

MODELING COLLEGIATE STUDENT-ATHLETE SPORT PERFORMANCE VIA SELF-
REPORT MEASURES

BY

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THESIS

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ABSTRACT

Purpose: Optimizing athlete performance is the central focus of players, coaches, and support staffs alike. For years, monitoring the stressors encumbering athletes has focused on the injury-risk dimension and has failed to look at sport-specific performance, the ultimate end goal. Self-report wellness measures have shown great promise in this realm and were implemented to track a wider range of metrics, including subjective performance. This study focused on mapping a combination of variables to each athlete's performance data to better understand the key indicators of our outcome variable on an individual basis. A secondary aim of this study was to uncover trends amongst the team in which certain variables behaved similarly in their relationships with performance.

Methods: Female collegiate volleyball student-athletes ($N=16$) completed daily wellness monitoring via an online questionnaire. Data from the fall competitive season was collected via Qualtrics[®] and later regression analysis was performed using R.

Results: Performance of the regression models ranged from an explained variance (i.e., adjusted- R^2) of 0.23 to 0.90 (i.e., 23-90%) indicating poor to strong results, dependent on the specific athlete as expected. Match-specific players averaged an explained variance in performance (adjusted- R^2) of 0.66 (66%) while practice-specific players averaged 0.44 (44%). Sleep duration appeared in half of all athlete models though with both positive and negative coefficients. RPE-based training load metrics, daily locus of control, and physical fatigue appeared at the next highest frequencies, respectively, though again the coefficients were not uniformly positive or negative for every athlete. Heart rate variability (HRV) was projected to play a prominent, positive role in athlete performance yet only appeared in two of the regression equations.

Conclusions: As expected, the regression models were quite varied across the athletes. The approach worked better for match-specific players, with nearly two-thirds of the variance in match performance explained by the models on average. This study supports the adoption of a

wider range of stressor metrics with specific emphasis on adding a locus of control dimension to monitoring systems. An expanded list of questions may be required to better encapsulate and map second order markers of athlete performance and this work provides additional rationale for tracking stressors outside of the sport-specific context as well as deeper use of cost-effective monitoring tools such as self-report measures to model performance in collegiate student-athletes.

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CHAPTER 1: INTRODUCTION

Optimizing athletic performance remains a fascinating and complex challenge which sport coaches, athletes, and support staff members must deal with on a daily basis. To this extent, monitoring and sport science have become buzzwords in the athletic communities as professionals seek to uncover the underpinnings of performance. Unfortunately, members of this field have yet to effectively piece together the entire puzzle. Too often sport coaches are solely concerned with the actual on-field sport performance of their players, while strength coaches focus on the physical loads placed on the athletes, and other support staff members may be more attuned to the psychological stressors athletes endure. Research has confirmed that an excess of physical loading can influence performance via overtraining syndrome and increased injury risk (Armstrong & VanHeest, 2002; Budgett, 1990; Kellmann, Foster, Gastmann, Keizer & Steinacker, 1999; Mackinnon, 2000; Meeusen et al., 2013) and that psychological stressors can hinder performance in similar fashions (Brink, Visscher, Coutts, & Lemmink, 2012; Kellmann, 2010; Main & Grove, 2009; Morgan, Brown, Raglin, O'Connor & Ellickson, 1987; Totterdell, 2000; Wiese-Bjornstal, 2010). However, there is a dearth of studies looking at the problem from a more global perspective, where a host of stressors intertwine to influence sport performance. The research that has been done using this integrated viewpoint typically focuses on injury prevention rather than actual performance evaluation; the present study seeks to address performance.

Selye's general adaptation syndrome (GAS; 1936) serves as the framework for athlete monitoring while Yakovlev's concept of supercompensation (1967), the idea that stressors must be accompanied by a period of rest for increases in performance to manifest, expands upon Selye's foundation. GAS consists of the arousal and alarm, resistance, and exhaustion phases in which a stressor is presented to the individual, resources are allocated to combat the stressor and return to homeostasis, and without proper adaptation, exhaustion sets in with detrimental consequences (Selye, 1936). Athlete monitoring is primarily concerned with the first two stages

of GAS and having keen awareness of incoming stressors and the degree to which an individual is affected by said stressors. To this extent, Yakovlev's framework is key to understanding the rise and fall within the stress-recovery balance. Fundamentally a physical load concept, Yakovlev's concept of *supercompensation* (1967) addresses how proper recovery is essential for actualizing gains in performance. If stressors continue to be piled atop athletes without a recovery period, performance declines at an increasing rate. For these reasons, both Seyle and Yakovlev laid the critical foundation for athlete monitoring as it is currently understood. Furthermore, their frameworks provide rationale for the need to better encapsulate incoming stressors which burden student-athletes on a daily basis.

