off rapidly with a small number of 1-second epochs recorded with very high accelerations (e.g., a full sprint; >200 m*g*). As individuals spend more time at higher accelerations, this drop is less steep. To operationalize the degree to which this drop-off occurs for each participant, the GGIR R-package transforms the curvilinear relationship into a straight-line. First, it places each 1-second epoch associated with being awake (see Sleep below) into an intensity bin (e.g., 0-25 mg, 25-50 mg, etc.). Next, it calculates the natural log for both the x-value: middle of each intensity bin (e.g., for the 0-25 m*g* bin, it calculates the log of 12.5 m*g*) and the y-value: the number of 1-second epochs recorded at that intensity bin (e.g., if a participant recorded 100 1-second epochs in the 0-25 m*g* bin, their new value would be the natural log of 100). GGIR then creates a line of best fit for this log-transformed data, recording its R^2, y-intercept, and slope. The slope of this line of best fit is the IG for that participant. A more negative (lower) gradient reflects a steeper drop with little time accumulated at moderate and higher intensities. In contrast, a less negative (higher) gradient reflects a shallower drop with relatively more time spent at moderate and higher intensities. A more detailed description of how the IG is calculated is on page 8 of Appendix 2.

Notably, the combination of these two variables, the IG and AvAcc, allows me to describe both overall activity levels and how this activity is distributed among a continuous spectrum of intensity, to provide a more complete depiction of an individual's activity profile. For some biomarkers and outcomes, the volume of activity has stronger associations than the pattern of intensity, but for others, the opposite is true. Consequently, this approach will allow me to investigate the independent, complementary, or interactive associations of volume and intensity distribution in future studies with biomarkers, such as telomere length in Paper 3 (Backes et al., 2022).

Sleep

When utilizing 24-hour recordings to assess physical activity, it is necessary to define sleep. Without doing this, the recorded accelerometry data will not separate time when a participant is awake and when they are asleep. The periods of low activity occurring during sleep will be considered sedentary behavior and bias interpretations of the activity data. Therefore, while sleep is not reported or analyzed in this study, it is necessary to define it in order to have accurate activity data of any sort. Further, describing the methods for its identification and separation from wake time physical activity is necessary to ensure transparency and comparability across accelerometry-based studies (Migueles et al., 2017). The GGIR R-package can apply algorithms to identify and delineate sleep-related behaviors from movement and non-movement patterns. Extensive validation work demonstrates high agreement between these algorithms and polysomnography (i.e., the gold standard to measure sleep patterns, e.g., Rosenberger et al., 2016). While many sleep researchers combine these algorithms with self-report measures such as sleep diaries, these measures substantially increase participant burden, and college students are unlikely to answer these accurately. Due to the high agreement with polysomnography and the busy schedules of my participants, I utilized the sleep algorithm developed by Sadeh and colleagues (1994) to define sleep periods and separate them from daily activity analyses as recommended by expert consensus opinion (Migueles et al., 2017).

Statistical Analyses

Raw physical activity data was exported to R to be processed with the GGIR R-package. Then, processed data was exported to Stata 17.0 for analysis. All descriptive statistics and statistical tests was performed in Stata version 17.0. Before conducting the following tests, I examined and compared major demographic variables between student-athletes and non-athletes and noted significant differences, including sex assigned at birth, gender identity, self-identified race, school year, and age.

Self-Report Measures

I first examined how self-report measurements of physical activity differed between student-athletes and non-athletes, as well as between sports. Since these reports included aspects that are both strictly numerical (e.g., hours of exercise in the past week) and free response (e.g., what sports did you participate in and at what ages?), I summarized the data in multiple ways. For example, I calculated the mean number of hours spent exercising in the past week as it is a purely quantitative response. For the free response questions, I categorized their responses based on shared characteristics. For example, I grouped the "types" of physical activity participants reported into several shared categories to examine the rates at which they participated in them.

I then conducted a set of ordinary least-squares regressions to test if the values of the quantitative variables differ between groups. First, I tested for differences based on student-athlete status. Then, I conducted five multiple linear regressions with these measures as the dependent variable, student-athlete status as the predictor variable, and several demographic variables as covariates: self-reported gender identity, self-identified race, and age. The point of conducting these tests was to see whether the differences or similarities between student-athletes and non-athletes align with our expectations (e.g., were student-athletes more likely to engage with sports growing up?). Further, I also examined whether one group is more likely to report whether their activity the past week differed from their typical levels of activity during COVID and their pre-COVID activity levels using these same steps.

Objective Measures

Next, I examined how the objective measurements of physical activity differed between student-athletes and non-athletes as well as between sports. I first visually examined the distributions of my objective measures: time wearing the Actigraph, time spent in each intensity category, AvAcc, IG, average total sleep time, and sleep efficiency. Then, I conducted a set of ordinary least-squares regressions to test if the values for these objective measures differ between groups. First, I test if student-athlete status is associated with these measures (Model 1 in Table 2). Then, I conducted multiple linear regressions with these measures as the dependent variable, student-athlete status as the predictor variable, and several demographic variables as covariates: self-reported gender identity (Model 2), self-identified race (Model 3), and age (Model 4). The point of conducting these tests is to see whether the differences or similarities between student-athletes and non-athletes align with our expectations (e.g., were student-athletes recorded engaging in more MVPA than non-athletes?). Lastly, I examined bivariate correlations between all measures of physical activity (i.e., self-report measures and objective measures) to examine how self-report measures predict objectively assess activity and to compare different objective measures.

Results

Demographic Statistics

Descriptive statistics of key demographic variables are displayed in Table 1. Not all participants who completed the post survey portion of the study also completed the accelerometry portion of the study. In total, 122 participants completed the post survey portion of the study, 65 were NCAA student-athletes, and 57 were non-athletes. Out of these 122 participants, 110 were included in the analysis of accelerometry data: 60 of whom were NCAA student-athletes and 50 were non-athletes. 7 participants collected accelerometry data that were not included in this analysis due to not having enough days of accelerometry data that fit my criteria for valid days (i.e., they needed at least 4 days consisting of at least 16 hours of accelerometry data) – 4 were student-athletes and 3 were non-athletes.

Similar proportions of student-athletes and non-athletes reported being assigned female at birth in both the post surveys (student-athletes: 72% female; non-athletes: 79% female) and the Actigraph portion (student-athletes: 72% female; non-athletes: 76% female). Gender identity was also similar across groups (*Post surveys* - student-athletes: 71% female; non-athletes: 76% female; *Actigraph participants* - student-athletes: 70% female; non-athletes: 73% female). However, the student-athlete group consisted of a higher percentage of participants identifying as white (*Post surveys* - student-athletes: 82%; non-athletes 60%; *Actigraph participants* - student-athletes: 82%; non-athletes 62%).

Non-athletes reported more ongoing chronic health problems compared to student-athletes; these mainly consisted of mental health-related conditions (e.g., depression), asthma, and previous injuries (7 student-athletes reported chronic health problems whereas 15 non-athletes did; see Appendix 1: Chronic Health for a full list of responses). The student-athletes are comprised mostly from three sports: Track and Field (N=22), Swimming (N=23), and Rowing (N=10). The student-athletes in “Other” sports were from tennis, softball, volleyball, gymnastics, and soccer (N=5). For the Track and Field athletes, 20 were mid- to long-distance runners, 1 was a thrower, and 1 was a pole vaulter. All of these N’s refer to the student-athletes who are included in the accelerometry analyses.

Table 1. Descriptive statistics of key demographic variables for participants who completed the post surveys and the participants who completed the accelerometry portion of the study of the study

	Post Surveys						Actigraph Participants					
	Whole Sample		Non-Athletes		Student-Athletes		Whole Sample		Non-Athletes		Student-Athletes	
Variable	**N**		**N**		**N**		**N**		**N**		**N**	
Sample size	122		57		65		110		50		60	
General Characteristics	**Mean (SD)**		**Mean (SD)**		**Mean (SD)**		**Mean (SD)**		**Mean (SD)**		**Mean (SD)**	
Age (years)	21.3 (3.1)		21.7 (4.1)		21 (1.9)		21.4 (3.2)		21.9 (4.3)		21 (2)	
Height (cm - converted from inches)	170.6 (9.4)		167.4 (9)		173.4 (8.9)		170.9 (9.6)		167.4 (9.4)		173.9 (8.8)	
Weight (kg - converted from pounds)	65.9 (12.3)		64.2 (13)		67.4 (11.6)		66.6 (12.5)		65.2 (13.2)		67.8 (11.9)	
BMI	22.6 (3.3)		22.8 (3.7)		22.3 (2.8)		22.7 (3.3)		23.2 (3.8)		22.3 (2.9)	
Sex assigned at birth	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**
Female	92	75%	45	79%	47	72%	81	74%	38	76%	43	72%
Male	30	25%	12	21%	18	28%	29	26%	12	24%	17	28%
Intersex	.		.		.		.		.		.	
How would you describe yourself?	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**
Woman	86	74%	42	76%	44	71%	76	72%	36	73%	40	70%
Man	27	23%	10	18%	17	27%	26	25%	10	20%	16	28%
Transgender - trans femme	.		.		.		.		.		.	
Transgender - trans masc	.		.		.		.		.		.	
Genderqueer/non-conforming	3	3%	2	4%	1	2%	3	3%	2	4%	1	2%
Prefer not to say	.		.		.		.		.		.	
Other	1	1%	1	2%	.		1	1%	1	2%	.	
How do you typically identify your race?	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**
American Indian/Alaska Native	.		.		.		.		.		.	
Hispanic or Latinx	2	2%	2	4%	.		2	2%	2	4%		0%
East Asian	4	3%	1	2%	3	5%	3	3%	1	2%	2	4%
Southeast Asian	4	3%	2	4%	2	3%	4	4%	2	4%	2	4%
South Asian	3	3%	3	5%	.		2	2%	2	4%	.	
Native Hawaiian or Other Pacific Islander	.		.		.		.		.		.	
Middle Eastern or North African	1	1%	1	2%	.		.		.		.	
Black or African American	1	1%		0%	1	2%	1	1%	.		1	2%
White	84	72%	33	60%	51	82%	76	72%	29	62%	47	82%
Unknown	.		.		.		.		.		.	
Other	.		.		.		.		.		.	
Multiple	18	15%	13	24%	5	8%	18	17%	13	28%	5	9%
Health	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**
Ongoing chronic health problem?	22	18%	15	26%	7	11%	22	20%	15	30%	7	12%
Intramural Sports	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**
Do you participate in a recreational or intramural sports team or activity?	16	13%	9	16%	7	11%	15	14%	9	18%	6	10%
Intercollegiate Sports	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**
Track and Field	NA		NA		24	37%	NA		NA		22	37%
Swimming	NA		NA		26	40%	NA		NA		23	38%
Rowing	NA		NA		10	15%	NA		NA		10	17%
Other	NA		NA		5	8%	NA		NA		5	8%

Cells labeled "." indicate that no participants selected that response (e.g., no participants reported "Other" for their self-identified race).

Missing Data: Non-athletes: 1 participant did not report a gender identity, 1 participants did not report their self-identified race; Student-athletes: 3 participants did not report a gender identity, 3 participants did not report their self-identified race

Self-Report Measures

Descriptive statistics of self-report measures of physical activity are displayed in Table 2 and included data gathered in both the Prescreening Survey and the Post Survey. Both groups reported high rates of participation in organized sports (student-athletes: 98.41%; non-athletes: 85.96%) and non-organized sports/physical activities (student-athletes: 54.23%; non-athletes: 55.36%) while growing up. The student-athlete who did not participate in organized sports growing up was a distance runner who grew up in another country without “organized sports” like those in the United States. Student-athletes were more likely to report that they regularly exercise (100% vs 58.18%) and reported more hours of exercise in the past 7 days, in both the prescreening survey (student-athletes: 12.18 ± 6.3 hours; non-athletes: 4.87±3.45) and the post survey (student-athletes: 12.52 ± 6.83 hours; non-athletes: 4.28±3.88). Most participants reported that the amount of physical activity they engaged in the past week is typical of their activity levels throughout the pandemic (60% of the total sample). Conversely, approximately half of the participants reported that the amount of physical activity they engaged in the past week was less activity than they typically engaged in before the pandemic (49% of the total sample).

Student-athletes were more likely than non-athletes to report a combination of strength and cardiovascular-targeted physical activity (e.g., lifting weights and running) (77% vs. 24%). Most participants reported that the types of physical activity they engaged in the past week was similar compared to the rest of the pandemic (88%). A larger proportion of student-athletes reported engaging in similar types of physical activity in the past week compared to before the pandemic than non-athletes (72% vs. 44%, respectively). Lastly, student-athletes were more likely to report an intense workout in the past 48 hours before their post surveys (37% vs. 18%).

Table 2. Summary scores for each self-report measure and the OLS and logistic regression models testing for the effect of being a student-athlete (i.e., coded as “1”) compared to being a non-athlete (i.e., coded as “0”).

	Whole Sample		Non-Athletes		Student-Athletes		Group Comparisons			
Pre-Screening Survey							**Model 1**	**Model 2**	**Model 3**	**Model 4**
Childhood Physical Activity	**N**	**%**	**N**	**%**	**N**	**%**				
Did you participate in organized sports as a child and/or adolescent?	120	92.50%	57	85.96%	63	98.41%	10.12*	8.96*		8.11+
Did you participate in "not organized" sports or activities?	118	54.24%	56	55.36%	62	53.23%	-0.09	-0.28	-0.52	-0.18
Current Physical Activity	**N**	**Mean (SD)/%**	**N**	**Mean (SD)/%**	**N**	**Mean (SD)/%**				
Do you exercise regularly?	117	80.34%	55	58.18%	62	100.00%				
How many hours did you exercise or train in the past 7 days?	113	8.88 (6.35)	51	4.87 (3.45)	62	12.18 (6.3)	7.31**	7.28**	7.24**	7.51**
Do you participate in recreational or intramural team or activity?	120	13.33%	57	15.79%	63	11.11%	0.92	0.76	0.60	0.84
How many hours do you participate in a typical week on your intramural activity?	14	4.43 (4.82)	9	4.67 (5.98)	5	4 (1.87)	-0.05	-0.07	-0.08	-0.04
Post Survey	**N**	**Mean (SD)**	**N**	**Mean (SD)**	**N**	**Mean (SD)**				
How many hours did you exercise or train in the past 7 days?	122	8.67 (6.98)	57	4.28 (3.88)	65	12.52 (6.83)	8.24**	7.68**	7.70**	8.32**
More, less, similar since COVID? (# of respondents)	122	%	57	%	65	%				
* More	14	11.48%	7	12.28%	7	10.77%				
* Similar	73	59.84%	35	61.40%	38	58.46%				
* Less	35	28.69%	15	26.32%	20	30.77%				
More, less, similar to pre-COVID? (# of respondents)	122	%	57	%	65	%				
* More	21	17.21%	10	17.54%	11	16.92%				
* Similar	41	33.61%	17	29.82%	24	36.92%				
* Less	60	49.18%	30	52.63%	30	46.15%				
What types of exercise or training did you partake in? (# of respondents)	120	%	55	%	65	%				
* Strength and Cardio	63	52.50%	13	23.64%	50	76.92%				
* Cardio	34	28.33%	24	43.64%	10	15.38%				
* Strength	10	8.33%	6	10.91%	4	6.15%				
* Yoga, mobility, at-home workout	6	5.00%	6	10.91%	.	.				
* Daily Activities	7	5.83%	6	10.91%	1	1.54%				
Similar types of activity since COVID? (# of respondents)	120	%	55	%	65	%				
* Yes	105	87.50%	49	89.09%	56	86.15%				
* No	9	7.50%	5	9.09%	4	6.15%				
* Mixed	6	5.00%	1	1.82%	5	7.69%				
Similar types of activity since pre-COVID? (# of respondents)	120	%	55	%	65	%				
* Yes	71	59.17%	24	43.64%	47	72.31%				
* No	35	29.17%	23	41.82%	12	18.46%				
* Mixed	14	11.67%	8	14.55%	6	9.23%				
Did you have an intense workout in the past 48 hours? (yes)	34	28.33%	10	17.54%	24	36.92%	2.91*	2.91*	3.67*	2.59*

Cells labeled "." indicate that no participants selected that response (e.g., no student-athletes reported "Yoga" as a type of exercise that they partook in the past week).

Group Comparisons: Values are β coefficients for continuous outcomes (e.g., hours exercising) and Odds Ratios for categorical outcomes (e.g., intense workout in the past 48 hours, do you exercise regularly?). Model 1 includes no covariates; Model 2 adjusts for self-reported gender; Model 3 adjusts for self-identified race; Model 4 adjusts for age (Note: these covariates are not cumulative, each model has 1 covariate at most).

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Model errors in group comparisons for Table 2:

- Model 3 for "Did you participate in organized sports..." is empty. The Odds Ratio for student-athlete status cannot be estimated for this model because several combinations of student-athlete status and race predicted participation in organized sports perfectly, violating the assumptions of logistic regression (i.e., there is not enough diversity in self-identified race across my groups to calculate the Odds Ratio).
- Regression models for “Do you exercise regularly” are empty because student-athlete status perfectly predicts exercising regularly, violating the assumptions of logistic regression. A Fisher’s Exact test indicates that student-athletes are more likely to report exercising regularly (p=.00000000132).

Objective Measures

Descriptive statistics of objective measures of physical activity are in Table 3. Figure 1 shows a sample day of accelerometry data from a student-athlete participant. Both student-athletes and non-athletes recorded a similar number of valid days overall (i.e., days with 16+ hours of wear time) and valid days that occurred during the workweek (i.e., Monday – Friday; 5.58±0.95 for non-athletes and 5.45 ±1.35 for student-athletes; p-value>0.10 for all comparisons). Non-athletes, however, recorded more valid days that occurred on the weekend on average (i.e., Saturday and Sunday; 1.92±0.34 days for non-athletes; 1.7±0.65 days for student-athletes; p-value<0.05 for Models 1, 2, and 4). Unsurprisingly, student-athletes recorded substantially less time in sedentary behavior and more time in physical activity than non-athletes across all models (p-value<0.01). Specifically, student-athletes recorded more time in light physical activity and MVPA across all models (p<0.01). They also recorded higher AvAcc, indicating that they engaged in more *total activity*, in addition to higher IG, indicating that a larger proportion of their physical activity took place at higher intensities (p<0.001 for all models).

When separating objective measures by sport (Tables 4 and 5; Figure 2), swimmers and participants in "other" sports recorded less time in MVPA, lower AvAcc, and lower IG than student-athletes on Rowing and Track and Field teams (Table 4 and Figure 2 for descriptive analysis; Table 5 shows direct comparisons between Track and Field). This may be due to them removing their Actigraph for training, at least for swimmers. However, the self-reported hours of exercise and training for the past week for Swimming (9.41±7.08 hours) and Other (9.6±7.09 hours) are also lower compared to Track and Field (13.39±4.91 hours) and Rowing (19.75±4.28 hours; comparison not shown). Swimming and Other groups may have lower levels of objectively recorded physical activity because they engaged in less activity during the study period. Notably, the majority of both Swimming (19 of 23 participants; 82.6%) and Other (4 of 5 participants; 80%) athletes reported that their physical activity over the past week was less than their typical levels of activity before the COVID pandemic.

Intriguingly, rowers recorded a higher mean time spent in MVPA per day (approximately 33 minutes more) compared to Track and Field athletes ($\beta=33.05$; $p=0.006$; Figure 2; Table 5). However, their AvAcc and IG were lower, indicating lower overall activity and less time at higher levels of activity (Table 5; $p<0.001$ for both; Figure 3). Thus, while they recorded more time above the minimum threshold of acceleration for MVPA, they recorded less overall activity and less time at higher accelerations. Importantly, these relationships do not change when only runners are considered (Table 5), so they are likely not an artefact of including athletes in non-running events such as throwing or pole vaulting. See Figure 4 for example acceleration data (person-level summary and acceleration data for one full day) of a Rower and a Track and Field athlete. The purpose of this figure is to illustrate how individuals can record more time spent in MVPA while recording lower overall physical activity.

Table 3. Descriptive statistics for objective measures of physical activity and ordinary least squares regression models testing for the effect of being a student-athlete (i.e., student-athletes are coded as "1") compared to a non-athlete (i.e., coded as "0").

	Total	Non-Athletes	Student-Athletes	Group Comparisons			
Measure				**Model 1**	**Model 2**	**Model 3**	**Model 4**
Sample size (N participants)	110	50	60	110	106	106	105
Valid Wear Time	**Mean (SD)**	**Mean (SD)**	**Mean (SD)**				
Number of Valid Days	5.51 (1.18)	5.58 (0.95)	5.45 (1.35)	-0.13	-0.10	-0.03	-0.16
Number of Valid Weekdays	3.71 (0.89)	3.66 (0.82)	3.75 (0.95)	0.09	0.13	0.125	0.07
Number of Valid Weekend days	1.8 (0.54)	1.92 (0.34)	1.7 (0.65)	**-0.22****	**-0.23****	-0.16	**-0.23****
Intensity Categories (minutes/day)	**Mean (SD)**	**Mean (SD)**	**Mean (SD)**				
Sedentary Behavior (<35 m*g*)	677.9 (73.14)	697 (69.1)	661.99 (73.14)	**-35.01****	**-33.61****	**-30.45****	**-35.76****
Light Intensity (35 - 99.9 mg)	147.14 (34.72)	137.71 (34.35)	154.99 (33.31)	**17.28*****	**17.62****	**14.90****	**17.67*****
Moderate-to-Vigorous Intensity (>100 m*g*)	106.76 (39.9)	91.17 (33.94)	119.75 (40.09)	**28.58*****	**27.48*****	**24.82*****	**27.56*****
Advanced Measurements of Physical Activity	**Mean (SD)**	**Mean (SD)**	**Mean (SD)**				
Average Acceleration (AvAcc) in m*g*	48.6 (28.06)	36.31 (14.77)	58.84 (32.23)	**22.53*****	**21.58*****	**18.90*****	**23.60*****
Intensity Gradient (IG)	-2.42 (0.34)	-2.55 (0.23)	-2.31 (0.37)	**0.25*****	**0.22*****	**0.22*****	**0.25*****

Group Comparisons: Values are β coefficients; Model 1 includes no covariates; Model 2 adjusts for self-reported gender; Model 3 for adjusts for self-identified race; Model 4 adjusts for age. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

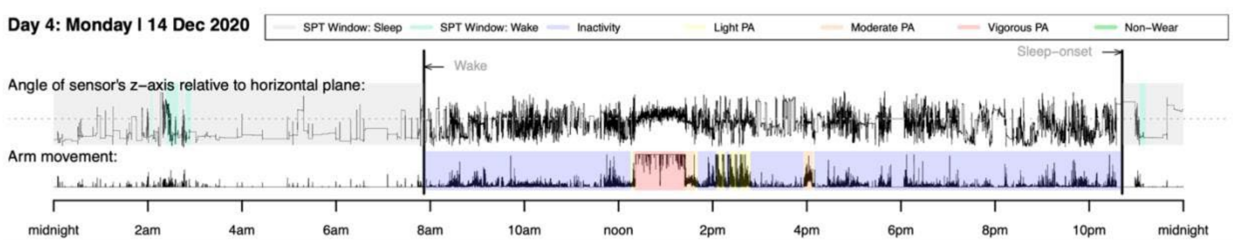


Figure 1. A sample day of acceleration data from a student-athlete in the study. This readout displays many of the recorded and calculated objective physical activity measures. For example, it shows a continuous graph of their recorded accelerations (i.e., "Arm movement"), how their acceleration is categorized into an intensity threshold (e.g., "Vigorous PA" is a pinkish color), and delineates when a participant is awake (i.e., from right before 8 am until shortly after 10 pm).

<u>Table 4.</u> Descriptive statistics for objective measures of physical activity separated by sports team

	All Sports		Track and Field		Swimming		Rowing		Other	
Measure										
Sample (N participants)	60		22		23		10		5	
Self-Reported Physical Activity	**Mean (SD)**		**Mean (SD)**		**Mean (SD)**		**Mean (SD)**		**Mean (SD)**	
How many hours did you exercise or train in the past 7 days?	12.61 (6.86)		13.39 (4.91)		9.41 (7.08)		19.75 (4.28)		9.6 (7.09)	
More, less, similar since COVID? (# of respondents)	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**
* More	6	10%	3	13.6%	2	8.7%	1	10%	0	0%
* Similar	36	60%	17	77.3%	8	34.8%	8	80%	3	60%
* Less	18	30%	2	9.1%	13	56.5%	1	10%	2	40%
More, less, similar to pre-COVID? (# of respondents)	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**
* More	10	17%	5	22.7%	1	4.3%	4	40%	0	0%
* Similar	23	38%	14	63.6%	3	13.0%	5	50%	1	20%
* Less	27	45%	3	13.6%	19	82.6%	1	10%	4	80%
Valid Wear Time	**Mean (SD)**		**Mean (SD)**		**Mean (SD)**		**Mean (SD)**		**Mean (SD)**	
Number of Valid Days	5.45 (1.35)		5.64 (0.9)		5.35 (1.75)		5.5 (0.97)		5 (1.73)	
Number of Valid Weekdays	3.75 (0.95)		3.91 (0.68)		3.7 (1.26)		3.7 (0.67)		3.4 (0.89)	
Number of Valid Weekend days	1.7 (0.65)		1.73 (0.63)		1.65 (0.71)		1.8 (0.42)		1.6 (0.89)	
Intensity Categories (minutes/day)	**Mean (SD)**		**Mean (SD)**		**Mean (SD)**		**Mean (SD)**		**Mean (SD)**	
Sedentary Behavior (<35 *mg*)	662.79 (72.8)		651.93 (72.55)		686.96 (51.97)		604.75 (79.26)		705.88 (86.91)	
Light Intensity (35 - 99.9 *mg*)	154.62 (33.16)		149.48 (36.03)		154.23 (33.56)		172.05 (26.37)		148.65 (29.06)	
Moderate-to-Vigorous Intensity (>100 *mg*)	119.34 (39.88)		132.31 (23.66)		92.07 (26.69)		165.36 (45.85)		100.54 (34.36)	
Advanced Measurements of Physical Activity	**Mean (SD)**		**Mean (SD)**		**Mean (SD)**		**Mean (SD)**		**Mean (SD)**	
Average Acceleration (AvAcc)	58.4 (32.14)		90.6 (31.08)		34.99 (7.5)		53.47 (11.66)		39.5 (16.67)	
Intensity Gradient (IG)	-2.31 (0.37)		-1.97 (0.32)		-2.53 (0.19)		-2.41 (0.27)		-2.55 (0.31)	

<u>Table 5.</u> Ordinary Least Square Regression models testing for the effect of specific sports on self-reported hours exercising and objective measures of physical activity from the past week (Track and Field is the reference group). **(A)** includes all Track and Field athletes. **(B)** includes only Track and Field athletes competing in running events.

(A)

	Hours exercise past week		Time in MVPA (minutes/day)		Average Acceleration (m*g*)		Intensity Gradient	
Sport	**β**	**SD**	**β**	**SD**	**β**	**SD**	**β**	**SD**
Track and Field (reference)	-	-	-	-	-	-	-	-
Swimming	-3.20+	1.71	-40.24**	9.01	-55.61**	6.16	-0.56**	0.08
Rowing	6.73**	2.28	33.05**	11.52	-37.13**	7.87	-0.44**	0.10
Other	-3.42	2.98	-31.77*	14.96	-51.11**	10.23	-0.58**	0.13
Adjusted R-squared	0.25		0.46		0.61		0.50	

+ p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001

(B)

	Hours exercise past week		Time in MVPA (minutes/day)		Average Acceleration (m*g*)		Intensity Gradient	
Sport	**β**	**SD**	**β**	**SD**	**β**	**SD**	**β**	**SD**
Track and Field (reference)	-	-	-	-	-	-	-	-
Swimming	-2.33	1.70	-41.82**	9.34	-60.10**	5.80	-0.58**	0.08
Rowing	7.59**	2.23	31.47*	11.52	-41.62**	7.34	-0.46**	0.10
Other	-2.56	2.90	-33.35*	15.28	-55.60**	9.47	-0.60**	0.14
Adjusted R-squared	0.27		0.47		0.68		0.51	

+ p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001

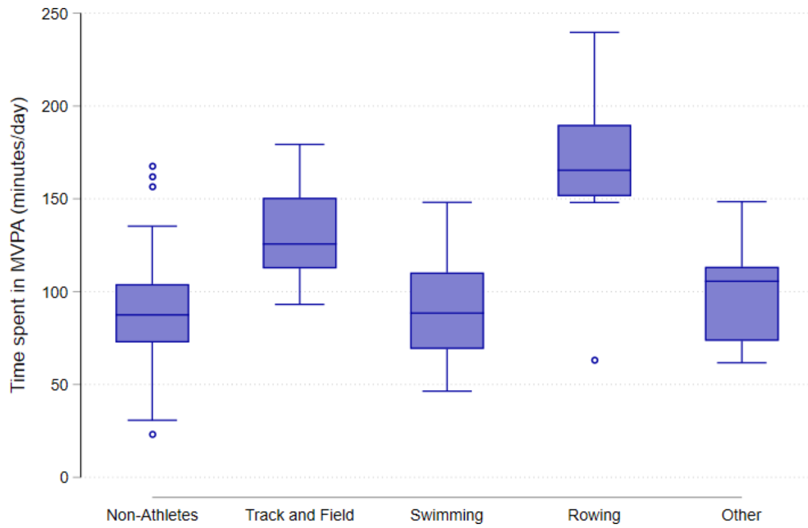
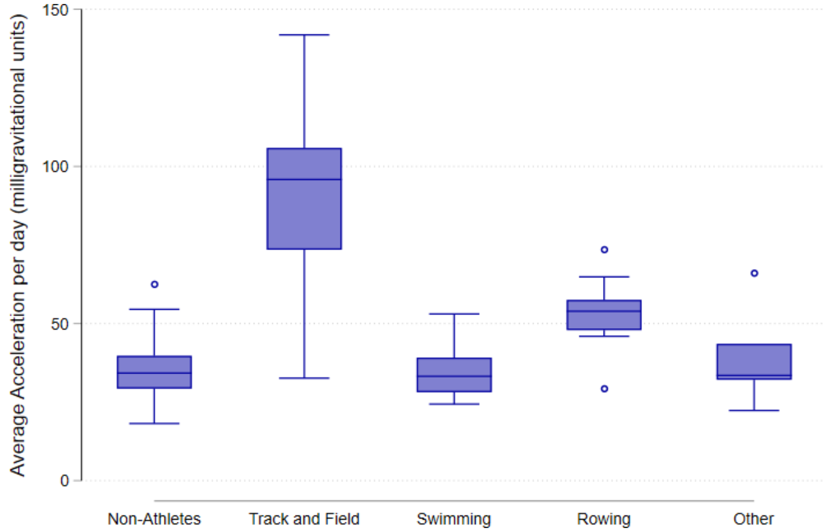
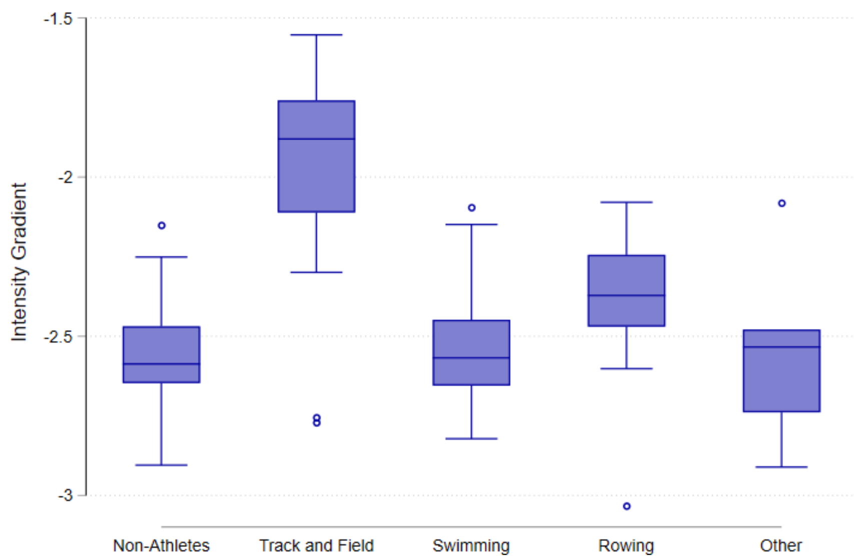


Figure 2. Box plots demonstrating time spent in Moderate-to-Vigorous Physical Activity (MVPA) per day across non-athletes and student-athletes, separated by sport. As a group, student-athletes recorded more time spent in MVPA. However, there is substantial variation across sports. Rowing recorded more time in MVPA than the other sports (see Table 5). Center lines are medians, boxes are 25th and 75th percentiles, the whiskers represent the range, and the circles are outliers.

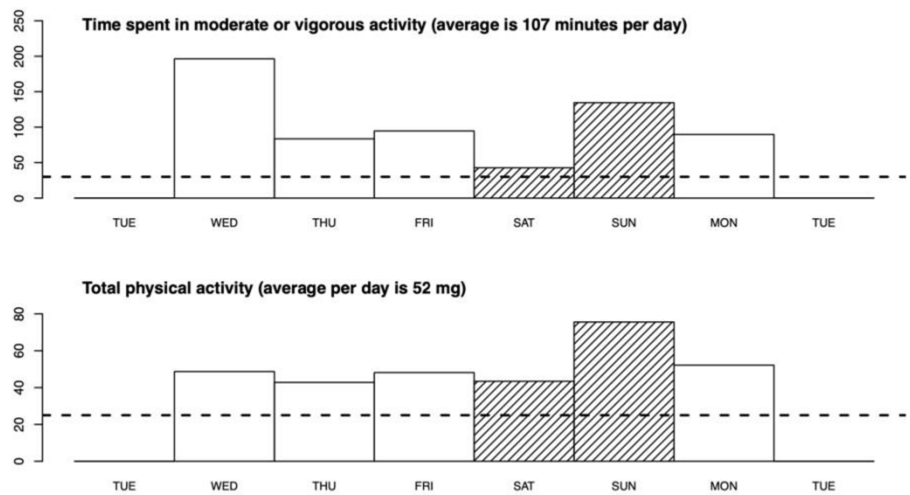


(A)

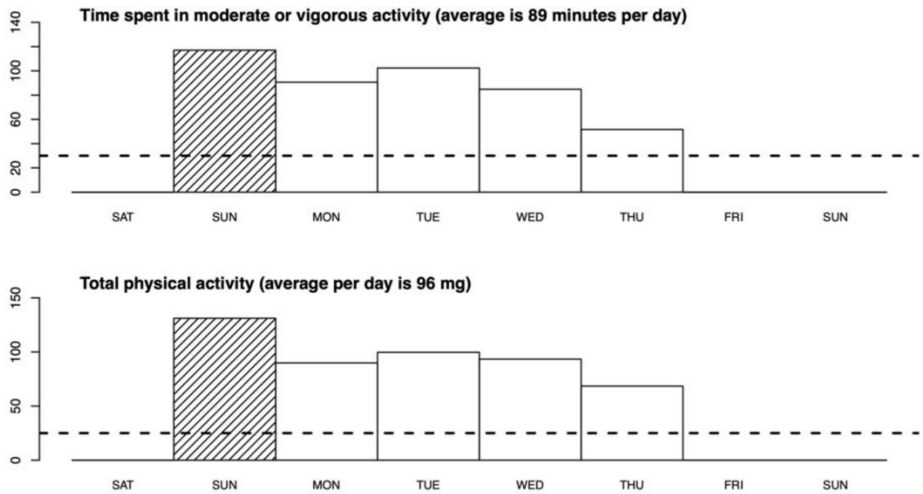


(B)

<u>Figure 3.</u> Box plots demonstrating **(A)** Average Acceleration (AvAcc; i.e., total physical activity) per day and **(B)** Intensity Gradients (IG; i.e., distribution of physical activity intensity) per day across non-athletes and student-athletes, separated by sport. As a group, student-athletes recorded higher AvAcc and IG than non-athletes (see Table 3), indicating higher total physical activity and more time spent at higher intensity levels of physical activity. However, there is substantial variation across sports. Track and Field recorded higher AvAcc and IG than all other sports (see Table 5). Center lines are medians, boxes are 25th and 75th percentiles, the whiskers represent the range, and the circles are outliers.

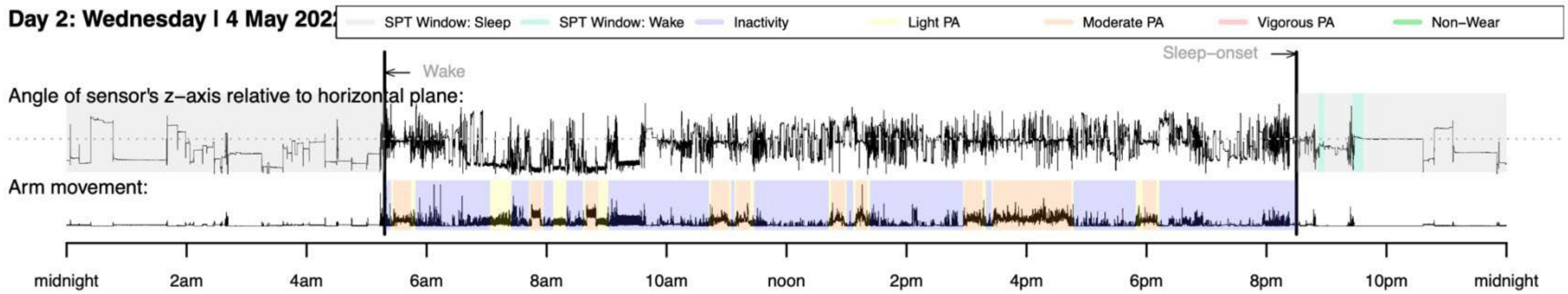


(A) Rower's summary data

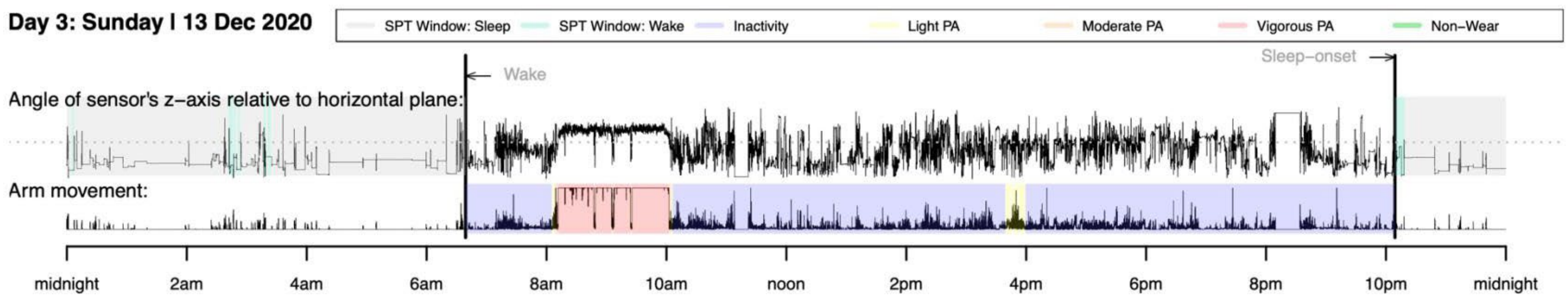


(B) Track and Field athlete's summary data

Figure 4. Summary plots demonstrating time spent in Moderate-to-Vigorous Physical Activity (MVPA) per day and average acceleration (AvAcc) per day for **(A)** a Rower and **(B)** a Track and Field athlete competing in mid- to long-distance running (Note: the y-axes are not equivalent because these are automatically adapted by the processing package to highlight within individual differences). You can see from these graphs that while the rower recorded more time in MVPA (107 minutes/day), they also recorded lower AvAcc (52m*g*) compared to the Track and Field athlete (89 minutes/day; 96m*g*). **(C)** is the daily graph of acceleration data for when the Rower recorded ~200 minutes in MVPA and an AvAcc of ~50 (i.e., "WED" in the Figure 4A). **(D)** is the daily graph of acceleration data for when the Track and Field athlete recorded less time spent in MVPA (~120 minutes) but higher AvAcc (~130 m*g*) compared to the Rower (i.e., "SUN" in Figure 4B). These plots demonstrate an example of how an athlete can record more time in MVPA but lower total physical activity via AvAcc.



(C) Rower's daily acceleration graph (note that the key overlapping the date is from original GGIR file)



(D) Track and Field athlete's daily acceleration graph

Correlations Between Measures

Most objective measures of physical activity were significantly correlated with each other (Table 6). Self-reported hours of exercise and training in the past week was associated with time spent in MVPA and IG, but not time spent in light intensity physical activity. This is likely because light intensity physical activity (as a category) includes most activities of daily living (e.g., chores, walking around the home, etc.) which are not included in the recall of exercise of training. Self-reported hours of exercise and training in the past week are also associated with AvAcc for the whole sample and non-athletes but not for student-athletes.

Table 6. Pairwise correlations between all quantitative physical activity measures (self-report and objective measures).