Entangled in both Seyle's and Yakovlev's ideas is the concept of *allostasis*– the adaptation phase in which bodily resources are mobilized and utilized to combat stressors and return to homeostasis. The intensity of these demands placed on the individual is referred to as *allostatic load*. This load reflects both the physical wear and tear, combined with the cognitive pressures an individual (e.g., a student-athlete) is dealing with; the larger this allostatic load, the greater the need for recovery (McEwen & Seeman, 1999). Kallus and Kellmann's (2000) model (see Figure 1) neatly illustrates this relationship and underscores the need for recovery as stressors begin to outgrow the resource limits of the individual. By increasing awareness of the multiple facets affecting the athlete's allostatic load, sport professionals may be better equipped for early detection of declining performance and intervene promptly and appropriately.

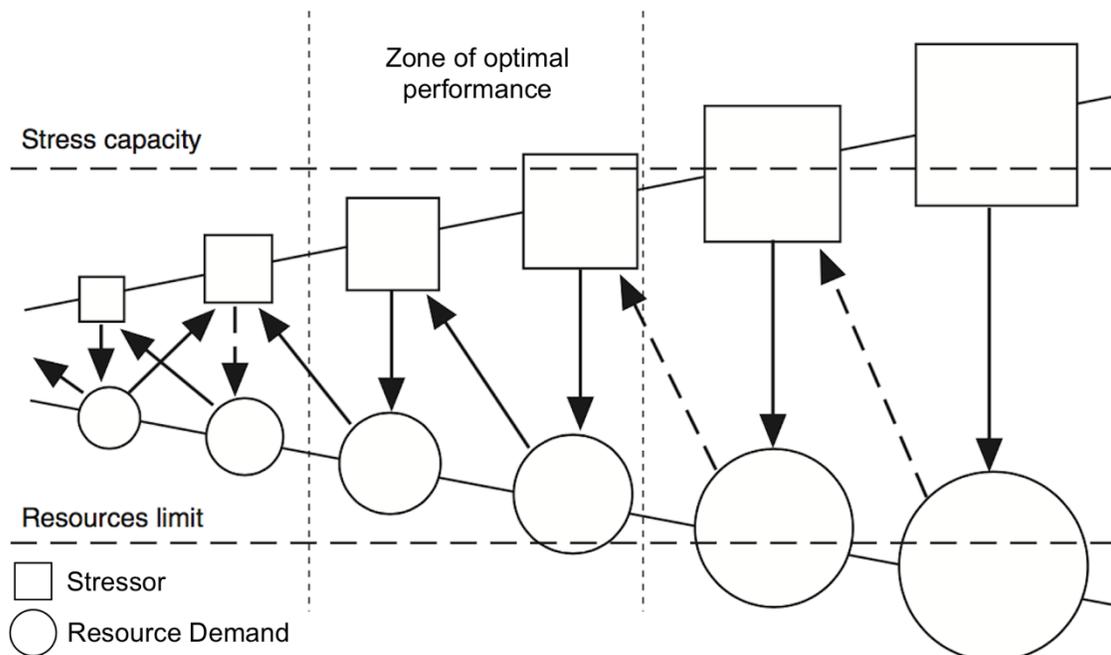


Figure 1. The “scissors-model” depicts the intertwined nature of stress states and demands for recovery (adapted from Kallus & Kellmann, 2000).

Collegiate student-athletes face a unique combination of stressors which may interact with one another and accelerate performance declines (Mann, Bryant, Johnstone, Ivey, & Sayers, 2016; Parham, 1993). This increase in load requires a parallel increase in recovery, which if interrupted by new stressors, can spiral further into overtraining syndrome (Budgett, 1998). As previously mentioned, most studies fail to examine the range of contributors to this athlete load, preferring to hone in on the physical or the psychological stressors independently. This study seeks to remedy this. Examining sport performance as the outcome measure rather than injury prevention, may increase both athlete and coach buy-in while more efficiently leading to optimized performance.