Whole Sample (n=110)

	Self-Report Measure	Intensity Categories			Advanced Measurements	
Measure	Hrs exercise in past week	Sedentary Behavior (<35 mg)	Light Intensity (35 - 99.9 mg)	Moderate-to-Vigorous Intensity (>100 mg)	Average Acceleration (AvAcc)	Intens ity Gradient (IG)
Self Report Measure						
Hrs exercise in past week	1	.	.	.	.	.
Intensity Categories						
Sedentary Behavior (<35 mg)	-0.3827*	1	.	.	.	.
Light Intensity (35 - 99.9 mg)	0.1227	-0.0514	1		.	.
Moderate-to-Vigorous Intensity (>100 mg)	0.5236*	-0.2165*	0.4829*	1	.	.
Advanced Measurements						
Average Acceleration (AvAcc)	0.3967*	-0.3924*	0.164	0.6318*	1	
Intensity Gradient (IG)	0.4820*	-0.3017*	0.0004	0.5474*	0.8662*	1

Student-Athletes (n=61)

	Self-Report Measure	Intensity Categories			Advanced Measurements	
Measure	Hrs exercise in past week	Sedentary Behavior (<35 mg)	Light Intensity (35 - 99.9 mg)	Moderate-to-Vigorous Intensity (>100 mg)	Average Acceleration (AvAcc)	Intensity Gradient (IG)
Self Report Measure						
Hrs exercise in past week	1	.	.	.	.	.
Intensity Categories						
Sedentary Behavior (<35 mg)	-0.3141*	1			.	.
Light Intensity (35 - 99.9 mg)	-0.1403	-0.3392*	1		.	.
Moderate-to-Vigorous Intensity (>100 mg)	0.4295*	-0.6175*	0.3463*	1	.	.
Advanced Measurements						
Average Acceleration (AvAcc)	0.1476	-0.4660*	0.0604	0.5724*	1	
Intensity Gradient (IG)	0.3231*	-0.3122*	-0.1705	0.4151*	0.8505*	1

Non-Athletes (n=49)

	Self-Report Measure	Intensity Categories			Advanced Measurements	
Measure	Hrs exercise in past week	Sedentary Behavior (<35 mg)	Light Intensity (35 - 99.9 mg)	Moderate-to-Vigorous Intensity (>100 mg)	Average Acceleration (AvAcc)	Intensity Gradient (IG)
Self Report Measure						
Hrs exercise in past week	1	.	.	.	.	.
Intensity Categories						
Sedentary Behavior (<35 mg)	-0.3241*	1		.	.	.
Light Intensity (35 - 99.9 mg)	0.1958	-0.4333*	1	.	.	.
Moderate-to-Vigorous Intensity (>100 mg)	0.4018*	-0.2304	0.3873*	1	.	.
Advanced Measurements						
Average Acceleration (AvAcc)	0.5448*	-0.3349*	0.2904*	0.7673*	1	
Intensity Gradient (IG)	0.4640*	-0.0917	-0.0158	0.5487*	0.7623*	1

Values are Pearson's R values; * $p < 0.05$

Discussion

To the best of my knowledge, this is the first study to compare daily physical activity levels across NCAA student-athletes in different sports and one of only two to compare NCAA student-athletes and non-athletes (Driller et al., 2017). Perhaps unsurprisingly, I found that student-athletes had both higher self-reported and higher objectively measured levels of physical activity when compared to non-athletes. I also found that student-athletes had lower levels of objectively measured sedentary behavior.

I utilized two strategies for operationalizing and comparing physical activity between groups from their accelerometry data. First, I calculated the amount of time each participant spent in different categories of physical activity intensity: sedentary behavior, light activity, and MVPA. Second, I calculated the AvAcc and IG for each participant, which provide an estimate of total physical activity and the distribution of physical activity across intensity levels, respectively. While these two methods led to congruent results between student-athletes and non-athletes (i.e., non-athletes were less active), they led to an interesting discrepancy in physical activity when separating student-athletes by sport. Specifically, Rowers recorded, on average, more time in MVPA when compared to Track and Field athletes (~33 minutes; $p=0.011$) but had lower AvAcc and IG, indicating lower overall activity and less time at higher levels of activity ($p=0.001$ for both). Thus, while they recorded more time above the minimum threshold of acceleration for MVPA, they recorded less overall activity and a smaller proportion of time at higher accelerations.

This difference may be due to the activity pattern required by each sport. Rowers engage in an incredibly energetically taxing activity while training and competing, but the acceleration of their movements is tightly controlled (see Worsey et al., 2019 for a detailed review of performance and movement tracking in rowers). Ultimately, the most important factor for performance in rowing is not quickly moving their body through space but maximizing the velocity of their team's boat through the water. When they are competing or training on the water, rowers need to match the pace of their oar strokes across multiple members of a boat (there are at least 4 rowers to a boat depending on their event). Further, their oars need sufficient time and surface area in contact with the water to continue to propel their boat forward, which will limit how quickly they move their hands and, thus, how quickly the attached accelerometer moves (Worsey et al., 2019).

Conversely, Track and Field athletes do not need to match the pace of their teammates nor is the speed of their arm swings limited by the kinetics of water. The most important factor for performance in Track and Field is accelerating their body through space more quickly than their competitors – particularly for runners. Thus, while consistency in movement is still important for runners, they are still aiming to maximize the speed of their body in space. This confluence of factors may mean that their accelerometers are more likely to experience higher accelerations during training and competition than those of the Rowers. Notably, the difference between Rowers and Track and Field athletes in all three metrics held when only runners were considered for Track and Field (Table 5). This example highlights how utilizing AvAcc and IG metrics can highlight important differences in activity patterns that would have been lost through simple categorization of physical activity. In the future, training logs could be used to document exactly when athletes are training or competing. This would allow researchers to directly examine how the accelerations in these two athletes compare during training and competitions. I can begin this process with my data in a future analysis by investigating periods of high acceleration across sports, but a training log would be important for comparing training and competition activity (e.g., if they are sprinting more in training).

Another takeaway from separating student-athletes by sport is that Swimmers recorded lower levels of physical activity compared to Track and Field and Rowing (p-value>0.001). This may be due to Swimmers removing their Actigraphs during training, leading to an under-estimation of their physical activity. However, it is difficult to tell if the lower accelerometry estimates in my study are solely from swimmers removing their Actigraphs for training or that their study participation overlapped with a period of lower-than-normal activity. Swimmers self-reported lower amounts of exercise and training compared to Track and Field (Table 5), so the lower objective measures of physical activity may be an accurate representation of their week of activity. One solution for future studies may be to keep a diary for swimmers where they report the times they remove their Actigraph for training. Then, researchers could develop an imputation procedure to account for the missing acceleration data. Unfortunately, I did not have such a log available while conducting these analyses. Since I only have data on when Actigraphs were removed and not why, it is unclear whether non-wear times are due to training or non-training activities.

Importantly, self-reported activity over the past week was significantly associated with all objective measures except time spent in light physical activity (Table 6) when looking at my whole sample. This is likely because light physical activity typically corresponds to activities of daily living (e.g., household chores) that individuals are likely not going to include when they are trying to recall “exercise” or sports training over the past week. It is critical to note, however, that this pattern changes when student-athletes and non-athletes are considered independently. Self-reported exercise time remains significantly associated with time spent in MVPA and IG but is not associated with AvAcc in student-athletes. That is, self-reported time spent exercising is not a significant predictor of a student-athlete's total physical activity for the week.

It could be crucial information for athletic trainers, coaches, and sports medicine staff if athletes' self-reported training times do not accurately reflect the actual training loads their bodies have experienced. Basing training decisions on self-report or recorded training times could thus lead to inappropriate rest times and training loads, predisposing athletes to overtraining syndrome or, conversely, not training enough to improve performance. The idea to use accelerometers (or even Actigraphs) to measure training load is not new to athletic training or sports medicine (Gómez-Carmona et al., 2020), but previous investigations have largely focused on categorical assessments of activity, highly advanced mathematical models, and highly specific placing that will not be reliably worn throughout the day by athletes. While Actigraphs appear bulky, the presence of a watch-like device is easily accommodated by athletes (many choose to track their activity like this already) and a measure like AvAcc is easily computed and would require comparatively little mathematical understanding for trainers to implement as a diagnostic or training tool. In follow-up work, I will investigate whether there is a consistent bias between self-report and total activity for student-athletes (i.e., reporting too much activity or reporting too little activity) or if this result is simply due to noise in the self-report. Future work could investigate whether AvAcc and other, newer accelerometry-based metrics could be used to improve training and health outcomes for athletes. With new developments in open-source software and literature showing high comparability between triaxial accelerometers (Migueles et al., 2022), this could be a practical and accessible sports medicine tool.

Regarding developmental physical activity, both groups reported high levels of engagement in organized sports in childhood and similar rates of engagement in “not organized” sports and activities during their youth. For this analysis, I grouped individuals into binary categories of whether they did or did not engage in these activities. Importantly, the amount of time and physical effort an athlete has put into youth sports may be drastically different even if they report similar rates of participation. For example, only a small percentage of high school varsity runners continue to compete at the college level in the US (2.1-2.7%; Estimated Probability of Competing in College Athletics - NCAA.Org). To earn a spot on an NCAA team requires more intense training: more training hours total alongside more years participating (Buckley et al., 2017; Feeley et al., 2016). Future work with this dataset will be able to extract more information on the qualitative differences in their training (i.e., ages of participation, qualitative interviews), but this was outside of the scope for this analysis.

Lastly, the COVID pandemic has impacted access to physical activity through the closures of gyms, pools, and many public spaces (Hasson et al., 2021). Student-athletes likely retained more regular access to training facilities and competitions through the NCAA’s use of intensive COVID testing programs (i.e., daily PCR and rapid testing before entering Athletics Facilities), competition “bubbles”, and small group training and practices (Schultz et al., 2022). This may have contributed to non-athletes being more likely to report that the types of activity they engaged in the past week differed from before the COVID pandemic. Many non-athletes reported having to change their physical activity types (i.e., less swimming) because the corresponding facilities were closed. However, student-athletes and non-athletes reported similar changes in the amount of physical activity they engage in. Specifically, about half of the participants in each group reported that they engaged in less physical activity the past week compared to their typical levels of activity pre-pandemic. Thus, although student-athletes likely had more access to their *preferred* types of physical activity, both groups reported changes in physical activity levels. An important next step on this topic will be to explore how these responses changed throughout the COVID pandemic (e.g., were non-athletes less likely to engage in "similar" levels as pre-pandemic when social-distancing restrictions were stronger?). Future analyses with this data will focus more specifically on the impacts of COVID-19 restrictions and these answers.

Future Research

This paper combines self-report and objective measures of physical activity to create a detailed description and comparison of physical activity between student-athletes and non-athletes. Future work with this dataset will entail an even more detailed analysis of their self-reported activity in youth (e.g., ages they engaged in organized sports and which sports), creating new metrics of physical activity (e.g., metrics of changes in acceleration), exploring some incidental findings in this dataset (e.g., why non-athletes recorded more acceleration day over the weekends than student-athletes), and incorporating a survey that more specifically interrogates how COVID impacted participants' day-to-day lives (this was collected in the post surveys). The discordance between the categorization approach (i.e., time spent in MVPA) and AvAcc/IG approach to operationalizing activity data presents many opportunities for interesting research projects. Almost all the current physical activity research and our understandings of physical activity's impacts on biology and health is built on the categorization of physical activity into MVPA, light intensity, and sedentary behavior (and similar such categories). The greater information provided by newer metrics of AvAcc and IG may allow us to uncover more nuanced understandings of physical activity and our biology. Moving forward, I will be designing analyses to test associations between these newer measures of activity and biomarkers in this dataset as well as investigating associations in other existing datasets and future research project.

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<u>Paper 3:</u> Does Physical activity moderate the association between psychosocial stress and telomere length in young adults?

<u>Outline:</u>

<u>Introduction</u>

Human survival and reproductive fitness rely upon navigating complex social environments and networks. We gain most, if not all, of our resources and energy through our connections to others (Bogin et al., 2014; Boyd et al., 2011; Kramer & Ellison, 2010). Strained, abusive, and lost relationships represent threats to our resources and, by extension, our reproductive fitness. Accordingly, increased exposure to psychosocial stress (e.g., childhood maltreatment, systemic racism) has repeatedly been associated with increased morbidity and mortality (Arnow, 2004; Bateson et al., 2004; Felitti et al., 1998; Hayward & Gorman, 2004; Smith & Christakis, 2008). Exposure to psychosocial stress increases the risk of cardiovascular disease (Non et al., 2014), mental illness diagnosis (Masten and Cicchetti, 2010), early mortality (Hayward and Gorman, 2004), and a range of chronic and age-related diseases (Smith et al., 1998; Danese and McEwen, 2012). Further, psychosocial stress is implicated in the etiology of racial and socioeconomic health disparities as well as the growing burden of chronic disease worldwide (Raffington et al., 2021; Shalev et al., 2013; Thayer & Kuzawa, 2011). It is becoming increasingly clear that this relationship exists, and is enabled, at least in part, by a biological component – our psychosocial experiences lead to long-lasting changes in our biology that impact our wellbeing and health.

While acute physiological responses to stress are adaptive, extreme and repeated exposure to psychosocial stress is associated with elevated inflammation, reduced adaptive immunity, and accelerated biological aging as measured by telomere length (TL) attrition and epigenetic aging (Segerstrom and Miller, 2004; Epel et al., 2004; Snyder-Mackler et al., 2020). These changes may occur through the repetitive over-activation of these physiological systems, damaging negative feedback mechanisms such that they are unable to return to or maintain a functional baseline (Danese & McEwen, 2012). Alternatively, these changes may be part of an evolutionarily adaptive response to calibrate our biology to a predicted future environment (Del Giudice et al., 2011). In the evolutionary past, these physiological shifts (e.g., elevated inflammation) may have enabled individuals to respond to psychosocial challenges in their environment in a way that improved their reproductive fitness. Regardless of the specific mechanism and evolutionary adaptiveness, these profiles are associated with increased morbidity and mortality throughout the lifespan in contemporary populations.

Research over the past two decades suggests that TL attrition is a particularly impactful pathway through which our environments and experiences interact with our long-term health. Telomeres are DNA sequences that protect the ends of chromosomes and shorten with cell replication, age, and oxidative stress. Their shortening can precipitate cellular senescence or apoptosis, leading to functional decline with age, linking shorter TL with worsened health outcomes (Aviv et al., 2008; Hamad et al., 2016). Individuals with increased exposure to infectious disease have shorter TL (Eisenberg et al., 2017; Zanet et al., 2014), and, conversely, individuals with shorter TL appear to be more susceptible to infections (S. Cohen et al., 2013). Lastly, individuals with shorter TL, after adjusting for age, have shorter life expectancies (Cawthon et al., 2003; Ehrlenbach et al., 2009; Wang et al., 2018). TL is often used as a proxy for cumulative inflammatory and innate immune activation over an individual's lifetime as well as a mark of current and future immunological functioning. In their fundamental work on the topic, Lopez-Otin and colleagues (2013) included TL attrition as one of their Hallmarks of Aging.

Recently, researchers have posited that individuals reporting increased exposure to psychosocial stress have shorter TL when compared to individuals of similar age. For example, exposures such as higher levels of perceived stress (Epel et al., 2004), major depressive disorder (MDD) (Ridout et al., 2016a), and lower socioeconomic status (SES) (Robertson et al., 2013) have each been associated with shorter TL. Psychosocial stress is thought to accelerate TL shortening through several non-exclusive pathways, including increasing systemic and cumulative oxidative stress, increasing susceptibility to infection, and reducing telomerase activity in the blood (Choi et al., 2008; Irie et al., 2003, 2001; Kawanishi and Oikawa, 2004; Oikawa and Kawanishi, 1999; Von Zglinicki, 2002). These processes are posited to accumulate to TL shortening over time such that longer lasting and more extreme disruptions to these systems are associated with noticeable changes in TL.

This accumulation may explain, in part, why meta-analyses of adulthood psychosocial stress and TL have only found a weak, negative association with considerable heterogeneity across studies (Mathur et al., 2016; Schutte & Malouff, 2015). Environments in childhood may be more likely to impact TL, particularly up until early adulthood. Telomeres shorten most quickly in early life and childhood (Frenck et al., 1998; Zeichner et al., 1999), so a relatively short-lasting exposure that accelerates the already hastened pace of attrition may lead to much larger and longer lasting differences between individuals. Patterns of TL shortening in mid- to late-adulthood is largely slow and consistent in comparison, so accelerations of this pace leave less of an impact. Further, external conditions have long-lasting impacts on many aspects of health and biology, so it is even likely that early life psychosocial stress may have larger associations with TL through its outsized impacts on other systems (Hayward & Gorman, 2004). At least one specialist meta-analysis has demonstrated a substantial association of childhood psychosocial stress (Ridout et al., 2017). However, investigations focusing on associations between early life psychosocial stress and adult TL are also inconsistent (Bürgin et al., 2019; Glass et al., 2010; Jodczyk et al., 2014; Oliveira et al., 2017; Price et al., 2013).

In this paper, I propose that variation in physical activity contributes to this heterogeneity. Specifically, I hypothesized that physical activity is associated with longer TL and, further, that physical activity moderates the relationship between psychosocial stress experienced in childhood and TL in a sample of NCAA student-athletes and university students not competing on an NCAA team. Despite eliciting short-term physiological responses that are almost identical to psychosocial stress (reviewed below), physical activity is associated with longer TL and positive long-term health outcomes like longer life expectancy, reduced risk of infection, and improved cardiovascular health. Investigating how physical activity and psychosocial stress interact to impact TL will provide insight into how psychosocial stress may have impacted our biology throughout evolution and broaden our understanding of how industrialized and sedentary environments impact our health.

The Human Evolutionary Biology of Psychosocial Stress, Physical Activity, and Telomere Length

Psychosocial stress was inextricably tied to physical activity throughout human evolution. In the past, stressors typically elicited both a psychological response (e.g., increased perceived stress, vigilance) and a physically active response (e.g., 'fight-or-flight'). Further, when psychological responses were not coincident with physical responses, they nonetheless occurred within a highly active lifestyle compared to most contemporary industrialized contexts (Nesse et al., 2016). Large populations of humans have only recently begun transitioning into more sedentary lifestyles, uncoupling psychosocial stress from acute and habitual physical activity (Antón et al., 2002; Neel, 1962).

Accordingly, our reactions to psychosocial stress and physical activity utilize similar behaviors and physiological systems. Immediately, our central nervous system is activated, leading to a cascade of electrical and chemical messengers (e.g., epinephrine) to coordinate a suite of cognitive, behavioral, and energetic responses. In the following minutes, hormonal and inflammatory responses mobilize energy for a prolonged response to the challenge and to scaffold recovery from it (e.g., Interleukin-6, Cortisol). Finally, we see longer term changes in inflammation and immunity that can last for over 24 hours (e.g., C-reactive protein). These immunological responses are thought to help with wound healing, muscle repair, and fighting immediate infectious challenges. The mobilization of these systems enable near-immediate responses to stressors and, importantly, support the longer-term processes needed to recover from them (del Giudice & Gangestad, 2018; Dhabhar, 2009; Flinn et al., 2011; Hermans et al., 2014; Nesse et al., 2016; Pedersen & Febbraio, 2012; Segerstrom, 2010).

Despite this overlap in acute responses, psychosocial stress and physical activity incur very different long-term effects on our biology and, more specifically, on our TL. As mentioned above, increased exposure to psychosocial stress is associated with chronically elevated inflammation and innate immune system activation (Segerstrom & Miller, 2004). There is further evidence that experiencing an early life adversity, such as low SES, is associated with increased inflammation in adulthood regardless of current stress levels (Miller et al., 2009). These elevated immune responses increase mitotic proliferation of white blood cells, oxidative stress, and susceptibility to infection. These processes, in turn, are believed to accelerate TL shortening and hasten the rate of functional decline in proliferation dependent processes (Choi et al., 2008; Eisenberg et al., 2017; Epel et al., 2004; Oikawa & Kawanishi, 1999; Osler et al., 2016; von Zglinicki, 2002). Researchers have, therefore, hypothesized that these pathways explain the broader negative associations between TL and psychosocial stress (Epel et al., 2004; Kawanishi & Oikawa, 2004; Manoliu et al., 2018; Osler et al., 2016).

Conversely, regular, habitual physical activity is associated with the improved clearance of oxidative species, reduced basal inflammation, and increased responsiveness to immunological and energetic challenges (Chow et al., 2022; Hamer et al., 2012; Lee et al., 2012; Sardeli et al., 2018). These phenotypes protective against TL attrition and likely underlie the common finding that TL is longer in physically active individuals (Abrahin et al., 2019; Edwards & Loprinzi, 2017; Ogawa et al., 2017; Tucker, 2017). Further, increased physical activity may directly attenuate the degree to which psychosocial stress affects chronic inflammation and innate immune activity (Blevins et al., 2017; Kohut et al., 2006; Silverman & Deuster, 2014). Kohut et al. (2006) found that an exercise intervention reduced the association between stress symptoms and inflammation. Additionally, Blevins et al. (2017) reported that individuals with high levels of physical activity and high perceived stress had lower levels of inflammation than those with low levels of physical activity and high perceived stress.

Through the attenuation of psychosocial stress-immune associations and protective influence on the immune system, physical activity might also weaken the broader association between psychosocial stress and TL (Puterman et al., 2010, 2015). In 2010, Puterman and colleagues found that post-menopausal women who met the Center for Disease Control's recommended activity levels did not exhibit associations between perceived stress and TL. However, individuals who did not reach these recommendations had shorter TL with increased perceived stress. Subsequently, in 2015, Puterman et al. also found that post-menopausal women who reported higher levels of physical activity showed no association between psychosocial stress and TL attrition over one year. Those women reporting low activity levels showed increased TL shortening with higher psychosocial stress.