By selecting concepts from relevant theories with regard to factors that influence performance, this study sought to uncover the interconnected relationship between physical and psychological variables and their combined relationship to sport-specific performance. To accomplish this, a battery of measures featuring questions about sleep, locus of control, daily

hassles, physical/mental fatigue, nutrition, and training load were completed on a daily basis, along with a daily assessment of heart rate variability (HRV) and post-sport subjective ratings of performance. Linear regression models were constructed in an attempt to determine which measures could track athlete performance, how effective they were at this tracking, and to uncover potential combinations of variables previously undocumented. While combining physical and psychological stressors to gain a more comprehensive understanding of athlete load is not an original idea, this study is novel in the sense that it examined the combined relationship to sport-specific performance and did so on an athlete-by-athlete basis.

The main objective of this study was to determine the effectiveness of using various self-report and physiological measures to track and model subjective performance in a sport-specific context. Specifically, the purpose of this research was to determine the nature of the relationships between metrics such as HRV, muscle soreness, academic/social/student-athlete stress, sleep, locus of control, physical/cognitive fatigue and self-rated athlete performance. A secondary aim of this study was to uncover trends amongst athletes in which the same cluster of variables behaved similarly in individual regression models. It was hypothesized that metrics with a traditionally positive connotation (e.g., sleep, HRV, nutrition) would have positive coefficients in the regression equations (i.e., higher values would benefit athlete performance); this is in contrast to traditionally negative variables (e.g., stress, soreness, fatigue, difficulty of day, external locus of control) such that an increase in these metrics would have a negative coefficient in regression models and therefore be associated with decreases in performance. It was also hypothesized that sleep and HRV, two of the most commonly used and studied variables in monitoring athlete performance, would appear most frequently in the regression equations.

CHAPTER 2: LITERATURE REVIEW

Athlete Monitoring

Lacking a precise definition, athlete monitoring encompasses a variety of techniques to track and support the athlete's path to increased performance. These techniques can range from tracking workouts with pencil and paper to GPS-based training loads and their effects on blood and salivary biomarkers of fatigue (e.g., cortisol, inflammatory cytokines, immunoglobulin A, blood lactate). These methodologies vary in both their costs (i.e., financial, time, ease of use) and benefits (i.e., effectiveness), yet research suggests that simpler methods may provide better insight than more expensive, objective counterparts (Saw, Main & Gastin, 2015).

The overarching goal of every athlete monitoring system is to track indicators of potential decreases in performance and intervene as early as possible to prevent such performance decrements from occurring. This is based on the idea that early identification of an athlete trending towards non-functional overreaching and overtraining (see Figure 2), and thus intervention can help mitigate the required recovery time and ideally prevent the athlete from slipping into full-blown overtraining syndrome (Budgett, 1990, 1998; Dong, 2016; Soligard et al., 2016; Schwellnus et al., 2016). Effective athlete monitoring is defined by the methodology's ability to detect trends which may be harmful to performance. Therefore, identifying and understanding the underlying factors impacting performance is crucial to this undertaking. To this end, researchers and practitioners have studied an assortment of variables which may impact athlete performance. This has included physical factors such as training load, muscle soreness, sleep, and heart rate variability (HRV). This has also included numerous psychological stressors like daily hassles, academic/social stressors, levels of cognitive fatigue, helplessness, and others. Implemented through questionnaires, GPS tracking, self-reporting, and the use of other technologies, athlete monitoring has taken a number of forms, but the end goal is constant: identify and remedy factors which may negatively impact performance.