It is important to note, however, that these studies suffer from several limitations. First, higher levels of perceived stress predict lower levels of physical activity and vice versa (Stults-Kolehmainen & Sinha, 2014). For example, while Puterman et al. (2010) found that active individuals did not demonstrate associations between perceived stress and TL, they also found that their more active participants reported significantly lower levels of perceived stress. Second, external stressors, such as low SES, are associated with reduced access to regular exercise and active leisure activities (Kondo et al., 2018). These studies do not interrogate how this may bias their outcomes or limit their statistical power to detect effects (e.g. because of less variation in stress in more physically active individuals). Third, these papers only utilized self-report measures of physical activity, which often show low concordance with objectively measured physical activity (Adamo et al., 2009; Prince et al., 2008). Thus, it's unclear whether these differences in TL associations are attributable to differences in physical activity, lower psychosocial stress, or a broader confounding variable.

Given the evolutionary ties between psychosocial stress and physical activity, better understanding their combined effects on TL will improve our ability to interpret psychosocial effects in modern humans and apply these interpretations to the evolutionary past. For example, previous work in ecological immunology has demonstrated that increased microbial exposure in early life may weaken the associations between psychosocial stress and immunological outcomes such as elevated inflammation (Harbuz et al., 2002; McDade et al., 2013; Yazawa et al., 2015). When our immune system faces challenges that require opposing long-term responses (i.e., increased vs reduced inflammation), it must balance the costs and benefits of accommodating one over the other (Georgiev et al., 2016). These findings imply that throughout our deeper evolutionary past where microbial challenges were omnipresent, psychosocial stress-immune associations may have been weaker or that a qualitatively different threshold was needed for psychosocial stress to leave distinct marks on our immune systems.

Successfully engaging in and sustaining physical activity is fundamental to addressing many of the most basic demands of evolutionary fitness, including gathering food, finding mates, rearing offspring, and fighting or fleeing predators. Thus, physical activity may represent an immunological challenge that similarly supersedes and limits our responses to psychosocial stress and its long-term adverse effects on our immune systems. In other words, the adverse effects of psychosocial stress may be exaggerated in sedentary environments due to the lack of competing pressures from physical activity on our immune system. Ultimately, establishing a more controlled test of the question: "Does physical activity moderate the associations between psychosocial stress and TL?" will help us begin to address this idea and better understand the role of psychosocial stress in more active contexts, including our evolutionary past.

Current Study

This paper examines whether higher physical activity levels predict weaker associations between childhood psychosocial stress exposure and capillary blood TL in adulthood. I investigated this question in a sample of NCAA student-athletes and their non-athlete counterparts in the general student population who do not compete on an NCAA team. Working with these populations offers a unique solution to many of the limitations of the existing literature. Collegiate student-athletes competing on NCAA Division-1 teams are obligated to maintain moderate to high levels of physical training year-round regardless of psychosocial stress (NCAA, 2013). Further, they maintained high levels of physical activity throughout childhood and adolescence to reach their current competitive niche. Importantly, NCAA student-athletes report similar levels of childhood psychosocial stress compared to non-athletes (Paper 1). Thus, examining this question with student-athletes and non-athletes allows me to better isolate how variation in physical activity impacts psychosocial stress-TL associations.

Specifically, I tested three hypotheses related to my research question. First, I hypothesized that individuals with higher exposure to psychosocial stress throughout childhood would have shorter TL. Second, I hypothesized that higher physical activity, proxied by student-athlete status combined with objectively measured physical activity, would predict longer TL. Lastly, I hypothesized that individuals with higher physical activity levels would show a weaker association between psychosocial stress exposure and TL when compared to their peers with lower levels of physical activity.

Methods

COVID-19

University of Washington's (UW) Human Subjects approved my project in February 2020 (IRB ID: STUDY00009691); it was initially designed to take place in person, focusing on student-athletes and non-athletes at UW. During the subsequent COVID-19 pandemic, however, I had to redesign my project to collect data within the shifting local and global guidelines for social distancing and research practices. As a result, my team and I collected much of the data remotely through online surveys, online video calls, and participant self-collection as described in "Study Protocol."

Participants

My project recruited intercollegiate student-athletes (Division-I and Division-III) from multiple schools throughout the US and students from these same schools who were not competing on an NCAA team. About half of the participants in the current sample are members of an NCAA intercollegiate team (N=52), and half are students who do not compete on an NCAA intercollegiate team (N=50).

Student-Athletes

My team recruited NCAA Division-I and Division-III student-athletes through three main strategies. First, we sent recruitment emails to the teams through a coach or team leader with the head coach's approval. Second, we provided recruitment materials to athletic trainers, who distributed them to their teams. Third, we sent recruitment materials to UW's Student-Athlete Academic Services, who distributed the materials among their student-athletes. My final sample includes student-athletes in Track and Field, Women's Rowing, Swimming, and multiple other teams (sample N's are listed in Results). The research team explicitly sought and gained clearance from the respective heads of research and compliance officers for each Athletics Department before recruitment.

General Student Population

Non-athletes were recruited through undergraduate anthropology and biology courses across several undergraduate universities. Research team members approached a course instructor and asked permission to share recruitment materials for the study. Then, depending on the teaching modality of the course, a research team member gave a short introduction to the study and how to join over Zoom or in person. There was no verbal or "live" introduction to the study on some occasions. For these situations, instructors forwarded study information and recruitment materials directly to their course without a recruitment pitch given by a research team member.

Study Protocol

All participants were directed to an online link to complete the prescreening survey and consent form. Following this, we introduced them to the data collection protocol. To increase accessibility and participant comfort levels, and to accommodate shifting social distancing guidelines, I developed two protocols for data collection: a "Remote Data Collection" and a "Hybrid Data Collection" protocol. For either collection protocol, participants completed a prescreening survey, a series of post-study surveys, psychometric assessments, and dried blood spot (DBS) collection. Participants also had the option to wear an accelerometer to collect objective measurements of their physical activity. A small subset of participants was invited to take part in semi-structured interviews. All participants received an online gift card for completing the study and will receive part of their study data once my analysis is complete.

Prescreening

Interested individuals were directed to a confidential online screening questionnaire on REDCap where they consented to the study and provided demographic information (e.g., gender identity, racialized group identity, height, weight, age), basic information about their health (e.g., ongoing health issues), and typical levels of physical activity. They were also asked to provide information about their participation in organized and non-organized sports throughout their childhood and adolescence, their enrollment status, student-athlete status, and whether they participate in intramural activities. The research team then reached out via email, phone call, or text message (according to participant preference) to schedule their participation in the study. I included all participants at this stage if they were enrolled as an undergraduate at an NCAA member institution and were not currently experiencing COVID-19 symptoms or other acute illnesses.

Remote Data Collection

For the remote protocol, all data collection occurred remotely or with minimal (~5 minutes) in-person contact between the research team and a participant. After recruitment and initial consent, the research team either shipped participants a study kit with all the materials to complete data collection at home or scheduled a time for the participant to pick up and return the study kit to a socially-distanced campus collection site.

Participants collected finger-prick DBS with a Hemaspot HF device (Spot On Sciences) according to written and video instructions on how and when to collect samples. Participants who chose to participate in the accelerometry portion of the protocol wore an accelerometer (Actigraph wGT3X-BT) for ~7 days before collecting finger-prick DBS. After DBS collection, participants returned their study kit with their sample on ice according to instructions from the research team with a prepaid shipping label. Lastly, the participants completed a series of online surveys on overall health, sports activity, detailed demographics, experiences with COVID-19, and psychosocial stress exposure.

Hybrid Data Collection

The hybrid protocol was developed as COVID-19 restrictions began to ease in Fall 2021 to offer more flexibility for participants and was approved by UW Human Subjects. Many participants chose to delay or withdraw their participation because they preferred a research team member to collect their finger-prick DBS. For this procedure, participants had one or two short appointments (~15 minutes) with the research team, depending on whether they opted to join the accelerometry portion of the study. In the first appointment, the participant was introduced to the study and asked to wear an accelerometer on their non-dominant wrist for approximately seven days. The second appointment was scheduled for at least seven days after the first. During this appointment, I collected the accelerometer and finger-prick blood in Hemaspot HF devices (Spot On Sciences). They were then asked to complete all psychometric surveys within the next 24 hours from their personal computers. If the participant opted out of the accelerometry portion of the study, they completed the finger-prick DBS collection and introduction to the online stress surveys in a single appointment. All appointments took place in the UW Biodemography Laboratory.

Psychometric assessments

Psychosocial stress is an umbrella term that includes perceived stress, stressors, and mental health diagnoses. *Perceived stress* is the individual's subjective experience of strain, negative emotions, and psychological distress (Selye, 1956), while *stressors* are potential stimuli of perceived stress exogenous to the individual (Nesse et al., 2016). *Mental health diagnoses* combine subjective experiences, cognitive and physiological symptoms interfering with daily life, and socially constructed categories of unacceptable psychological-emotional traits (Kleinman, 2008). Each of these three factors is associated with immune function (e.g., Ridout et al., 2016; Yang et al., 2018). Here, I am utilizing a survey that assesses both perceived stress and external stressors experienced throughout development: The Childhood Trauma Questionnaire – Short Form (CTQ-SF; Bernstein & Fink, 1998). The CTQ-SF is well-validated and has been associated with TL in multiple previous studies (Ridout et al., 2017). Importantly, I have previously compared my two study groups (student-athletes and non-athletes) and found that it appears to assess childhood psychosocial stress comparably across both groups (See Paper 1 for more details). Specifically, I used the total score on the CTQ-SF to assess associations with TL in this analysis.

Physical Activity Measurement

Physical activity was assessed through objective monitoring via Actigraph wGT3X-BT worn on the non-dominant wrist. Sampling frequency was set at 90Hz with the default filter. Epoch lengths were set at 1-second to optimize the capture of short bouts of activity (Migueles et al, 2017). Data was exported from the Actilife software to the GGIR R-package which was used to calculate Average Acceleration (AvAcc), and the intensity gradient (IG) of their activity. Student-athlete status is also used as a proxy measure of physical activity.

Telomere Length

Specimen Storage

All DBS were collected as described above. In the remote data collection, participants were instructed to collect their capillary DBS on their Hemaspot HF device, let the sample dry for 5-10 minutes, and then keep their Hemaspot HF device in their freezer until returning the sample to the research team. Samples were then returned in an insulated package with a refreezable cold pack either through socially distanced drop off or via UPS Shipping. Hemaspot HF devices were then stored at -80 degrees Celsius until DNA extraction. In the hybrid collection, Hemaspot HF devices were allowed to dry at least 5-10 minutes before being stored at -80 degrees Celsius until DNA extraction. After DNA extraction, all samples underwent two freeze-thaws: first, to create single-use aliquots and second, for TL assessment via qPCR.

DNA Extraction

DNA was extracted from Hemaspot HF devices (Spot On Sciences) using a modified version of Qiagen's protocol for "Isolation of total DNA from FTA and Guthrie cards" using the QIAamp DNA Investigator Kit from Qiagen (Rej et al., 2021). The modifications from Rej et al. were applied to the January 2022 version of the QIAamp

DNA Investigator Handbook downloaded June 1, 2022 from: https://www.qiagen.com/us/products/human-id-and-forensics/investigator-solutions/qiaamp-dna-investigator-kit/. To modify this protocol for the Hemaspot HF, I removed one blade from the Hemaspot HF collection paper. This provides ~9 uL of blood which is approximately equivalent to six 3 mm hole punches from the Whatman 903 card as described in Rej et al (2021). If the Hemaspot HF lacked a fully saturated blade, I removed the unsaturated portion and conducted the extraction with as many partial blades necessary to total the equivalent blood volume of one full blade. A summary of lab notes and detailed list of further modifications for extraction from Hemaspot HF will be posted on Open Science Frameworks after submission of this dissertation.

In total, 129 Hemaspot HF devices were collected as part of the study. 17 of which were excluded from extraction due to insufficient sample (i.e., not enough blood for the equivalent of a full blade, ~9 uL). One was excluded due to mishandling during a step of the extraction process. The remaining 111 Hemaspot HF devices were all successfully extracted from. The DNA yields from these extractions were quantified by spectrophotometry using a NanoDrop Spectrophotometer (ThermoScientific) and demonstrated comparable yields to previous work performed in our lab extracting DNA from Whatman 903 cards.

Telomere Length Measurement

I analyzed TL in the DNA extracted from these samples using a modified version of the monochrome multiplex quantitative polymerase chain reaction (MMQPCR) assay described previously (Cawthon, 2009; Eisenberg et al., 2012, 2015). Specifically, I assayed relative TL on a CFX 384 real-time PCR detection system (Bio-Rad, Hercules, CA) using the cycling profile of Eisenberg et al., (2012) and the primer pairs reported by Tackney et al. (2014). I used PowerUp SYBR Green master mix (Applied Biosystems, Waltham, MA). My final reaction volumes were 5 µL total and each reaction contained 1.0 µL DNA at approximately 6.25 ng/uL, 2.5 µL SYBR Green master mix, 1.1 µL primers, and 0.4 µL water.

I estimated relative telomere length by calculating the T/S ratio for each sample. The T/S ratio is the estimated starting quantity (SQ) of the telomere amplicon (T) divided by the estimated SQ of the albumin amplicon (S). The SQ for each amplicon was calculated in reference to the standard curve described above. The average T/S ratio across these triplicates was divided by the average T/S ratio for the positive control to control for plate effects (same positive control was used across both plates, described below). Then, for samples assayed over both plates (n=96), I averaged the two plate averages to calculate their final T/S ratio for analyses.

I used high-quality/quantity (260/280 ratio = 1.79; conc. = 498.23 ng/µL) DNA extracted in-house from whole blood to create a six-point standard reference curve. This standard curve was used to determine the quantity of my target amplicons. The standard curve concentrations ranged from 25 ng/µL to 0.10 ng/µL using a 3-fold serial dilution. I performed the TL assay twice for which the standard curve R^2 values were 0.99 (SD < 0.01) for the telomere (T) amplicon and 0.98 (SD < 0.01) for that of the albumin (S) amplicon. Plate assay efficiency was 106.5% and 98.2% (SD = 1.3%) for T, and 95.4% (SD < 0.95%) and 89.1% (SD<0.95%) for S for my first and second run, respectively. I used the same high-quality DNA as a positive control diluted to 6.25 ng/µL. One sample failed to amplify properly on the first plate, but amplified successfully when re-run on the second plate. Besides this, one well of a triplicate failed to amplify on one plate, but the other two wells on the first plate and all three replicates on the second plate amplified properly. All other samples amplified as expected. I did not remove any other replicates, wells, or samples from the current analyses.

I assessed the measurement reliability of my T/S ratios by calculating the intraclass correlation coefficient (ICC; Eisenberg, 2016; Verhulst et al., 2016) of the average of triplicate values for 96 samples run on my two plates with the ICC command in Stata 17: ICC(A,1) = 0.64, 95% CI = 0.50, 0.74; ICC1(A, k) = 0.78, 95% CI = 0.67, 0.85. It is important to note that these reliability estimates of my sample measurements are lower than previous work in our lab and, specifically, previous work with TL estimated from DBS from Whatman 903 cards in our lab (Rej et al., 2021). Rej and colleagues in 2021 reported ICC(A, 1) = 0.86, 95% CI = 0.74, 0.92; ICC1(A, k) = 0.92, 95% CI = 0.85, 0.96. However, my values were closer to the ICCs of TL recently estimated from venous whole blood in our lab: ICC(A, 1) = 0.79, 95% CI = 0.70, 0.86; ICC1(A, k) = 0.88, 95% CI = 0.82, 0.92.

Practically, while these values are “acceptable” according to conventional rules of thumb for ICC values (Cicchetti, 1994), this lower performance means that I have less confidence in the reliability of these individual estimates. Given my standard curve performed as expected, this lower reliability may result from the more varied ways in which my Hemaspot samples were handled compared to the DBS validation study in our lab (Rej et al., 2021). I plan to investigate further into adjusting for handling method (e.g., shipping, collected at home, collected in the lab) and other contributions to this relatively low ICC before submitting for publication. This ICC may also have resulted from different treatment of my PCR plates. My second plate was prepared in advance and stored in a 4-degree Celsius freezer for 2 hours before the MMQPCR protocol while my first plate was run immediately. Previous work in our lab had demonstrated acceptable results with this pre-preparation, but it is a difference in handling that could add to this lower ICC.

Measures of external validation suggest that my TL measures are largely behaving as expected. The observed TL-age correlation in my sample was in the expected direction, but not significantly (β=-0.0014, 95% CI= -0.07, 0.06). This weak association is likely due to the combination of a small sample size and the limited age range in my study (i.e., 18 to 24.9 years of age). Importantly, this association appears to strengthen once additional covariates and other predictors are adjusted for (e.g., β<-0.02 once physical activity and psychosocial stress are included in regression models; Table 2). Further, TL appears to be shorter in participants who were assigned male at birth compared to female

(β=-0.25, 95% CI:-0.73, 0.22). My small sample size and the fact that my sample is largely female (78% for the whole sample) may contribute to this association being smaller than expected (Rej et al., 2021).

Previous Work with these samples

I have conducted successful extractions from Hemaspot HF devices on a subset of our samples (N=32) as part of a collaboration to examine whether TL differed between Swimmers and non-athletes from the same universities. While our extractions were successful (i.e., they yielded similar DNA concentrations and quality to the work in Rej et al. (2021)), the MMQPCR did not appear to be successful. They had a positive association with age and failed multiple quality control checks. These samples were re-extracted for this analysis and are included in the total sample.

Covariates

In addition to my measures of psychosocial stress and physical activity, I included three potential mediator variables and a series of control variables that have been associated with TL in previous studies. Body mass index (BMI), smoking status ("never", "former", or "current"), and sleep efficiency are included as potential mediators because they may lie within my hypothesized pathways of interest. Individuals with increased psychosocial stress are often more likely to smoke, have higher BMI, and have worse sleep (Ng & Jeffery, 2003). These three factors have all been associated with shorter TL (Astuti et al., 2017; Gielen et al., 2018; Jin et al., 2022). BMI is calculated using self-reported height and weight collected during the prescreening survey. Smoking status is also self-reported on the prescreening survey. Sleep efficiency will be calculated from Sadeh et al.'s (1994) sleep algorithm for accelerometry. Sleep efficiency is the percentage of time spent asleep from the onset of sleep at night to waking in the morning.

My control variables lie outside of my hypothesized pathways of interest and include age on the day of DBS collection, sex at birth, and the interaction between age and sex. Older age and being male are commonly associated with shorter TL, and, further, age-related TL shortening is thought to be accelerated in males compared to females (reviewed in Lansdorp, 2022). Age was centered on zero for all analyses to reduce nonessential collinearity with other variables (Cohen et al., 2014).

Statistical Approach

I designed a series of ordinary least squares regression models to test my three central hypotheses. TL is the outcome variable for all models and was z-transformed prior to analyses (Verhulst, 2020). The predictor variables change depending on the hypothesis tested. These models include a minimally controlled model and a maximally controlled model. If the coefficients of the key independent variables (i.e., psychosocial stress, physical activity, and their interactions) are reduced substantially as additional covariates are added, I interpreted this as evidence that these covariates are at least partially confounding or mediating the association of interest. The minimally controlled models (Models 1, 3, and 5) include sex assigned at birth, age on the day of DBS collection, and the interaction of these two variables. The maximally controlled models (Models 2, 4, and 6) additionally include BMI, smoking status, and sleep efficiency.

The first group of models test the main effects of childhood psychosocial stress on TL (Models 1 & 2) and my predictor variable was score on the CTQ-SF. My second group of models test the main effects of physical activity on TL (Models 3 & 4) and my predictor variables are student-athlete status, AvAcc, and IG. My third group of models combine the first two groups such that my predictor variables include my psychosocial stress and physical activity measures as well as the interactions between them (Models 5 & 6). To address multiple-testing and the correlation between variables within multiple regression models, I utilized Wald joint-significance tests (Cohen et al., 2014). These tested the null hypotheses that: (1) all physical activity measures are not associated with TL and (2) all CTQ-SF*physical activity interactions are not associated with TL and were performed for each appropriate regression model. In addition to these *a priori* tests, I conducted two *post hoc* models to assess the impacts of a significant interaction variable in Model 5.

I designed and coded my statistical models before the data for physical activity was calculated and before I had calculated my TL estimates (https://osf.io/s2cuj/). All regressions were designed and conducted in Stata 17.0.

Results

Descriptive Statistics

Descriptive statistics of key variables are displayed in Table 1. The mean CTQ-SF score was 33.1 with a standard deviation of 10. The student-athletes had a significantly lower score compared to non-athletes (β=-4.33; p=0.032). Further, the more extreme scores for the CTQ-SF in this sample are largely in the non-athlete groups. Since these groups did not show a difference in means in my earlier analysis (Paper 1), this may be a result of fewer highly stressed student-athletes successfully completing the Hemaspot collection compared to less stressed student-athletes. Student-athletes and non-athletes in this sample also differ significantly in both metrics of physical activity ($p<0.001$ for both), but this is consistent with my results from Paper 2. Importantly, these substantial differences may limit our ability to discern the effects of physical activity on any childhood psychosocial stress-TL associations. Lastly, direct comparisons of TL did not differ between groups (β=-0.01; p=0.734 where "1" is student-athlete and "0" is non-athlete).