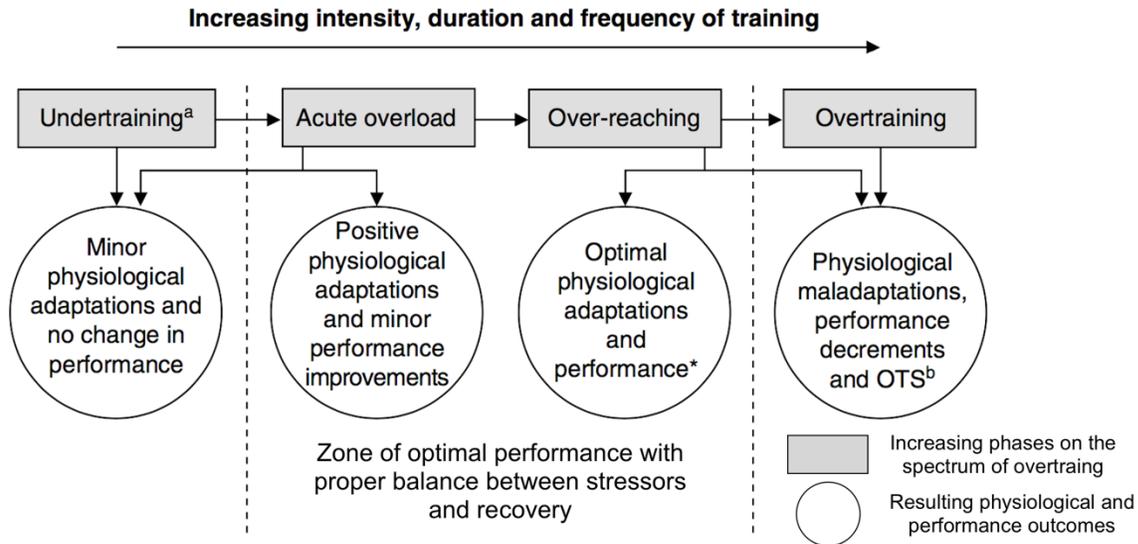


Figure 2. The timeline of undertraining to overtraining as a function of increasing stressor burdens upon athletes (adapted from Armstrong & VanHeest, 2002).

Overtraining Syndrome & Other Outcome Measures

Overtraining receives the majority of attention in the field of athlete monitoring. Positioned as the worst outcome on the training level spectrum, overtraining syndrome (OTS) is sometimes referred to as athlete burnout – a level of fatigue so severe that its symptoms mimic depression and carry with them a corresponding collapse in performance (Armstrong & VanHeest, 2002; Fry et al., 1994; Morgan et al., 1987; Ryu, Kim, Ali, Choi, Kim & Radlo, 2015). Unsurprisingly, OTS often serves as the outcome variable that monitoring systems are in place to detect. Aside from decreases in performance, markers of OTS include reduced ability to perform high intensity exercise, persistently high fatigue ratings, decreased maximal heart rate, worsening of self-reported wellness indicators, and symptoms akin to depression (Budgett, 1990, 1998; Kentta & Hassmen, 1998; Mackinnon, 2000). Because of the prolonged recovery time associated with OTS, athletes with indicators trending in this direction require swift intervention to prevent weeks or months of recovery and suboptimal performance (Meeusen et al., 2013). Research into OTS has examined both the physical and psychological well-being of the athlete and those relationships to overtraining. Whether using on-field performance testing,

some assessment of aerobic fitness (e.g., VO_{2max}), or some other physical output measures in a laboratory setting, a plethora of research into the physiological component of OTS has been conducted as a means to better identify the warning signs (Coutts, Slattery & Wallace, 2007; Coutts, Wallace & Slattery, 2007; Fry et al., 1994; Koutedakis, Budgett & Faulmann, 1990). Similarly, work revolving around the psychological indicators of OTS has provided better insight for detecting declining performance. However, these studies often rely heavily on previously crafted questionnaires such as the Profile of Mood States (POMS; McNair, Droppleman & Lorr, 1992) or Recovery-Stress Questionnaire for Athletes (RESTQ-Sport; Kellmann & Kallus, 2001). Measures like these may fail to fully capture stressors affecting student-athletes in the collegiate setting (Brink et al., 2012; Fry et al., 1994; Coutts, Wallace & Slattery, 2007; Morgan et al., 1987). To this extent, an optimal strategy may be to combine the best of these measures to better summarize athlete stressors.