A total of 129 Hemaspot HF devices were used to collect capillary blood spots throughout the duration of the study. From these, 18 were excluded in the extraction step (see Methods for details). All 111 remaining samples resulted in an estimated mean TL via the MMQPCR assay. However, only 102 of these 111 had all available data for all control variables. Regression tables below include all samples for which I have all relevant variables. Before submission for publication, more data cleaning will take place and imputation attempted to improve the sample size of these analyses.

Table 1. Descriptive statistics of key variables included in the regression models below and the p-values of comparisons between group means and counts.

Variable	Whole Sample	Student-Athletes	Non-Athletes	p-values of differences
Sample size (n)	102	52	50	
Control Variables	**Mean (SD)/%**	**Mean (SD)/%**	**Mean (SD)/%**	
Age (years)	21.4 (3.3)	20.9 (1.9)	21.8 (4.3)	0.183
Sex assigned at birth (% Female)	78%	77%	80%	0.81
Mediator Variables				
BMI (kg/m^2)	22.5 (3.3)	21.9 (2.5)	23 (3.8)	**0.095**
Current Smoker (% yes or sometimes)	11%	6%	17%	0.218
Sleep Efficiency (%)	66% (0.09)	65% (0.10)	66% (0.09)	0.726
Childhoood Psychosocial Stress Measure				
Childhood Trauma Questionnaire-SF	33.1 (10)	31 (6.3)	35.3 (12.4)	**0.032**
Physical Activity				
Average Acceleration (mg)	47.6 (27.6)	57.8 (31.8)	36.1 (15.7)	**>0.001**
Intensity Gradient	-2.4 (0.3)	-2.3 (0.4)	-2.6 (0.2)	**0.001**
Telomere Length				
T/S ratio (unadjusted)	0.9 (0.1)	0.8 (0.1)	0.9 (0.2)	0.734

p-values of differences are calculated from ordinary least square regressions for continuous measures (e.g., Age) and Fisher's Exact Test for categorical outcomes (e.g., Sex assigned at birth).

Association between childhood psychosocial stress and TL

First, I tested whether increased childhood psychosocial stress was associated with shorter TL by evaluating whether self-reported scores on the CTQ-SF were significantly associated with TL. The CTQ-SF was not associated with TL in any of the six planned models (Table 2). Examining the regression results shows that the β coefficients for the CTQ-SF–TL associations were substantially stronger once physical activity measures were included (Models 5 and 6 in Table 2) and were in the hypothesized direction. However, they were not statistically significant (β=−0.40 and -0.39; p=0.178 and 0.237). Reporting higher levels of childhood psychosocial stress via the CTQ-SF does not appear to be associated with TL in my sample.

Association between Physical Activity and TL

For my second hypothesis, I tested whether objectively measured physical activity predicts TL by evaluating whether both measures, AvAcc and IG, jointly contributed to explaining variation in TL (Table 2). None of the four models including these measures demonstrated significant associations for the Wald joint significance tests ($p>0.40$ for all). Examining the individual β coefficients for each variable also reveals that neither variable is individually associated with variation in TL. Engaging in more total physical activity (AvAcc) and more high intensity activity does not appear to be directly associated with TL in my sample either individually or jointly.

Moderation of psychosocial stress and TL associations by physical activity

Lastly, I tested whether physical activity levels moderate the association between psychosocial stress and TL by evaluating whether all physical activity*CTQ-SF interaction variables jointly contributed to explaining variation in TL. These joint significance tests did not reveal any significant associations between the interaction variables and TL ($p>0.15$ for both). Thus, it is unlikely that physical activity, more broadly construed, moderates the relationship between childhood psychosocial stress-TL in my sample.

The interaction term between student-athlete status and CTQ-SF is not significant ($\beta=-0.01$, $p>0.50$ for both), which likely indicates that the relationship between CTQ-SF score and TL does not change based on whether a participant was a student-athlete or not. Further, the interaction term between IG and CTQ-SF score is also not significant (Model 5: $\beta=-0.13$, $p=0.199$; Model 6: $\beta=-0.12$, $p=0.261$), so we are also unable to reject the null hypothesis that the associations between CTQ-SF and TL do not change depending on IG. However, the interaction term between AvAcc and CTQ-SF is significant in Model 5 ($\beta=0.003$; $p=0.048$) and maintains a similar association in Model 6 once more covariates are added ($\beta=0.002$; $p=0.085$). This suggests that the association between CTQ-SF score and TL may differ based on the individual's recorded

AvAcc, which would indicate that total physical activity moderates the associations between childhood psychosocial stress and TL.

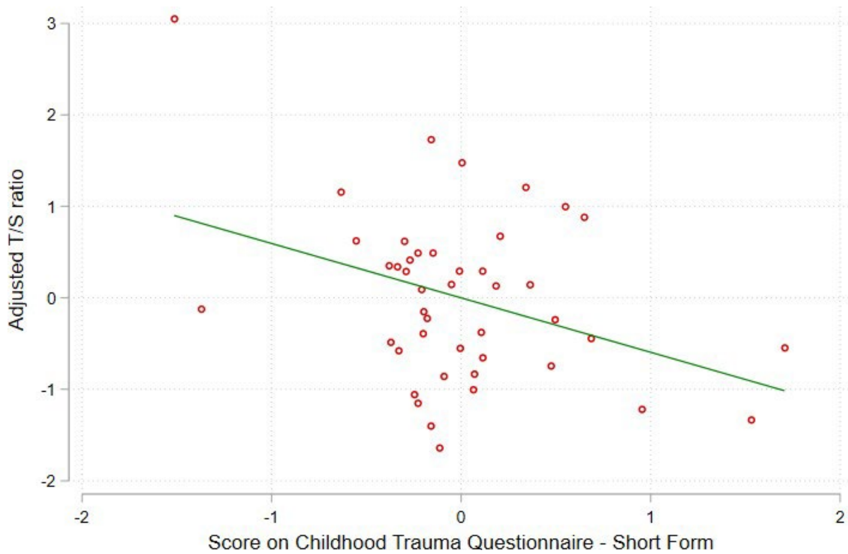
To more clearly understand the nature of this interaction, I conducted a *post hoc* analysis to examine how CTQ-SF score is associated with TL in individuals with high AvAcc (>median AvAcc) and how it is associated with individuals with low AvAcc (<median AvAcc), independently (Table 2; "Post hoc test" Models 7 and 8). This analysis demonstrated two intriguing findings. First, CTQ-SF is significantly associated with TL in *opposite* directions for those above the 50% percentile for AvAcc versus those below the 50% percentile (Figure 1; Model 7: β=0.322; p=0.044 for the more active; Model 8: β=-0.595; p=0.027 for the less active). These β's indicate that reporting higher psychosocial stress is significantly associated with longer TL for more active participants while higher psychosocial stress is significantly associated with shorter TL for less active participants. Second, for the less active group, the IG is significantly associated with TL (β=6.98; p=0.043) as is its interaction with CTQ-SF score (β=-0.234; p=0.023). The positive association between IG and TL indicates that as the IG increases (i.e., an individual spends a greater proportion of their time engaging in more intense physical activity), they have longer TL. However, the negative β for the interaction between IG and CTQ-SF appears to indicate that CTQ-SF scores are more strongly associated with shorter TL as IG increases. In other words, childhood psychosocial stress negatively impacts TL more strongly as an individual engages in more intense physical activity,. It is important to note that these analyses were constructed *post hoc*, were not supported by the Wald test for joint significance, and the significant associations have not been corrected for multiple comparisons. However, taken together these findings may suggest that AvAcc and IG could be impacting TL and CTQ-SF~TL associations in complex ways that are hidden in the larger linear model.

Table 2. Regression models examining whether psychosocial stress, physical activity, and stress*activity interactions are associated with TL in a sample student-athletes and non-athletes

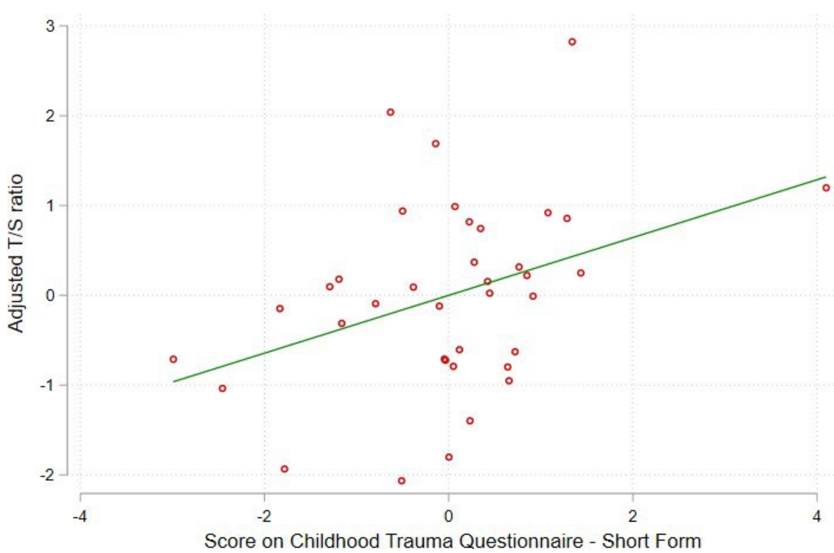
(Note that the n's for Models 7 and 8 are not equal – this is because the median for splitting the 50% percentile was based on my whole Actigraph sample, not the TL sample)

	Hypothesis 1		**Hypothesis 2**		**Hypothesis 3**		**Post Hoc Test**	
Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**
Sample size (n)	91	78	86	82	81	78	37	44
Childhood Psychosocial Stress								
Childhood Trauma Questionnaire-SF	0.02	0.02			-0.40	-0.39	0.322*	-0.595*
Physical Activity								
Student-athlete Status			-0.22	-0.27	0.28	0.11	0.51	0.45
Average Acceleration			0.01	0.01	-0.07	-0.06	0.01	-0.077+
Intensity Gradient			0.03	-0.19	3.62	3.42	-4.08	6.984*
Covariates								
Age	-0.01	0.02	0.00	0.01	-0.04	-0.02	-0.09	-0.06
Sex assigned at birth (Female=0; Male=1)	1.23	0.35	1.15	0.63	4.887+	4.98	5.29	1.05
Age*Sex assigned at birth	-0.07	-0.03	-0.07	-0.04	-0.24+	-0.24	-0.259	-0.09
BMI		-0.06		-0.05		-0.05		
Smoking Status		-0.07		0.07		0.07		
Sleep Efficiency		-0.77		-0.50		-0.51		
Interactions								
CTQ*Student-athlete Status					-0.01	-0.01	-0.02	-0.02
CTQ*Average Acceleration					0.003*	0.002+		
CTQ*Intensity Gradient					-0.13	-0.12	0.119*	-0.234**
Joint Significance of Physical Activity Variables (p-value)			0.50	0.77	0.40	0.50	0.40	0.50
Joint Significance of Interaction Variables (p-value)					0.16	0.31	0.16	0.31
adjusted R-squared	0.048	0.063	0.039	0.051	0.152	0.128	0.152	0.128

Values are β coefficients unless otherwise noted; + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Models 7 and 8 were not preregistered. Model 7 includes only participants who recorded over the 50% percentile of AvAcc. Model 8 includes only participants who recorded under the 50% percentile of AvAcc.



(A)



(B)

<u>Figure 1.</u> Added Value Plots demonstrating the relationships between scores on the Childhood Trauma Questionnaire-Short Form (CTQ-SF) and Adjusted Telomere Length (TL) for **(A)** participants below the 50th percentile for Average Acceleration (i.e., less physically active than the median) and **(B)** participants above the 50th percentile for Average Acceleration (i.e., more physically active than the median). Individuals who are less physically active demonstrate a negative association between their scores on the CTQ-SF and their TL while those who are more physically active demonstrate a positive association between their scores on the CTQ-SF and their TL.

Discussion

I examined predictors of capillary blood TL to test three hypotheses: 1) that increased exposure to childhood psychosocial stress is associated with shorter TL, 2) that higher physical activity is associated with longer TL, and 3) that higher physical activity levels attenuate the association between psychosocial stress and adult TL. Using data collected from a sample of NCAA student-athletes and non-athletes, I did not find strong support for any of these hypotheses in my *a priori* defined joint significance tests.

However, I did find a significant positive association between the interaction term of CTQ-SF score*AvAcc with TL, indicating that the association between childhood psychosocial stress and TL changed as the participant's total physical activity increased. This significant association became insignificant once the covariates BMI, smoking status, and sleep efficiency were included in the regression, but the strength and direction of the β coefficient remained similar (i.e., 0.003 vs 0.002). I conducted a brief *post hoc* analysis to investigate this relationship, which indicated that there may be a complex relationship between physical activity and the associations between psychosocial stress and TL. Specifically, more active individuals had longer TL when they reported higher levels of childhood psychosocial stress, while less active individuals demonstrated shorter TL when they reported higher levels of childhood psychosocial stress.

This positive relationship between childhood psychosocial stress and TL in more active participants is surprising. As mentioned in the Introduction, many published findings show a negative association between psychosocial stress and TL (Ridout et al., 2017) and previous publications do not hypothesize a pathway through which psychosocial stress could lead to longer TL. Given this background, it will be important to investigate potential sources of self-selection in these groups (e.g., are there shared demographic factors among the highly active group?). Further, I will investigate whether more active participants reported different kinds of stress on the CTQ-SF compared to the less active participants. My analysis in Paper 1 indicated that the Physical Neglect and Physical Abuse subscales may have been performing differently across student-athletes and non-athletes. Different types of psychosocial stress (e.g., threat and deprivation) are known to impact human biology differently (e.g., McLaughlin et al., 2014), so it will be important to better understand if these two groups (more and less active) differ in their survey responses. Lastly, I will need to confirm that batch effects with the DBS samples (i.e., when and how Hemaspots were collected) are not introducing bias into my TL estimates. Given my potential issues with measurement reliability (i.e., lower than ideal ICC values), this will be an important issue to address.

It is also important to note that the literature investigating associations between childhood psychosocial stress and adult TL is heterogeneous (reviewed above). Studies demonstrating associations are often smaller and underpowered compared to those that fail to find a significant association, indicating a high risk for publication bias in this literature (Pepper et al., 2018). Part of this pattern may also be due to differences in psychosometric assessments. For example, studies utilizing more comprehensive assessments and in-depth scales tend to find stronger associations between childhood psychosocial stress and TL (Ridout et al., 2017). The lack of findings with my *a priori* Wald Tests and the peculiar association between psychosocial stress and TL in active participants is not particularly surprising given this literature. While I utilized a measurement of childhood psychosocial stress that incorporates a wide set of childhood stresses and I invested time in ensuring it performed appropriately (Paper 1), my sample size is underpowered and half of my sample (i.e., NCAA student-athletes) represent a population in the

US that has undergone extreme self-selection. Perhaps if I perform more modifications of this scale for this population or include a larger and broader sample of student-athletes, I may improve my ability to test for psychosocial stress-TL associations.

Similarly, while increased physical activity is strongly associated with many systems that protect TL (i.e., improved cardiovascular health outcomes, e.g., Kraus et al., 2019) many studies fail to find an association with TL (Valente et al., 2021). Part of this may be due to the reliance on questionnaires. It may also be because objective measures only assess an individual's physical activity over a fraction of their lifetime. Since we expect that longer, habitual exposures are needed to substantially impact TL (especially in adulthood) it is difficult to accurately assess chronic or lifelong exposure to higher levels of physical activity in industrialized settings. My strategy to include NCAA student-athletes begins to address this, but this population experiences a range of other environmental factors that we should expect to interact with and confound physical activity's associations with biology. Further, athletes engage in different behaviors depending on their sport, and it is unclear what aspects of these behaviors will be the most impactful (Merghani et al., 2016). The literature is currently limited in that objective measurements almost focus solely on time spent in MVPA and not on more nuanced measures such as the AvAcc and IG. The fact that student-athletes engage in a range of different behaviors and that different data operationalization strategies (e.g., MVPA vs AvAcc and IG) lead to different results (Paper 2) highlights the need for more work to be done with more nuanced objective measures of physical activity. My finding that the AvAcc*CTQ-SF interaction term was significant while student-athlete status*CTQ-SF was not, further reifies the need for more types of measurement.

Lastly, it is important to review some of the major limitations of this study. First, my TL measurements showed less than ideal reliability (i.e., low ICC values compared to previous studies). qPCR estimates of TL are notoriously noisy measures and assessing TL from minimally invasive DBS have only recently been validated across multiple labs (e.g., Rej et al., 2021). It will be important to delve more deeply into the particular conditions that may be impacting this reliability. Storage conditions, for example, are known to impact TL assessed via qPCR (Dagnall et al., 2017), so examining the impact of shipping vs collecting Hemaspots locally in the lab is an immediate next step for me to take. Second, in tandem with this noisy measure of TL, my sample size is relatively small (n<100 for my regression models). It is difficult to assess whether the lack of significant associations in my analyses are due to the lack of real relationships in my data or due to my lack of statistical power. The converse may also be true, it is also difficult to assess the veracity of my significant interaction term (i.e., AvAcc*CTQ-SF) with low statistical power – this finding is more likely to be spurious. Lastly, I am likely to come across at least one significant association given the number of the models tested. A larger and more reliable test of my significant interaction is warranted, however, given the discrete changes to other predictions in my *post hoc* regression models.

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Conclusion

The overall goal of my dissertation project was to test my hypothesis that physical activity moderates the associations between psychosocial stress and human biology by focusing on telomere length (TL) and NCAA student-athletes and non-athletes. To do this, I collected demographic, psychosocial stress, physical activity, and TL data from just over 100 participants. I built a detailed description and comparison of psychosocial stress in these two groups, developing a better understanding of how their experiences are similar and different. Quantitatively, I found that student-athletes reported similar or lower levels of psychosocial stress depending on the specific construct. Then, I investigated how these groups engage in physical activity and how our understandings change with different assessment tools and activity metrics. Specifically, I found that Rowers appeared to be the most active subgroup when using time spent in moderate-to-vigorous physical activity (MVPA) as the dependent variable. Conversely, Track and Field athletes seemed to be the most active when I used average acceleration and the intensity gradient of their activity as the dependent variables.

I utilized the results of these two papers to formalize the analyses testing my overall question: does physical activity moderate the association between childhood psychosocial stress and TL? While I did not find strong support for my central hypothesis, my findings provide a roadmap for me to continue examining this question and link it more securely to human health and evolution. Psychosocial stress is associated with increased morbidity and mortality throughout the lifespan, but it is still unclear how it may have impacted our biology throughout evolution. It is also unclear why it affects individuals differently. Much of the heterogeneity in psychosocial stress-biology findings (particularly with psychosocial stress and TL associations) is due to social processes on the side of researchers, notably publication bias and data mining (intentionally or unintentionally). However, it is also widely accepted that personal and ecological factors lead stress to impact people and populations differently. Physical activity is a highly variable individual and environmental facet of our lives that is likely to be one of these factors because of its shared evolutionary history with stress and its impacts on shared physiological systems.

In this study, I was motivated, in part, to focus on student-athletes because it allowed me to utilize widely validated and reliable measures of psychosocial stress with a study population that has engaged in high levels of physical activity up until this point in their life. This approach allowed me to isolate the impacts of high vs. low physical activity levels. However, a valuable takeaway from this project is that we can utilize accelerometry to study many "types" of "high physical activity levels." My original hypothesis connecting physical activity and psychosocial stress was necessarily naïve – popular conceptions of physical activity still focus on time spent in MVPA as the primary variable of interest. Moving forward, however, I am interested in building more specific hypotheses based on direct associations between the type of activity and our biological responses to it. For example, in Paper 3, I found that the interaction term between average acceleration and childhood psychosocial stress was significantly associated with TL, while my metric for intense physical activity (i.e., intensity gradient) was not. Does engaging in high overall activity incorporate different immunological and hormonal responses compared to engaging in more "intense" activity? Answering this and related questions will allow me to connect this work with the variety of physical activities our ancestors likely performed and the type of activities modern humans engage in.

Ultimately, I feel this project is only the start of me addressing my central question (i.e., does physical activity moderate the impacts of psychosocial stress on biology?), and it has allowed me to work directly with student-athletes. Biological anthropology has much to gain from a more regular and rigorous investigation into sports. Athletes offer a uniquely diverse insight into how different behaviors can exact different responses in our biology (e.g., what is the impact of increased stress loading vs. increased cardiovascular training on immune function?). This variety of behaviors can provide a more controlled lens through which to build and test evolutionary hypotheses and better investigate populational health patterns.