Another outcome that monitoring seeks to detect is increased risk of injury. Highlighted by Hulin and Gabbett's acute to chronic workload ratio, and separate from OTS, is the idea that spikes in stressors (via physical training load) are accompanied by an increased likelihood of injury and, in turn, decreased performance (Gabbett, 2016; Hulin, Gabbett, Blanch, Chapman, Bailey & Orchard, 2014; Hulin, Gabbett, Lawson, Caputi & Sampson, 2015). This research revolves around determining what the athlete's body is ready to handle via chronic loading (e.g., the previous 4 weeks) versus the demands placed on the individual through acute loading (e.g., the previous 7 days). The farther from the chronic baseline an athlete is pushed, the greater the chance of injury (Gabbett, Hulin, Blanch & Whiteley, 2016). Conceptually, this closely parallels the idea of monitoring the allostatic load placed on the individual as a function of how far off the centerline that person is pushed and therefore the quantity of resources required to return to homeostasis.

Though not specific to the sphere of daily athlete monitoring, research examining the relationship between stressors and reaction time, agility, decision-making, and technical sport

ability have concluded that decreased performance accompanies increased fatigue. While touching on the idea that physical and psychological stress impact injury risk, researchers have expanded into factors even more closely linked to sport performance. Outcome measures like power output, psychomotor vigilance testing, self-rated performance, reaction time, and others may provide deeper insight into accurate indicators of sport performance. While more similar to sport-specific performance, these second order indicators also suffer from limitations. Lack of baseline measurements, difficulties with standardizing measures, and the need for maximal effort during testing all hinder performance testing in ways which compromise their implementation and usefulness (Meeusen et al., 2013). This is where self-rated performance may provide an answer. Universally applicable to all athletes across all sports, subjectively rating one's own performance may provide a valuable outcome measure, sensitive enough to allow meaningful insight into performance (Stavrou, Zervas, Karteroliotis & Jackson, 2007).

Physical Load

As we seek to assess the aggregate allostatic load placed on an individual, we must first identify its component parts. Physical load quickly comes to mind when dealing with athletes, especially for those in the strength and conditioning field who keenly understand that physically exhausted athletes are not prime for training. From a performance standpoint, increased muscle soreness often indicates the need for recovery (Budgett, 1990; Drew & Finch, 2016; Kentta & Hassmen, 1998; Taylor, Chapman, Cronin, Newton & Gill, 2012). and excessive physical fatigue may lead to sport performance decrements (Borresen & Lambert, 2009; Coutts, Wallace & Slattery, 2007; Koutedakis et al., 1990; Rampinini, Impellizzeri, Castagna, Assalin, Bravo & Wisløff, 2008).

In recent years, Hulin and Gabbett have published and popularized the concept of acute to chronic training load – previously discussed as the idea that abrupt changes in training load relative to the body's baseline correlate with increased injury risk (see Figure 3; Gabbett, 2016).

To this end, the rate of change in training load should be accounted for in any athlete monitoring program seeking to minimize injury risk and maximize performance.

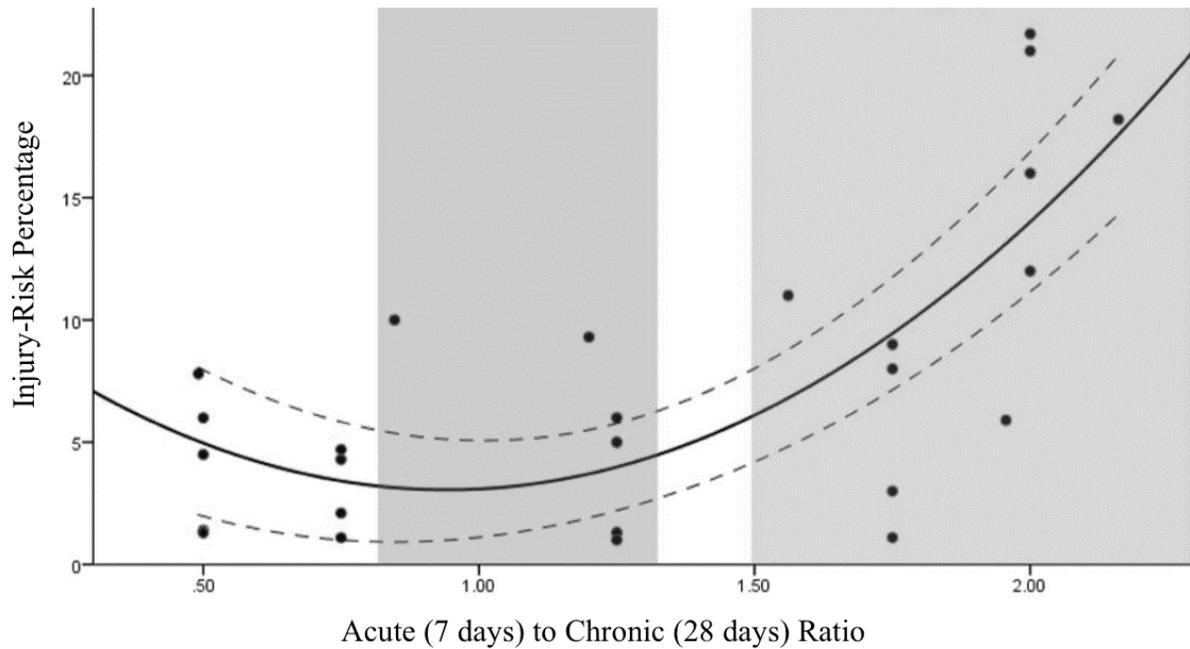


Figure 3. Visual to help navigate the acute to chronic workload ratio and the risk of injury. The darker shaded portion represents ratios close to 1 and the lowest risk of injury. Ratios both below and above this level show increased injury-risk potential (adapted from Gabbett, 2016).

Other components of physical load, such as muscle soreness and physical fatigue, also play key roles in athletic performance. Recurrent soreness not only serves as a potential indicator of OTS (Budgett, 1990), but it also affects muscle force and function (MacIntyre, Reid & McKenzie, 1995). As athletes experience increased physical fatigue and muscle soreness, strength/power output, range of motion, and performance are negatively impacted (Cheung, Hume & Maxwell, 2003). An inverse relationship is also apparent for psychomotor speed as a function of high load training (Nederhof, Lemmink, Zwerver & Mulder, 2007). So while these may be second order indicators of performance, they represent the cornerstones of the physical component of total athlete load. This idea has also been applied in a sport-specific setting where physical fatigue has been shown to have an inverse relationship with technical ability in soccer (Rampinini et al., 2008). Though not a match-level outcome variable, studies such as

this provide bridges between high levels of physical loading and sport-specific performance outcomes.

Psychological Load

Psychological factors may comprise the majority of load an athlete finds him/herself under while simultaneously serving as mediators for the impact of incoming load overall. Playing a key role in performance, psychological factors may also serve a secondary purpose as mediators in the balance between stressors and recovery. Assessing the psychological load of an individual is an imperfect science and therefore a multitude of potential indicators are likely to better encapsulate this component.

Cognitive fatigue may occur from a variety of situations, yet it plays a crucial role in both the physical and mental performance of the athlete. This type of fatigue has been shown to decrease physical performance in general (Cutsem, Marcora, Pauw, Bailey, Meeusen & Roelands, 2017; Marcora, Staiano & Manning, 2009; Otter, Brink, van der Does & Lemmink, 2016; Pageaux & Lepers, 2016), but also in numerous sport-specific circumstances as well (Badin, Smith, Conte & Coutts, 2016; Smith, Coutts, Merlini, Deprez, Lenoir & Marcora, 2016; Smith, Fransen, Deprez, Lenoir & Coutts, 2016; Smith, Marcora & Coutts, 2015; Smith, Zeuwts, Lenoir, Hens, De Jong & Coutts, 2016; Veness, 2016). These performance decrements manifest as slower reaction times, decreased power outputs, increased perceptions of effort, and decrements in technical skill – all second order markers likely to inhibit actual sport performance of the athlete.

Possibly contributing to the impact of certain stressors is the concept of locus of control, the degree to which a person feels they have agency over the outcomes in her/his life (Rotter, 1966). Typically assessed as a trait-level measure, locus of control has also been used at the state-level as a potential mediator for the load an athlete is under (Johnson & Sarason, 1978). This idea was furthered in a study by Au where she noted that an external locus of control (i.e., less perceived control by the individual) was positively correlated with increases in perceived

stress (Au, 2015). Locus of control has been shown to impact how an individual perceives stressors and this cognitive appraisal has performance implications (Bernardi, 1997). While previously unexamined as a daily athlete monitoring metric, locus of control may serve as an insightful mediator to better decipher changes in performance.