Importantly, conducting this study has also highlighted that the unique context of NCAA student-athletes cannot be discounted when including them in research. They have unique social experiences and undergo intense selective processes before they even arrive at college to begin competing. These exceptional circumstances and their ties to mental and physical health require their own focus – independent of broader evolutionary connections. These unique circumstances may help me isolate specific features of psychosocial stress, physical environments, and physical activity types in my future research. Lastly, this work offers an opportunity to tie my work directly with colleagues in sociocultural subfields of anthropology to investigate specific examples of power, racism, and sexism in our society. Incorporating collaborations with more well-trained colleagues in these areas will only enrich my work (and hopefully add some biological context to theirs).

This project sets up a springboard for establishing my long-term research trajectory in multiple ways. First, it has offered me training across various aspects of biological anthropology: developing and working with behavioral and self-report assessments, measuring physical activity and dealing with the complexities of accelerometry, setting up my own lab goals, and executing a well-designed lab plan. These skills and the track record I will gain from publishing these papers will help me continue to pursue my hypothesis and research interests in bigger and better ways. Second, I have a list of research questions and data to begin pursuing them. I have multiple COVID-related questions to pursue that will touch upon the experiences of student-athletes and the general college student population. While my sample size is small for TL research, it is a comparatively large sample of accelerometry data with many measures of environment and health. I also have at least several sample handling and TL-specific measurement questions to investigate, such as storage conditions and history of COVID infection. Third, I have been able to use this project as a tool to mentor multiple young researchers – two of whom won our department's award for undergraduate honors projects. Further, one of them presented a podium presentation at the AABA this year, which allowed me to develop scientific communication and presenting skills in a mentee. Mentoring is vital to me enjoying and improving my research. Fourth, I was able to create a recruiting pipeline that I will utilize in future studies outside of UW in my future positions. While it is an open question whether I will be able to gather specimens for TL over the mail this way, there are many other related questions that I can pursue with this type of collection. Fifth, and lastly, it will help situate me in this field of the biological anthropology of sports, where I can pursue these exciting and interesting questions while collaborating with the community and increasing scientific engagement with our broader society.

Appendix 1

Table of Contents:

(All page numbers are in reference to Appendix 1 page numbers – not the numbers associated with each questionnaire/survey or the overall Dissertation document)

Pre-Screening Consent Form

)<23@AB/<27<5 HC;/< A2/>B/B7=<A B= %6GA71/: A1B7D7BG

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%:3/A3 @3/2 B63 7<4=@;/B7=< =< B67A >/53 1/@34C::G /<2 @3/16 =CB B= B63 @3A3/@16 B3/; @35/@27<5 /<G ?C3AB7=<A =@ 1=<13@<A. C=<B/1B 7<4=@;/B7=< 4=@ B63 @3A3/@16 B3/; 1/< 03 4=C<2 /B B63 0=BB=; =4 B67A >/53.

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Additional Information and Questions

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$$$$$$

Mood

I7 8,)6) %2=8,-2+ -2 4%68-'90%6 %&398 =396 133(36 786)77 0):)07 3:)6 8,) 4%78 ;))/ 8,%8 =39 8,-2/ ;) 7,390(/23;?

().+. ';36/ ;%7 4%68-'90%60= ,%6(','I ;%7 '3140)8-2+ *-2%07',)8'.)

$$$$$$

I7 8,)6) %2=8,-2+ -2 4%68-'90%6 %&398 =396 70))4 8,%8 =39 8,-2/ ;) 7,390(/23;?

().+.'I 70)48 % 038 136) 8,%2 979%0 8,-7 ;))/'; 'I 78%=)(94 0%8) ;-8, *6-)2(7 % *); 136) 8-1)7 8,%2 I 8=4-'%00= (3')

$$$$$$

Study Questionnaire

B-47? 1;) ;=:>-A .7+=;-, 76 A7=: 0-)4<0)6, ?0-:- A7= 0)>- 41>-, <0:7=/07=< A7=: 41.-. 4-);-)6;?-:)44 9=-;<176; <0)<):- :-4->)6< <7 A7=.

IM O!#AN#: #0-:-):- 67 :1/0< 7: ?:76/)6;?-:;. 4-);-)6;?-: <0- 9=-;<176; *-47? 076-;<4A)6, <7 <0- *-;< 7. A7=:)*141<A.

#0)63 A7= .7: A7=: <15-!

Residence and Moving Residences

#0- .7447?16/ 9=-;<176; .7+=; 76 ?0-:- A7= 0)>- 41>-, <0:7=/07=< A7=: 41.-.

4-);-)6;?-: <0-5 <7 <0- *-;< 7. A7=:)*141<A.

L7+)<176 7. B1:<0 (C1<A, "<)<-, C7=6<:A 1. 67< $"A): ((((((

'I C7,- (I. 16 $"A): ((((((

M7<0-:'; L7+)<176 7. B1:<0 (C1<A, "<)<-, C7=6<:A 1. 67< $"A): ((((((

F)<0-:'; L7+)<176 7. B1:<0 (C1<A, "<)<-, C7=6<:A 1. 67< $"A): ((((((

D1, A7= 57>- +1<1-; *-.7:- <0-)/- 7. 5? ((((((

I. A-;, 84-);-)6;?-: <0- .7447?16/ 9=-;<176;:

%0-:- ,1, A7= 57>- .:75? (C1<A, "<)<-, C7=6<:A 1. 67< $"A) ((((((

'I C7,- (1. A7= :-+)44): ((((((

%0-:- ,1, A7= 57>- <7? (C1<A, "<)<-, C7=6<:A 1. 67< $"A) ((((((

'I C7,- (1. A7= :-+)44): ((((((

D1, A7= 57>- +1<1-; 5=4<184- <15-;? I. ;7, 84-);- ,-;+:1*- A7=: 7<0-: 57>-; 0-:-.

((((((

D1, A7= 57>- +1<1-; *-<?--6 <0-)/-; 7. 5-18? ((((((

I. A-;, 84-);-)6;?-: <0- .7447?16/ 9=-;<176;:

%0-:- ,1, A7= 57>- .:75? (C1<A, "<)<-, C7=6<:A) ((((((

'I C7,- (1. A7= :-+)44): ((((((

%0-:- ,1, A7= 57>- <7? (C1<A, "<)<-, C7=6<:A) ((((((

'I C7,- (1. A7= :-+)44): ((((((

D1, A7= 57>- +1<1-; 5=4<184- <15-;? I. ;7, 84-);- ,-;+:1*- A7=: 7<0-: 57>-; 0-:-.

((((((

Motivations for college and professional sports

A:- A7=)6 16<-:+744-/1)<- 7: 8:7.-;;176)4)<04-<-?
- ◯ &-;
- ◯ N7

#0- .7447?16/ 9=-;<176;):-)15-,)< =6,-:;<)6,16/ A7=: 57<1>)<176; .7: +758-<16/. 4-);-)6;?-: <0-5 076-;<4A)6, <07:7=/04A.

A< ?0)<)/- ,1, A7= ;<):< +758-<16/ 16 A7=: +=::-6< ;87:<? ((((((

H7? ,1, A7= +75- <7 *-) +744-/1)<- 7: 8:7.-;;176)4)<04-<-?

((((((

H7? 5=+0 7.) :74- ,1,)<04-<1+ ;+074):;018 84)A 16 A7=: ,-+1;176 76 ?0-:- <7 +758-<- 16 +744-/-?

((((((

H7? 5=+0 7.) :74- ,1, A7=: 8):-6<; 7: +7)+0-; 84)A 16 A7=: ,-+1;176 76 ?0-:- <7 +758-<- 16 +744-/-?

((((((

I. /1>-6 <0- 7887:<=61<A, ?7=4, A7= 413- <7 *-) 8:7.-;;176)4)<04-<-? ("-4-+< "&-;" 1.)4:-),A 8:7) ((((((

I. A-;, ?0-6 ,1, A7= 367? <0)< A7= ?)6<-, <7 *-) 8:7.-;;176)4)<04-<-?

((((((

%-:- <0-:-)6A 7<0-: .)+<7:; <0)< +76<:1*=<-, <7 A7=: ,-+1;176 76 ?01+0 ;+0774 <7)<<-6,)6, ?0-:- <7 +758-<- 8:7.-;;176)44A (1.)8841+)*4-) <0)< A7=', 413- <7 ;0):-?

((((((

C)6 A7= ;-4-+< <0- 57;< 1587:<)6< .)+<7: <0)< 16.4=-6+-, A7=: ,-+1;176 76 ?0-:- <7)<<-6, +744-/-? ((((((

C)6 A7= ;-4-+< <0- 4-);< 1587:<)6< .)+<7: <0)< 16.4=-6+-, A7=: ,-+1;176 76 ?0-:- <7)<<-6, +744-/-? ((((((

Brief Health History

#0- .7447?16/ ;-+<176 ?144);3)*7=< A7=: 0-)4<0.

A:- A7= +=::-6<4A <)316/)6A 5-,1+)<176;? ((((((

I. A-;, +7=4, A7= *:1-.4A ,-;+:1*- <0- 5-,1+)<176; A7=):- <)316/? (-./.)44-:/A 5-,1+)<176;, *1:<0 +76<:74,)6<1,-8:-;;)6<;, -<+.)

N7<-: %-):-);316/ <01; 9=-;<176 *-+)=;- ;75- 5-,1+)<176; 158)+< 16.4)55)<7:A :-;876;-;)6, +-44=4):)/16/. K67?16/ A7=: 5-,1+)<176; ?144 0-48 =;)6)4AB- A7=: ,)<) 57:-)++=:)<-4A.

((((((

D7 A7= 0)>-)44-:/1-;? ((((((

I. A-;, ?0)<):- <0-A? ((((((

A:- A7= +=::-6<4A -@8-:1-6+16/)44-:/A ;A58<75;? ((((((

D7 A7= 0)>- #A8- 2 D1)*-<-;? ((((((

H)>- A7= ->-: *--6 ,1)/67;-, ?1<0 7: ;=;8-+<-, <7 0)>-) +76+=;;176? ((((((

I. A-;,)< ?0)<)/-(;) ?-:- A7= ,1)/67;-, ?1<0 7: ;=;8-+<-, <7 0)>-) +76+=;;176? ((((((

H)>- A7= 0),)6A 5)27: 162=:1-; 7: ;=:/-:1-; NO# :-4)<-, <7 ;87:<; 16 <0- 8);< 5 A-)::;?

((((((

I. A-;, +7=4, A7= 84-);- *:1-.4A ,-;+:1*- A7=: 162=:1-;)6, :-+7>-:A <15-?

((((((

H)>- A7= 0),)6A 5)27: ;87:<; 162=:1-; 7: ;=:/-:1-; 16 <0- 8);< 5 A-):;?

((((((

I. A-;, +7=4, A7= 84-);- ,-;+:1*- A7=: 162=:1-;)6, :-+7>-:A <15-?

((((((

D7 A7= ;573- :-/=4):4A? ((((((

D7 A7= >)8- :-/=4):4A? ((((((

Piercings and Tattoos

D7 A7= 0)>- 7: 0)>- A7= ->-: 0),)6A *7,A 81-:+16/;? ((((((

I.)8841+)*4-, 16,1+)<- <0-):-)(;) +=::-6<4A 81-:+-,:

((((((

I. 7<0-:, 84-);- ,-;+:1*-: ((((((

I.)8841+)*4-, 16,1+)<- <0-):-)(;) .:75 ?01+0) 81-:+16/ 0); *--6 :-57>-,:

((((((

I. 7<0-:, 84-);- ,-;+:1*-: ((((((

D7 A7= 0)>- 7: 0)>- A7= ->-: 0),)6A <)<<77;? ((((((

I.)8841+)*4-, 16,1+)<- <0-):-)(;) +=::-6<4A <)<<77-,:

((((((

I. 7<0-:, 84-);- ,-;+:1*-: ((((((

I.)8841+)*4-, 16,1+)<- <0-):-)(;) .:75 ?01+0) <)<<77 0); *--6 :-57>-,:

((((((

I. 7<0-:, 84-);- ,-;+:1*-: ((((((

A:-)6A 7. A7=: <)<<77; :-4)<-, <7) +744-/- 7: =61>-:;1<A (-./.,) 47/7, 5);+7<, -<+. 7. A7=: .)>7:1<- <-)5)?

((((((

A:-)6A 7. A7=: <)<<77; :-4)<-, <7) 8:7.-;;176)4 ;87:<; <-)5?

((((((

I. A7= 67? 0)>- 7: 0)>- ->-: 0),) *7,A 81-:+16/, 0)>- A7= ;=..-:-,)6A 5-,1+)4 +75841+)<176;?

((((((

I. A-;, 84-);- 16,1+)<- ?01+0 +75841+)<176(;) A7= -@8-:1-6+-,:

((((((

I. 7<0-:, 84-);- ,-;+:1*-: ((((((

I. A7= 0)>- 7: 0)>- ->-: O),) <)<<77, 0)>- A7= ;=..-:-,)6A 5-,1+)4 +75841+)<176?

((((((

4-);- 16,1+)<- ?01+0 +75841+)<176(;) A7= -@8-:1-6+-,:

((((((

I. 7<0-:, 84-);- ,-;+:1*-: ((((((

Additional Information and Questions

I; <0-:-)6A<016/ -4;- A7= ?7=4, 413- =; <7 367?)*7=<
?0-:- A7= 0)>- 41>-,, A7=: 80A;1+)4)+<1>1<A, A7=:
0-)4<0, 7: A7=: 81-:+16/;/<)<<77;? A:- <0-:-)6A ((
9=-;<176; A7= 0)>- .7: <0- :-;-):+0 <-)5?

Childhood Trauma Questionnaire SF Pilot

-*8* 6:*89.438 &80 &'4:9 842* 4+ >4:7 *=5*7.*3(*8 ,74<.3, :5 &8 & (-.1) &3) & 9**3&,*7.

F47 *&(- 6:*89.43, (.7(1* 9-* 3:2'*7 9-&9 '*89)*8(7.'*8 -4< >4: +**1. A19-4:,- 842* 4+ 9-*8* 6:*89.438 &7* 4+ & 5*7843&1 3&9:7*, 51*&8* 97> 94 &38<*7 &8 -43*891> &8 >4: (&3. $4:7 &38<*78 <.11 '* 0*59 (43+.)*39.&1.

When I was growing up...

		N*;*7 97:*	R&7*1> 97:*	S42*9.2*8 97:*	O+9*3 97:*	"*7> 4+9*3 97:*	P7*+*7 349 94 &38<*7	!3(1*&7 I9*2
1)	I).)3'9 -&;* *34:,- 94 *&9.	○	○	○	○	○	○	○
2)	I 03*< 9-&9 9-*7* <&8 842*43* 94 9&0* (&7* 4+ 2* &3) 5749*(9 2*.	○	○	○	○	○	○	○
3)	P*451* .3 2> +&2.1> (&11*) 2* 9-.3,8 1.0* "89:5.)", "1&?>", 47 ":,1>".	○	○	○	○	○	○	○
4)	M> 5&7*398 <*7* 944)7:30 47 -.,- 94 9&0* (&7* 4+ 9-* +&2.1>.	○	○	○	○	○	○	○
5)	-*7* <&8 842*43* .3 2> +&2.1> <-4 -*15*) 2* +**1 .25479&39 47 85*(.&1.	○	○	○	○	○	○	○

When I was growing up, . . .

		N*;*7 97:*	R&7*1> 97:*	S42*9.2*8 97:*	O+9*3 97:*	"*7> 4+9*3 97:*	P7*+*7 349 94 &38<*7	!3(1*&7 I9*2
6)	I -&) 94 <*&7).79> (149-*8.	○	○	○	○	○	○	○
7)	I +*19 14;*).	○	○	○	○	○	○	○
8)	I 9-4:,-9 9-&9 2> 5&7*398 <.8-*) I -&) 3*;*7 '**3 '473.	○	○	○	○	○	○	○
9)	I ,49 -.9 84 -&7) '> 842*43* .3 2> +&2.1> 9-&9 I -&) 94 8** &)4(947 47 ,4 94 9-* -485.9&1.	○	○	○	○	○	○	○
10)	-*7* <&8 349-.3, I <&39*) 94 ○ (-&3,* &'4:9 2> +&2.1>.	○	○	○	○	○	○	

When I was growing up,...

		N*;*7 97:*	R&7*1> 97:*	S42*9.2*8 97:*	O+9*3 97:*	"*7> 4+9*3 97:*	P7*+*7 349 94 &38<*7	!3(1*&7 I9*2
11)	P*451* .3 2> +&2.1> -.9 2* 84 -&7) 9-&9 .9 1*+9 2* <.9- '7:.8*8 47 2&708.	○	○	○	○	○	○	○

12)

I <&8 5:3.8-*) <.9- & '*19, & '4&7), & (47) (47 842* 49-*7 -&7) 4'/*(9).

13) P*451* .3 2> +&2.1> 1440*) 4:9 +47 *&(- 49-*7.

14) P*451* .3 2> +&2.1> 8&.) -:79+:1 47 .38:19.3, 9-.3,8 94 2*.

15) I '*1.*;* 9-&9 I <&8 5->8.(&11> ◯ &':8*).

When I was growing up,...

	N*;*7 97:*	R&7*1> 97:*	S42*9.2*8 97:*	O+9*3 97:*	"*7> 4+9*3 97:*	P7*+*7 349 94 &38<*7	!3(1*&7 I9*2

16) I -&) 9-* 5*7+*(9 (-.1)-44).

17) I ,49 -.9 47 '*&9*3 84 '&)1> 9-&9 .9 <&8 349.(*) '> 842*43* 1.0* & 9*&(-*7, 3*.,-'47, 47)4(947.

18) S42*43* .3 2> +&2.1> -&9*) 2*.

19) P*451* .3 2> +&2.1> +*19 (148* 94 *&(- 49-*7.

20) S42*43* 97.*) 94 94:(- 2* .3 & 8*=:&1 <&> 47 97.*) 94 2&0* 2* 94:(- 9-*2.

When I was growing up,...

	N*;*7 97:*	R&7*1> 97:*	S42*9.2*8 97:*	O+9*3 97:*	"*7> 4+9*3 97:*	P7*+*7 349 94 &38<*7	!3(1*&7 I9*2

21) S42*43* 9-7*&9*3*) 94 -:79 2* 47 9*11 1.*8 &'4:9 2* :31*88 I).) 842*9-.3, 8*=:&1 <.9- 9-*2.

22) I -&) 9-* '*89 +&2.1> .3 9-* <471).

23) S42*43* 97.*) 94 2&0* 2*)4 8*=:&1 9-.3,8 47 <&9(- 8*=:&1 9-.3,8.

24) S42*43* 241*89*) 2* (9440 &);&39&,* 4+ 2* 8*=:&11>).

25) I '*1.*;* 9-&9 I <&8 *249.43&11> ◯ &':8*).

When I was growing up,...

	N*;*7 97:*	R&7*1> 97:*	S42*9.2*8 97:*	O+9*3 97:*	"*7> 4+9*3 97:*	P7*+*7 349 94 &38<*7	!3(1*&7 I9*2
26) -*7* <&8 842*43* 94 9&0* 2* 94 9-*)4(947 .+ I 3**)*) .9.	○	○	○	○	○	○	○
27) I '*1.*;* 9-&9 I <&8 8*=:&11> ○ &':8*).	○	○	○	○	○	○	
28) M> +&2.1> <&8 & 84:7(* 4+ 897*3,9- &3) 8:55479.	○	○	○	○	○	○	○

Surve Feedback

-* 3*=9 +*< 6:*89.438 <.11 '* &80.3, +47 >4:7 45.3.438 43 9-.8 8:7;*>, 84 9-&9 <* (&3 (439.3:* 94 .2574;* -4< 9-* 6:*89.438 &7* &80*) &3) <-.(- 6:*89.438 &7* &80*).

P1*&8* 9&0* & +*< 2.3:9*8 94 8-&7* >4:7 9-4:,-98 &8 7*1*;&39.

I+ >4: <4:1) 57*+*7 94 &38<*7 9-*8* 6:*89.438).7*(91> <.9- & 2*2'*7 4+ 9-* 7*8*&7(- 9*&2, 51*&8* (&11 R4' &9: (612) 547-9404 '*9<**3 10&2 &3) 952 P&(.+.(.2*.

29) I+ >4: 8*1*(9*) "!3(1*&7 .9*2" &'4;* +47 &3> 4+ 9-* 6:*89.438/89&9*2*398 &'4;*, (4:1) >4: '7.*+1>)*8(7.'* <->?

%%

F47 *=&251*: "9-* <47).3, .8 897&3,* +47 6:*89.43 4", "I)43'9 :3)*789&3) <-&9 5 .8 &80.3,", "I)43'9 9-.30 89&9*2*39 7 .8 &551.(&'1*", "S9&9*2*39 8)4*8 349 4++*7 9-* 7.,-9 &38<*7 +47 2*"

30) -* ,4&1 4+ 9-.8 8:7;*> .8 94 &88*88 -4< 2:(- 897*88 >4: *=5*7.*3(*) <-.1* ,74<.3, :5. D4 >4: +**1 9-&9 9-.8 8:7;*> &((4251.8-*8 9-&9 ,4&1? #-> 47 <-> 349?