Sleep

A mainstay in athlete monitoring, sleep may provide the most cost-effective option for an athlete looking to improve performance. A sizable body of work has been conducted in this realm, not only examining aerobic/anaerobic performance and muscle strength, but also sport-specific outcomes as well. Time to exhaustion often decreases in aerobic testing with increasing decrements in sleep. Similar findings have been shown for power outputs in anaerobic testing. Both of these are second order indicators of sport-specific performance. Specific testing of muscle outputs mirrors this trend as well, with decreases in measures such as bench press, leg press, deadlift, bicep curl, handgrip, and vertical jump with decreases in sleep duration (Fullagar, Skorski, Duffield, Hammes, Coutts & Meyer, 2014; Van Dongen & Dinges, 2005; Van Dongen, Maislin, Mullington & Dinges, 2003). Sport-specific performance reductions have also been examined, typically in closed-loop skills focused on accuracy (e.g., darts, rifle shooting, tennis serving, and free throws/three pointers in basketball; Fullagar et al., 2014; Mah, Mah, Kezirian & Dement, 2011). As such, there is overwhelming evidence that both primary and secondary indicators of sport performance are impacted by sleep.

From the cognitive standpoint, psychomotor vigilance tests (PVT) and other mentally challenging tasks have been conducted to assess the correlation between sleep and performance. In such studies, reaction times often increase, PVT scores decrease, and working memory performance drops; all are likely second order indicators of on-court performance (Fullagar et al., 2014). For these reasons, in combination with its cost-benefit balance, sleep assessment remains a prominent cornerstone in monitoring athletes.

Heart Rate Variability (HRV)

HRV appears in athlete monitoring systems typically as a potential marker for overtraining syndrome. Though HRV monitoring is not universally accepted in the sport domain, HRV has been acknowledged as having the potential to track the body's readiness to accommodate incoming stressors. Many practitioners succumb to the "higher is better" philosophy of HRV, referring to the Root Mean Square of the Successive Differences (RMSSD) metric, a time-domain tool for assessing HRV. However, like sleep duration, there are nuances to this claim such that it cannot be universally applied. HRV and overtraining have been connected in multiple studies (Aubert, Seps & Beckers, 2003; Dong, 2016) and due to its relative ease of implementation, HRV has grown in popularity in recent years.

Expanding on the concept of readiness to perform, Buchheit and colleagues mapped HRV against endurance run times as a means to model performance (Buchheit, Chivot, Parouty, Mercier, Haddad, Laursen & Ahmaidi, 2009). Though insufficient on its own, HRV's potential in this field, specifically as an objective measure, has validated its inclusion in athlete monitoring systems. HRV has also been used in relation to reaction time, similar to other aforementioned variables, resulting in the association between higher HRV and quicker reaction times (Porges, 1973). Though not always thought of as a performance-specific metric, HRV is a frequent component of athlete monitoring systems and a worthwhile variable to examine in this study as it relates to fatigue and stress.

CHAPTER 3: METHODS

To investigate the research hypotheses, this study sought to analyze the relationships between student-athlete responses to a battery of questionnaires, daily HRV measures, and their self-reported performance ratings. To accomplish this, participants were asked to complete a morning, pre-sport, and post-sport survey to report on different variables. Self-rated performance served as the dependent variable, while all remaining metrics served as independent variables. Linear regression models were built to assess the unique combinations of variables which jointly accounted for the greatest explanation of variance in each participant's sport-specific performance.

Participants

Data were provided by 16 female Division-1 collegiate volleyball players (M age = 19.6 ± 1.4 yrs) from the same team during the fall competitive season. While the volleyball coaching and support staffs have collected data regarding athlete wellness for multiple seasons, only data from the start of preseason training to approximately three-quarters into one competitive season were used in this study. Because of the abnormal nature of preseason competition, self-rated performance data were only used for conference play, yet data from before that date were used via rolling averages and other training load metrics. In total, 50 days of data were used, which included 14 matches and 15 full practices. Because some participants did not play in matches, only their self-rated performance data from practices were used (referred to as Practice players, M age = 19.3 ± 1.6 yrs). For players who were significant contributors in matches, their self-rated performance data from matches were used (Match players, M age = 19.8 ± 1.3 yrs). This was a breakdown of nine starters (Match players; match data used) and seven non-starters (Practice players; practice data used).