%%

31) A7* 9-*7* 945.(8, 6:*89.438, 47 89&9*2*398 9-&9 <*7* 7*1*;&39 &3)/47 .25479&39 +47 >4: ,74<.3, :5 9-&9 >4: <4:1) &)) 94 9-.8 8:7;*>? #4:1) >4: 7*24;* &3> .9*28 +742 9-.8 8:7;*>?

%%

Brugha's List Of Threatening Events Pilot

I3 9-.8 6:*89.433&.7*, 12 :351*&8&39 *;*398 &7* 1.89*). P1*&8* .3).(&9* .+ >4: -&;* *=5*7.*3(*) 9-*8* *;*398 .3 9-* 5&89 12 2439-8.

		N4	$*8	P7*+*7 349 94 &38<*7	!3(1*&7 I9*2
1)	$4: >4:78*1+ 8:++*7*) & 8*7.4:8 .113*88, .3/:7>, 47 &3 &88&:19.	○	○	○	○
2)	A 8*7.4:8 .113*88, .3/:7>, 47 &88&:19 -&55*3*) 94 & (148* 7*1&9.;*.	○	○	○	○
3)	$4:7 5&7*39, (-.1), 47 854:8*).*).	○	○	○	○
4)	A (148* +&2.1> +7.*3) 47 &349-*7 7*1&9.;* (&:39, (4:8.3, ,7&3)5&7*39)).*).	○	○	○	○
5)	$4: -&) & 8*5&7&9.43):* 94 2&7.9&1).++.(:19.*8.	○	○	○	○
6)	$4: '740* 4++ & 89*&)> 7*1&9.438-.5.	○	○	○	○
7)	$4: -&) & 8*7.4:8 574'1*2 <.9- & (148* +7.*3), 3*.,-'47, 47 7*1&9.;*.	○	○	○	○
8)	$4: '*(&2* :3*2514>*) 47 >4: <*7* 8**0.3, <470 :38:((*88+:11> +47 247* 9-&3 1 2439-.	○	○	○	○
9)	$4: <*7* +.7*) +742 >4:7 /4'.	○	○	○	○
10)	$4: -&) & 2&/47 +.3&3(.&1 (7.8.8.	○	○	○	○
11)	$4: -&) 574'1*28 <.9- 9-* 541.(* &3) & (4:79 &55*&7&3(*.	○	○	○	○
12)	S42*9-.3, >4: ;&1:*) <&8 1489 47 8941*3.	○	○	○	○

Survey Feedback

-* 3*=9 +*< 6:*89.438 <.11 '* &80.3, +47 >4:7 45.3.438 43 9-.8 8:7;*>, 84 9-&9 <* (&3 (439.3:* 94 .2574;* -4< 9-* 6:*89.438 &7* &80*) &3) <-.(- 6:*89.438 &7* &80*).

P1*&8* 9&0* & +*< 2.3:9*8 94 8-&7* >4:7 9-4:,-98 &8 7*1*;&39.

I+ >4: <4:1) 57*+*7 94 &38<*7 9-*8* 6:*89.438).7*(91> <.9- & 2*2'*7 4+ 9-* 7*8*&7(- 9*&2, 51*&8* (&11 R4' &9: (612) 547-9404 '*9<**3 10&2 &3) 952 P&(.+.(.2*.

13) I+ >4: 8*1*(9*) "!3(1*&7 .9*2" &'4;* +47 &3> 4+ 9-* 6:*89.438/89&9*2*398 &'4;*, (4:1) >4: '7.*+1>)*8(7.'* <->?

%%

F47 *=&251*: "9-* <47).3, .8 897&3,* +47 6:*89.43 4", "I)43'9 :3)*789&3) <-&9 5 .8 &80.3,", "I)43'9 9-.30 89&9*2*39 7 .8 &551.(&'1*", "S9&9*2*39 8)4*8 349 4++*7 9-* 7.,-9 &38<*7 +47 2*"

14) -* ,4&1 4+ 9-.8 8:7;*> .8 94 &88*88 -4< 2:(- 897*88+:1 47 549*39.&11>)&3,*78 (.7(:289&3(*8 >4: *=5*7.*3(*) .3 9-* 5&89 >*&7. D4 >4: +**1 9-&9 9-.8 8:7;*> &((4251.8-*8 9-&9 ,4&1? #-> 47 <-> 349?

%%

15) A7* 9-*7* 945.(8, 6:*89.438, 47 89&9*2*398 9-&9 <*7* 7*1*;&39 &3)/47 .25479&39 +47 >4: 4;*7 9-* 5&89 >*&7 9-&9 >4: <4:1) &)) 94 9-.8 8:7;*>? #4:1) >4: 7*24;* &3> .9*28 +742 9-.8 8:7;*>?

(N49* 9-&9 <* <.11 '* &80.3, >4: 842* 85*(.+.(6:*89.438 &'4:9 CO"ID .3 &349-*7 8:7;*>)

%%

Perceived Stress Scale 10 Pilot

T+(48(67,216 ,1 7+,6 6859(< $6. <28 $%287 <285)((/,1*6 $1' 7+28*+76 '85,1* 7+(/$67 0217+. I1 ($&+ &$6(, <28 :,// %($6.(' 72 ,1',&$7(%< 6(/(&7,1* $ %87721 +2: 2)7(1 <28)(/7 25 7+28*+7 $ &(57$,1 :$<.

		N(9(5	A/0267 N(9(5	S20(7,0(6	F$,5/< O)7(1	!(5< O)7(1	P5()(5 127 72 $16:(5	1&/($5 I7(0
1)	I1 7+(/$67 0217+, +2: 2)7(1 +$9(<28 %((1 836(7 %(&$86(2) 620(7+,1* 7+$7 +$33(1(' 81(;3(&7('/<?	○	○	○	○	○	○	○
2)	I1 7+(/$67 0217+, +2: 2)7(1 +$9(<28)(/7 7+$7 <28 :(5(81$%/(72 &21752/ 7+(,03257$17 7+,1*6 ,1 <285 /,)(?	○	○	○	○	○	○	○
3)	I1 7+(/$67 0217+, +2: 2)7(1 +$9(<28)(/7 1(59286 $1' "675(66("?	○	○	○	○	○	○	○
4)	I1 7+(/$67 0217+, +2: 2)7(1 +$9(<28)(/7 &21),'(17 $%287 <285 $%,/,7< 72 +$1'/(<285 3(5621$/ 352%/(06?	○	○	○	○	○	○	○
5)	I1 7+(/$67 0217+, +2: 2)7(1 +$9(<28)(/7 7+$7 7+,1*6 :(5(*2,1* <285 :$<?	○	○	○	○	○	○	○
6)	I1 7+(/$67 0217+, +2: 2)7(1 +$9(<28)281' 7+$7 <28 &28/' 127 &23(:,7+ $// 7+(7+,1*6 7+$7 <28 +$' 72 '2?	○	○	○	○	○	○	○
7)	I1 7+(/$67 0217+, +2: 2)7(1 +$9(<28 %((1 $%/(72 &21752/ ,55,7$7,216 ,1 <285 /,)(?	○	○	○	○	○	○	○
8)	I1 7+(/$67 0217+, +2: 2)7(1 +$9(<28)(/7 7+$7 <28 :(5(21 723 2) 7+,1*6?	○	○	○	○	○	○	○
9)	I1 7+(/$67 0217+, +2: 2)7(1 +$9(<28 %((1 $1*(5(' %(&$86(2) 7+,1*6 7+$7 :(5(2876,'(2) <285 &21752/?	○	○	○	○	○	○	○
10)	I1 7+(/$67 0217+, +2: 2)7(1 +$9(<28)(/7 ',)),&8/7,(6 :(5(3,/,1* 83 62 +,*+ 7+$7 <28 &28/' 127 29(5&20(7+(0?	○	○	○	○	○	○	○

Survey Feedback

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I) <28 :28/' 35()(5 72 $16:(5 7+(6(48(67,216 ',5(&7/< :,7+ $ 0(0%(5 2) 7+(5(6($5&+ 7($0, 3/($6(&$// R2% $7: (612) 547-9404 %(7:((1 10$0 $1' 930 P$&,),& T,0(.

11) I) <28 6(/(&7(' " 1&/($5 ,7(0" $%29( )25 $1< 2) 7+(48(67,216/67$7(0(176 $%29(, &28/' <28 %5,()/< '(6&5,%(:+<?

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12) T+(*2$/ 2) 7+,6 6859(< ,6 72 $66(66 +2: 675(66(' <28 :(5(7+,6 3$67 0217+. D2 <28)((/ 7+$7 7+,6 6859(< $&&203/,6+(6 7+$7 *2$/? "+< 25 :+< 127?

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13) A5(7+(5( )((/,1*6, 48(67,216, 25 67$7(0(176 7+$7 :(5(5(/(9$17 $1'/25 ,03257$17)25 <28 29(5 7+(3$67 0217+ 7+$7 <28 :28/' $" 72 7+,6 6859(<? "28/' <28 5(029($1< ,7(06)520 7+,6 6859(<?

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Hospital Anxiety And Depression Scale Pilot

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D76B< <)3- <77 476/ <7 <0163 7>-: A7=: :-841-;: A7=: 155-,1)<- :-;876;- 1; *-;<.

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1) I .--4 <-6;- 7: '?7=6, =8':
- ◯ M7;< 7. <0- <15-
- ◯ A 47< 7. <0- <15-
- ◯ F:75 <15- <7 <15-, 7++);176)44A
- ◯ N7<)<)44
- ◯ P:-.-: 67< <7)6;?-:

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2) I ;<144 -627A <0- <016/; I =;-, <7 -627A:
- ◯ D-.161<-4A); 5=+0
- ◯ N7< 9=1<- ;7 5=+0
- ◯ O64A) 41<<4-
- ◯ H) :,4A)<)44
- ◯ P:-.-: 67< <7)6;?-:

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3) I /-<) ;7:< 7. .:1/0<-6-, .--416/); 1. ;75-<016/)?.=4 1;)*7=< <7 0)88-6:
- ◯ %-:A ,-.161<-4A)6, 9=1<- *),4A
- ◯ '-;, *=< 67< <77 *),4A
- ◯ A 41<<4-, *=< 1< ,7-;6'< ?7::A 5-
- ◯ N7<)<)44
- ◯ P:-.-: 67< <7)6;?-:

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4) I +)6 4)=/0)6, ;-- <0- .=66A ;1,- 7. <016/;:
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- ◯ N7< 9=1<- ;7 5=+0 67?
- ◯ D-.161<-4A 67< ;7 5=+0 67?
- ◯ N7<)<)44
- ◯ P:-.-: 67< <7)6;?-:

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5) &7::A16/ <07=/0<; /7 <0:7=/0 5A 516,:
- ◯ A /:-)< ,-)4 7. <0- <15-
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- ◯ F:75 <15- <7 <15-, *=< 67< <77 7.<-6
- ◯ O64A 7++);176)44A
- ◯ P:-.-: 67< <7)6;?-:

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6) I .--4 +0--:.=4:
- ◯ N7<)<)44
- ◯ N7< 7.<-6
- ◯ "75-<15-;
- ◯ M7;< 7. <0- <15-
- ◯ P:-.-: 67< <7)6;?-:

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7) I +)6 ;1<)< -);-)6, .--4 :-4)@-,:
- ◯ D-.161<-4A
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- ◯ N7<)<)44
- ◯ P:-.-: 67< <7)6;?-:

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8) I .--4); 1. I)5 ;47?-, ,7?6:
- ◯ N-):4A)44 <0- <15-
- ◯ %-:A 7.<-6
- ◯ "75-<15-;
- ◯ N7<)<)44
- ◯ P:-.-: 67< <7)6;?-:

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9) I /-<) ;7:< 7. .:1/0<-6-, .--416/ 413- '*=<<-:.41-;' 16 <0- ;<75)+0:
- ◯ N7<)<)44
- ◯ O++);176)44A
- ◯ =1<- O.<-6
- ◯ %-:A O.<-6
- ◯ P:-.-: 67< <7)6;?-:

10) I 0)>- 47;< 16<-:-;< 16 5A)88-):)6+-:

- ◯ D-.161<-4A
- ◯ I ,76'< <)3-); 5=+0 +):-); I ;07=4,
- ◯ I 5)A 67< <)3- 9=1<-); 5=+0 +):-
- ◯ I <)3- 2=;<); 5=+0 +):-); ->-:
- ◯ P:-.-: 67< <7)6;?-:

11) I .--4 :-;<4-;;); I 0)>- <7 *- 76 <0- 57>-:

- ◯ %-:A 5=+0 16,--,
- ◯ =1<-) 47<
- ◯ N7< >-:A 5=+0
- ◯ N7<)<)44
- ◯ P:-.-: 67< <7)6;?-:

12) I 4773 .7:?):, ?1<0 -627A5-6< <7 <016/;:

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- ◯ !)<0-: 4-;; <0)6 I =;-, <7
- ◯ D-.161<-4A 4-;; <0)6 I =;-, <7
- ◯ H):,4A)<)44
- ◯ P:-.-: 67< <7)6;?-:

13) I /-< ;=,,-6 .--416/; 7. 8)61+:

- ◯ %-:A 7.<-6 16,--,
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14) I +)6 -627A) /77, *773 7: :),17 7: #% 8:7/:)5:

- ◯ O.<-6
- ◯ "75-<15-;
- ◯ N7< 7.<-6
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Survey Feedback

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16) #0- /7)4 7. <01; ;=:>-A 1; <7);;-;; A7=: :-+-6< 577,;)6, -@8-:1-6+-;. D7 A7= .--4 <0)< <01; ;=:>-A)++75841;0-; <0)< /7)4? &0A 7: ?0A 67<?

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Baron Depression Screener For Athletes Pilot

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4)	I $0 +$9,1* 352%/(06 :,7+ 0< $33(7,7($1' :(,*+7	○	○	○	○	○	○
5)	I '2 127)((/ 5(67(' $1' 5()5(6+(' :+(1 I :$.(83	○	○	○	○	○	○
6)	I $0 +$9,1* 352%/(06 0$,17$,1,1* 0<)2&86 $1' &21&(175$7,21	○	○	○	○	○	○
7)	I)((/ /,.($)$,/85($6 $1 $7+/(7($1' 3(5621	○	○	○	○	○	○
8)	I &$1127 6723 7+,1.,1* $%287 %(,1* $)$,/85($1' 48,77,1* 632576	○	○	○	○	○	○
9)	I $0 '5,1.,1* $/&2+2/ 25 7$.,1* 6833/(0(176 72 ,03529(0< O22'	○	○	○	○	○	○

Survey Feedback

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P/($6(7$.($)(: 0,187(6 72 6+$5(<285 7+28*+76 $6 5(/(9$17.

I) <28 :28/' 35()(5 72 $16:(5 7+(6(48(67,216 ',5(&7/< :,7+ $ 0(0%(5 2) 7+(5(6($5&+ 7($0, 3/($6(&$// R2% $7: (612) 547-9404 %(7:((1 10$0 $1' 930 P$&,),& ,0(.

10) I) <28 6(/(&7(' "!1&/($5 ,7(0" $%29( )25 $1< 2) 7+(48(67,216/67$7(0(176 $%29(, &28/' <28 %5,()/< '(6&5,%(:+<?

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F25 (;$03/(: "7+(:25',1* ,6 675$1*( )25 48(67,21 4", "I '21'7 81'(567$1' :+$7 5 ,6 $6.,1*", "I '21'7 7+,1. 67$7(0(17 7 ,6 $33/,&$%/(", "S7$7(0(17 8 '2(6 127 2))(5 7+(5,*+7 $16:(5)25 0("

11) +(*2$/ 2) 7+,6 6859(< ,6 72 $66(66 O22' ,1 $7+/(7(6. D2 <28)((/ 7+$7 7+,6 6859(< $&&203/,6+(6 7+$7 *2$/? "+< 25 :+< 127?

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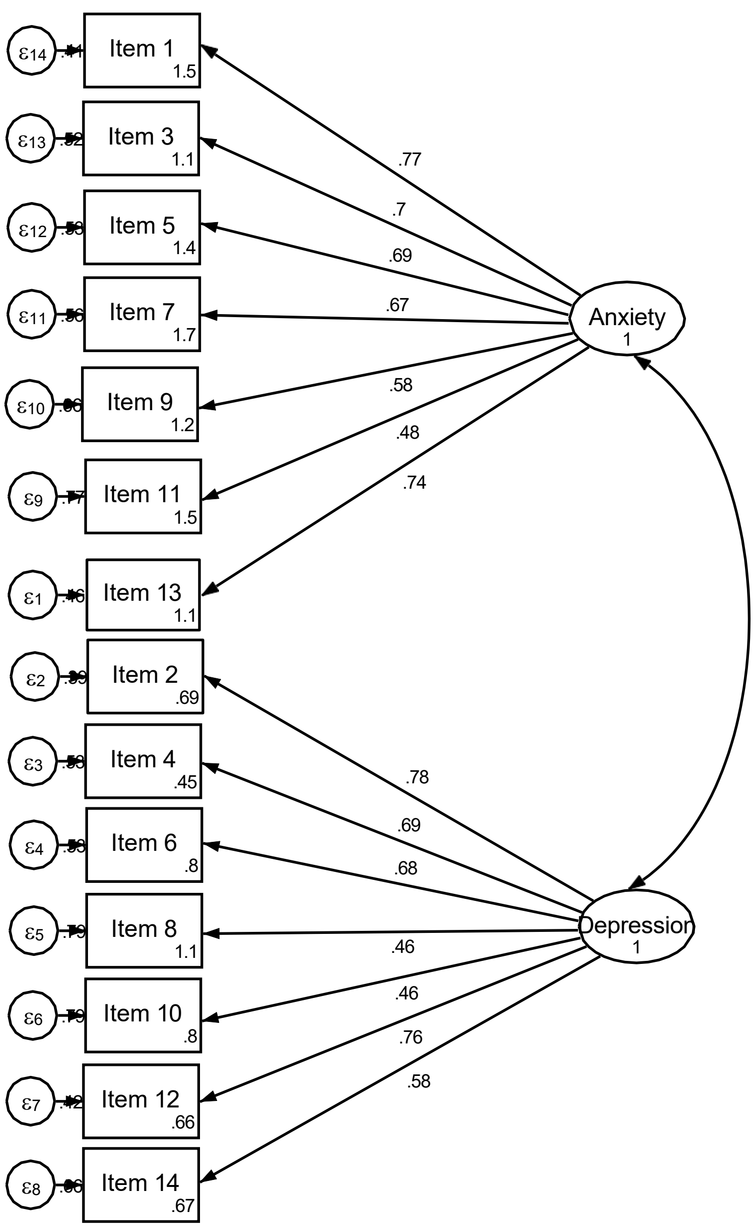
12) A5(7+(5(723,&6, 48(67,216, 25 67$7(0(176 7+$7 :(5(5(/(9$17 $1'/25 ,03257$17)25 <285 022' ($1' $7+/(7,&6) 7+$7 <28 :28/' $" 72 7+,6 6859(<? "28/' <28 5(029($1< ,7(06)520 7+,6 6859(<?

##

Descriptions of chronic health issues reported by participants in the pre-screening survey

Note: The negative Study IDs are individuals who did not receive a Study ID because they did not complete a stage beyond the pre-screening surveys. They are associated with Prescreening IDs not shown here.

Study ID	Student-Athlete in Prescreening Survey?	Student-athlete in post surveys?	Chronic Health Issue?	Descriptioon of Chronic Health Issue
1057	No	No	Yes	Chronic lower back pain Chronic migraines Anxiety Depression ADHD Remnant pain from knee surgery
1056	No	No	Yes	depression social anxiety
1002	No	No	Yes	Grae
1053	No	No	Yes	have been taking an SSRI for ~5 yrs to treat depression and anxiety
1111	No	No	Yes	Episodic migraine disorder, depression + anxiety disorders under treatment, digestive health.
1058	No	No	Yes	exercise-induced asthma/general breathing difficulties, and I'm not sure if these count but well-managed and treated anxiety and depression, and in the process of evaluating for ADHD
1112	No	No	Yes	asthma
1039	No	No	Yes	Exercise induced asthma, Cholinergic Urticaria
1145	No	No	Yes	Hypothyroidism
1107	No	No	Yes	I have Crohn's Disease
1100	No	No	Yes	Asthma
1059	No	No	Yes	Repaired Tetralogy of Fallot
1142	No	No	Yes	I have a lung disorder called PCD (primary ciliary dyskinesia) that will cause me to have lung problems every now and again and makes me more prone to infection, it was more prominent in my childhood and doesn't have any severe effects on my health at the moment.
1054	No	No	Yes	post traumatic migraine
1063	No	No	Yes	dysphasia from a traumatic brain injury in 2011
-34	No	.	Yes	Depression and anxiety
-17	No	.	Yes	ADHD, anxiety, depression
-11	No	.	Yes	Asthmatic - Diagnosed about a year ago.
-14	No	.	Yes	Asthma
-22	No	.	Yes	Crohn's disease
1154	No	.	Yes	GAD and major depressive disorder
-10	No	.	Yes	I have Betathalassemia, which is a blood disorder.
-8	No	.	Yes	Osteochondritis Dissecans (OCD) of the talus in my left ankle.
1098	No	.	Yes	Chronic back pain as a result of an injury
1092	Yes	Yes	Yes	Shoulder injuries
1091	Yes	Yes	Yes	COVID complications
1064	Yes	Yes	Yes	unspecified gastrointestinal issues as well as a heart arrhythmia.
1084	Yes	Yes	Yes	Grave's Disease (autoimmune disorder; affected my thyroid but I had my thyroid removed when I was 11, and have had no issues since. I take a thyroid horomone pill every morning)
1115	Yes	Yes	Yes	Above-knee amputee 4 years post-cancer treatment
1075	Yes	Yes	Yes	Chronic fatigue and joint pain. Currently working with doctors for a diagnoses.
1080	Yes	Yes	Yes	depression, anxiety, bronchitis, asthma
1048	Yes	.	Yes	I have asthma, if you count that as an ongoing chronic health issue.
-51	Yes	.	Yes	I have POTS, postural orthostatic tachycardia syndrome



ε14
Item 1
1.5
ε13
Item 3
1.1
ε12
Item 5
1.4
ε11
Item 7
1.7
ε10
Item 9
1.2
ε9
Item 11
1.5
ε1
Item 13
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Item 2
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Item 4
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Item 6
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Item 8
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Item 12
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Item 14
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.67
.58
.48
.74
Anxiety
1
.78
.69
.68
.46
.46
.76
.58
Depression
1

Appendix 2

Table of Contents:

(All page numbers are in reference to Appendix 2 page numbers – not the numbers associated with each questionnaire/survey or the overall Dissertation document)

Survey Questions

Below is a list of the self-report survey questions included in the online surveys. Italicized and underlined headings are the specific survey section under which the questions were included.

Prescreening survey:

Brief Health History

- Do you exercise regularly? (regular training for a sport or related activity counts)
  - How many hours have you exercised in the past 7 days, specifically? (including training for a sport or related activity)

Youth Sports

- Did you participate in organized sports as a child and/or adolescent?
  - If yes, at what ages did you regularly participate in organized sports and which sports did you play?
- Did you participate in sports or physical activities that were not "organized" but you devoted a substantial portion of time to? (e.g. recreational skiing, hiking, weightlifting, hunting, etc.)
  - If yes, at what ages did you regularly participate in these activities and what activities did you participate in?

Intramural Sports in College

- Do you participate in a recreational or intramural sports team or activity?
  - If yes, please answer the following:
    - What recreational or intramural sport(s) do you participate in?
    - For how many hours do you participate in a typical week?

Track and Field

- Are you currently a professional runner or a member of a collegiate track and field team?
  - If yes, please answer the following questions where relevant:
    - What is your event?
    - If you selected "other," please indicate your event(s) here:
    - What is your weekly mileage?
    - How many hours a week do you typically spend preparing for, participating in, and recovering from your sport/event?

Intercollegiate Sports

- Are you on a school-sponsored intercollegiate sports team (not including track and field)?
  - If yes, please answer the following questions:
    - What sports team are you on?
    - What position/event do you play?
    - How many hours per week do you typically spend preparing for, participating in, and recovering from your sport?

Post study survey:

Physical Activity

These questions focus on your physical activity this past week.

- Approximately how many hours did you spend exercising or training for a sport over the last 7 days?
    - Is this more, less, or similar to the amount of time you typically exercise/train since COVID restrictions began?
    - Is this more, less, or similar to the amount of time you typically exercised/trained before COVID?
- What types of exercise or training did you partake in the past week? (e.g. running, rowing, lifting weights, etc.)
    - Is/are these the typical types of exercise/raining you typically engage in since COVID restrictions began?
    - Is/are these the typical types of exercise or training you typically engaged in before COVID restrictions began?
- Did you have an *intense* workout in the past 48 hours?
- Is there anything else noteworthy about your physical activity from the past week that you think we should know? (e.g. 'I hurt my ankle, so I did not run as much as normal'; 'I had more free time, so I ran more than normal', etc.)

Accelerometry Criteria

Migueles and colleagues (2017) published a list of criteria for accelerometry-based studies to report to improve comparability and validity across studies, samples, and devices. I provide some context for these criteria and report on my decision-making process for each below.

Data Collection Protocols

The decisions that need to be made before data collection include selection of measurement device, device placement, and sampling frequency.

Selection of Measurement Device

Multiple different devices exist for objectively measuring physical activity in humans, including pedometers, global positioning system, and accelerometry. However, accelerometry is by far the most used method and the ActiGraph GT3X+ accelerometer (ActiGraph, FL, USA) is the most popular and most widely validated motion sensor for activity research, accounting for >50% of published studies (Wijndaele et al., 2015). Although open-source applications have made comparison across monitors easier, acceleration signals are still filtered and pre-processed by proprietary algorithms. Therefore, utilizing the Actigraph GT3X+ improves the likely validity and comparability of my measures across other studies.

Device Placement

For device placement, researchers must optimize measurement specificity and participant compliance within their sample. Data recorded from accelerometers worn on one location (e.g., the hip) are not directly comparable to another location (e.g., the wrist). An accelerometer worn on the hip will only record whole body acceleration whereas the dominant wrist may pick up movement even while the participant has remained sedentary (Buchan et al., 2019). However, if participants are removing their monitors or wearing them incorrectly, then activity data will be useless. Placing accelerometers on the non-dominant wrist is thought to demonstrate the best compliance among participants while limiting the incidence of false activity records (Center for Health Statistics, 2011; Park et al., 2019). In fact, it is the most common placement in large population surveys (Doherty et al., 2017), the Whitehall II cohort (Menai et al., 2017) and the US National Health and Nutrition Examination Survey (NHANES) (Belcher et al., 2021). Considering both activity specificity and compliance, I chose to place the accelerometer on the non-dominant wrist.

Sampling Frequency

Research-grade accelerometers have the option to designate how many times per second that acceleration is measured (i.e., Hertz, Hz). Collecting at a higher Hz allows researchers to assess more short-term bouts of activity and better differentiate various intensities of activity. The downsides of sampling at a higher frequency are that it leads to a shorter battery life and may record higher activity counts for the same movements. The proprietary filtering process for the Actigraph GT3X was developed for 30 Hz so sampling frequencies in multiples of 30 produce the most accurate, reliable estimates while other sampling frequencies (e.g., 40, 100) offset the filter resulting in higher activity counts for the same movement (Brond & Arvidsson, 2016). Importantly, all participants within a study should be recorded at the same sampling frequency and comparisons against other sampling frequencies are not directly possible (Migueles et al., 2017). Since the Actigraph GT3X can collect frequencies up to 100 Hz, I collected data at 90 HZ to accommodate the Actigraph proprietary filtering process and maximize the specificity of my data collection.

<u>Data Processing Criteria</u>

While processing accelerometry data, researchers need to set inclusion criteria for non-wear time, define how much data is needed to establish a valid “day” or “week” for analysis, decide on a filter for recording movement, set an appropriate epoch length, and select an algorithm to assess sleep.

Non-wear time

In studies measuring activity continually (i.e., 24-hour daily activity), participants are asked to wear their accelerometer at all times and asked to only remove accelerometers when they will be in the water for an extended period of time (e.g., swimming or bathing) or when it may be dangerous for themselves or others to keep wearing it (e.g., collision sports). Occasionally participants might forget to replace the accelerometer afterward, leading to a day or part of a day without continuous measurement. Further, participants may decide that the Actigraph is too much of a nuisance and may remove it for periods at a time. Therefore, researchers need to identify non-wear-time and exclude it from downstream analysis, otherwise it may be miscategorized as a period of little or no activity. This is done through a combination of self-report (e.g., a diary) or through algorithms that detect and label non-wear times based on specified intervals of time without movement. For example, if an accelerometer measured 30 minutes below a movement threshold, the data processing software will label it as “non-wear-time” and this data will be excluded. Different settings for this algorithm can lead to substantive differences in recorded activity and there is a cost-benefit tradeoff of what will most likely bias data (Toftager et al., 2013). For example, elderly adults will need a different setting than adolescents based on the higher degree of expected sedentary behavior in the elderly. Setting a lower amount of time without recorded movement like 20 minutes, which is a common setting, will result in more time lost per participant and, likely, more participants dropped from the sample while potentially losing “real” sedentary time. On the other hand, a more stringent setting like 90 minutes may miss shorter bouts of non-wear time and categorize them as low activity (Peeters et al., 2013). For the current study, non-wear time is set at 60 consecutive minutes of no movement as recommended for young adults (Migueles et al., 2017).

Valid Day and Valid Week

Since few participants will have perfect 24-hour wear time for each day of a study (and if they are engaging in recommended hygiene, they should not have 100% wear time), researchers need to decide how many hours of wear-time are required for a 24-hour period to be included in their analyses as well as how many valid days are needed to be representative of the total assessment period. Increasing requirements for what is considered a valid day and a valid week will often reduce the sample size and statistical power of a study (Toftager et al., 2013). However, reducing requirements (i.e., fewer hours in the day, fewer days in the week) may lead to unknown biases in the data or generally misrepresent time spent in physical activity (Migueles et al., 2017). Current published recommendations are to accept days with a minimum of 10 hours and weeks with a minimum of 4 valid days (Donaldson et al., 2016; Migueles et al., 2017). However, the software I am utilizing to process my data (GGIR, see below) requires ≥16 hours per day to calculate its full suite of metrics for activity and sleep. Therefore, I will be including all days with ≥16 hours of wear time and all participants with at least 4 valid days.

Filter Settings

All accelerometers utilize a filter to exclude accelerations occurring at frequencies that are interpreted as either too low or too high to be compatible with human movement. An example of this may be when an individual is using a jackhammer – the accelerations recorded by a wrist-worn accelerometer would be well above what a human could produce. While these filters are typically proprietary, so their formulas are not released, wearables often have at least two options of filter. Actilife software, the proprietary software for Actigraph GT3X+ accelerometers, allows users to choose between normal (default) and low-frequency extension (LFE) filters. The LFE filter establishes a lower threshold for recording acceleration to capture slower movements. However, it is unknown how much lower this threshold is since the algorithms for these filters are proprietary information. Previous studies indicate that LFE may overcount activity for more active young adults (Cain et al., 2013; Lyden et al., 2012; Ried-Larsen et al., 2012), so I have decided to use the default filter setting. However, it is important to note that Actigraph's default filtering process will exclude accelerations above 2.5 Hz while the human body can produce accelerations greater than 3.4 Hz at the wrist. Therefore, ActiGraph's filtering process might remove accelerations associated with vigorous physical activity, misclassifying them as moderate physical activity (Brond & Arvidsson, 2016; John et al., 2012). This is a consideration will be addressed in my statistical analyses.

Epoch Length

To estimate time spent in different categories of physical activity intensity and estimate sleep and wake states, activity counts need to be summed across specific time intervals (i.e., epochs). The counts that occur in an epoch are used to categorize the activity levels of that epoch (e.g., if there is a lot of activity, it is classified as moderate or vigorous activity). In general, shorter epoch lengths (e.g., 1-15 seconds) are recommended for individuals where short bursts of activity are expected (e.g., athletes) (Migueles et al., 2017). Longer epochs (e.g., 60 seconds and longer) will tend to miss short bursts of activity because they average the activity over a longer period. For example, if a participant sprints 100 meters in 10 seconds and walks the remaining 50 seconds, the data may appear similarly as a brisk walk or jog for 60 seconds. However, most common sleep algorithms have all been validated using 60 second epochs, so many researchers support using that epoch length (Migueles et al., 2017; Sadeh et al., 1994). Given these competing pressures, I will be assessing physical activity in the wake states with 1 second epochs since I expect that student-athletes engage in a lot of short bursts of activity and I will be assessing sleep separately using 60 second epochs.

Sleep-related behaviors

Actilife Software applies algorithms to identify sleep-related behaviors from movement and non-movement patterns by applying sleep algorithms to activity counts (Sadeh et al., 1994). Extensive validation work in this area demonstrates high agreement between these algorithms when accelerometers are worn on the wrist and polysomnography (i.e., the gold standard to measure sleep patterns; e.g., Rosenberger et al., 2016). While many sleep researchers will combine these algorithms with self-report measures such as sleep diaries to help validate specific sleep metrics, these measures greatly increase participant burden and college students are unlikely to answer these accurately. Due to the high agreement with polysomnography and busy schedules of my participants, I am only utilizing the sleep algorithm developed by Sadeh and colleagues (Sadeh et al., 1994) as recommended in the literature Migueles et al (2017) and not using a sleep diary. Specifically, I am creating two measures of sleep as potential covariates in downstream analysis: Average Total Sleep Time and Sleep Efficiency.

Data Analysis Criteria

Accelerometers produce a rich and complex set of physical activity data that is often reduced for statistical analysis. These reductions and operationalization of the data impact what statistical models can be used and limits interpretations of the data.

Physical Activity Categorization

Traditionally, the most common strategy to compare patterns of physical activity intensity across individuals is to compare time spent in various levels of physical activity, such as sedentary behavior or vigorous activity (Hildebrand et al., 2014). Researchers will set cut points or thresholds of activity counts per epoch to assign each epoch an intensity level, then sum or average the number of epochs in each intensity level across the study period. These calculations are used to estimate how much time participants spend in each category of intensity. The time spent in each category is easy to calculate (most software programs do so automatically), can be directly input in linear regression models, and are easy targets for health guidelines and interventions (Migueles, Aadland, et al., 2022).

Despite the ease of these measures, there are potential shortcomings with their use. First, multiple established cut points for these categories exist and they will provide different estimates of time spent in each category (Migueles et al., 2017). Second, these cut points are typically derived from indirect calorimetry (VO2) studies with participants on a treadmill and, therefore, lack ecological validity for free-living activities (Bammann et al., 2021). Third, differences in pre-processing setups, including device selection and placement will lead to different counts and time spent in each category (i.e., cut points for hip-worn accelerometers do not translate practically to wrist-worn protocols) (Gao et al., 2021; Migueles et al., 2017). Fourth, in general, categorizing continuous data leads to a loss of statistical power and introduces other biases to the data. For example, participants with similar levels of activity will score very differently if one has activity falling just above a cut point and one has activity falling just below the same cut point (Dempsey et al., 2022). Lastly, because the time during the day is finite, the sums and averages of time spent in each category are co-dependent (Backes et al., 2022). As time in one category increases, time in at least one other category decreases. This relationship violates assumptions of linear modelling.

Despite the shortcomings listed previously, I will be including categorical variables such as time spent in MVPA in both the current and downstream analyses. There are no current meta-analyses comparing the validity of various cut-points and the comparisons between them will differ based on the activity types of your sample. Therefore, there is not a single recommended group of intensity thresholds for free-living assessment. However, Hildebrand et al. (2014) used indirect calorimetry from young adults performing over a dozen "daily activities" to define a series of cut points with the Actigraph GT3X+ worn on the non-dominant wrist. These cut-points are the most widely recommended for continuous physical activity monitoring in young adults (Migueles et al., 2017).

Advanced Analytical Methods of Physical Activity Assessment

As mentioned above, conventional categorization of physical activity for analysis only reflects a part of the reality of physical activity and introduces complications with statistical modeling that many researchers fail to address (Backes et al., 2022; Migueles, Aadland, et al., 2022). To overcome these issues, there has been a push to develop more advanced measures of physical activity to identify and investigate activity profiles that have so far been missed and to subsequently gain better insights into the role of physical activity in biology and overall health. While there are a number of these measurements, only two (i.e., average acceleration and intensity gradients) have demonstrated replicable associations with health across multiple age groups (Backes et al., 2022). Notably, the combination of these two variables allows me to describe both overall activity levels and how this activity is distributed among a continuous measure of intensity, providing a more complete depiction of an individual's activity profile. For some biomarkers and outcomes, the volume of activity has stronger associations than the pattern of intensity, but for others, the opposite is true. Consequently, this approach will allow me to investigate the independent, complementary, or interactive associations of volume and intensity distribution with telomere length in Paper 3 (Backes et al., 2022). This analysis will only include AvAcc and intensity gradients, but more complex measures will be investigated in future analyses, particularly as the methods become more widely accessible and replicable.

Average Acceleration

The AvAcc is the average daily volume of recorded acceleration data, providing a single metric for the total volume of daily activity (Dygrýn et al., 2021). Statistical interpretation of findings using linear regression is straightforward since there is a single variable representing the overall activity volume and codependence with other explanatory variables is not usually a concern in linear regression models. A recent expert consensus statement suggests that this is a useful measure when total physical activity is of interest (Migueles, Aadland, et al., 2022).

Intensity Gradient

As physical activity intensity increases, the time spent at that intensity will decrease in a curvilinear fashion. That is, humans typically spend the most time engaging in low levels of activity and substantially lower levels in the highest levels of activity. For example, the total time spent at a walk will be much larger than the total time spent at a sprint. The IG is a single value for each participant that represents the negative curvilinear relationship between physical activity intensity and the time accumulated at that intensity, utilizing the continuous distribution of acceleration intensity across all recorded activity and time (Rowlands et al., 2018). It is calculated from accelerometry data in several steps. First, one must transform the curvilinear relationship between time and intensity into a linear relationship by taking the natural log of time and accelerations/epoch. Then, the line of best fit for this linear relationship is calculated. The IG is the slope of this line of best fit. A more negative (lower) gradient reflects a steeper drop with little time accumulated at midrange and higher intensities (Figure 1A), whereas a less negative (higher) gradient reflects a shallower drop with more time spread across the intensity range (Figure 1B). The IG overcomes many of the limitations of cut-points and does not break activity into co-dependent categories (i.e., since the time spent in all activity categories add up to 1, one activity cannot increase without decreasing another).

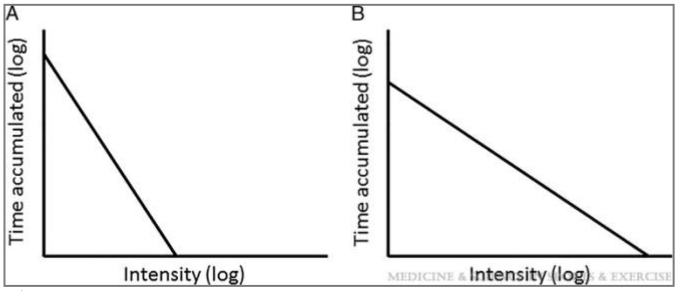

Figure 1
Image is from (Rowlands et al., 2018)

Analysis Software

Previously, researchers had to rely upon the proprietary software and proprietary "activity counts" associated with their activity monitor (e.g., Actilife for the Actigraph GT3X) to create their estimations of activity. This is still a common practice, but it gives less control of the data to the researcher and limits comparability between monitors and studies (Migueles, Aadland, et al., 2022). Fortunately, the newer generations of accelerometers can export the raw accelerometry data to outside programs, such as GGIR, that allow researchers to process data from multiple devices in an identical manner. GGIR is an open-source R-package specially developed for this purpose (Migueles et al., 2019). It processes acceleration signals using local gravity as a reference, calculating the average magnitude of dynamic acceleration corrected for gravity (Euclidean Norm minus 1*g*, ENMO) averaged over the researcher-selected epochs and expressed in milligravitational units (m*g*). Using m*g* instead of counts allows GGIR to process and analyze the raw data and generate meaningful physical behavior variables for statistical analyses that are more comparable across accelerometry devices (Migueles, Molina-Garcia, et al., 2022). Exporting raw data to GGIR, specifically, is becoming increasingly common, including among biological anthropologists (Raichlen et al., 2019).

Statistical Testing

In practice, most researchers conduct ordinary least square regression analyses with the time spent at a specific intensity of physical activity as an independent variable. However, as mentioned in the categorization section, perfect multicollinearity exists among the mutually exclusive categories of physical activity and sleep (Migueles, Aadland, et al., 2022). In other words, you cannot increase one of these variables without simultaneously impacting at least one other variable. Thus, researchers need to limit their inclusion of time-use behaviors (e.g., MVPA, sleep, etc.) to one or two categories that do not cover much of the day when added together. Another method for sleep, specifically, is to include a variable like sleep efficiency that is not based on time but quality of sleep. Because of the potential for multicollinearity, I am limiting my downstream analyses to include time spent in MVPA and sleep efficiency. IG and AvAcc do not have these same issues with collinearity (Migueles, Aadland, et al., 2022).

Participant Burden

Wearables introduce a unique type of participant burden. While they do not necessarily increase the time spent in the study, they can be uncomfortable, and the participant will feel obligated to care for the device while it is in their care. Further, the more common and accurate accelerometers (e.g., Actigraph GT3X) are not necessarily aesthetically appealing. While this may reduce the chance that wearables are stolen or kept by participants on accident, it also makes them less likely to be worn reliably or for individuals to be interested in joining that portion of a study. Further, the device may make certain activities more difficult or get in the way at places of employment or during certain types of activity (e.g., swimming). However, participant compliance may be improved through more creative forms of compensation, including sharing data. For the current study, compliance appeared to be higher in individuals who were more interested in receiving their activity data.

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