Equipment

The research platform Qualtrics[®] was used to design and distribute the questionnaires, as well as to collect the resulting data from the participants. The questionnaire was distributed using a specific URL emailed to the participants daily at 8:00 am and was also saved on the homescreen of two iPads used to collect pre and post sport survey data for practices. To record match data, participants were reminded verbally or via text message to complete their pre and post sport surveys on their personal smartphones using the same URL. Heart rate variability (HRV) was recorded each morning using the HRV4Training App (Altini, Casale, Penders & Amft, 2016). This app uses the light emitting diode and camera from a smartphone to detect blood volume changes through measurements of changes in light absorption (i.e., photoplethysmography) from the user's fingertip as a result of heartbeats. Based on changes in autonomic nervous system function, and subsequently variations in heartbeats (i.e., HRV), this provides a measure of our body reacts to stressors and how long it takes to recover from the stressors once they are over. Each participant had this application installed on her smartphone to increase ease of completion each morning. All values were recorded via a single Qualtrics[®] survey and all measures besides HRV were subjective and self-reported by the participants.

Data Collection

Data collection occurred at three timepoints during a practice or match day and only once during an off day. Participants were sent a reminder email at 8:00 am to complete the morning survey through the Qualtrics[®] platform. Participants were aware that they should record their HRV data as soon as possible after waking to ensure consistency and reliability within the data. If they forgot to do this before leaving their residence or before doing anything that would significantly increase their body's arousal level (e.g., intake of caffeine), they were instructed to skip the HRV question for that morning. Using the HRV4Training app, participants followed standard on-screen instructions to cover the camera of their phone with their finger and breathe in a relaxed manner for 60 seconds while the app collected data. After completion, the HRV4Training app provided a score calculated primarily from the user's RMSSD. This score

was reported on the morning questionnaire by the participant. The morning questionnaire also instructed participants to input the total hours of sleep from the previous night and to provide a subjective rating for quality of sleep, their current muscle soreness level, and the projected difficulty of their day.

While the HRV and quantity of sleep questions required a numerical input by the participants, a sliding scale with no visible numeric rating was used to record the other subjective measures. For quality of sleep, the anchor points of “extremely bad” to “extremely good” were used with 0 and 100 being the respective numeric translations. For muscle soreness, the anchor points of “no soreness” to “extremely bad” soreness were used with the same numeric translation. For the difficult of day question, “extremely easy” to “extremely difficult” were used as the anchor points. Finally, on Thursday and Sunday mornings, participants were also asked to rate their friends/family/social stress, academic stress, and student-athlete stress over the previous five days using the anchor points of “minimal” to “maximal” levels of stress.

The pre-sport survey consisted of six questions asking about mental/emotional fatigue, physical fatigue, current stress level, state level locus of control, optimal fueling, and how their day is going. For both the mental/emotional and physical fatigue questions, anchor points of “none at all” to “max fatigue” were used. For the question reading “how is your day going so far?” the anchor points of “terrible” and “excellent” were used – and for current stress level, “no stress” and “max stress” were used. For the question reading “who is in control of your day today?” the anchor points of “myself” and “others” were used. Finally, for the question asking “have you fueled optimally for this upcoming session?” the anchors of “absolutely not” and “absolutely yes” were used.

The post-sport survey asked the participant to select which sessions she participated in that day (e.g., weights, practice, match) and then asked for her rating of perceived exertion (RPE) and duration of each selected session. These RPE ratings were given based on the Borg

CR 10 RPE scale (Borg, 1998). The duration of the session was recorded by either a coach or support staff member to ensure accuracy. Following these questions, the participant reported her rating of performance via the question “how did you play today?” with the anchor points of “my worst performance” to “my best performance.” Questions were randomized within each survey every time to prevent order bias. See Appendix B for full layout of each survey.

Each day, results from the morning questionnaire and previous day’s practice/match were compiled and reports were shared with coaching and support staff members for the purposes of daily wellness monitoring and appropriate interventions (see Appendix A).

Statistical Analysis

Statistical analysis was performed using R and Tableau. Collected data were inputted into Tableau through which Z-scores and rolling averages were computed and visualized for daily reports. All measures were compared using Z-scores with the exception of the acute, chronic, and acute-to-chronic ratio training load metrics. In addition to daily Z-scores, rolling 3-day averages for all metrics, as well as additional rolling 2-day averages for sleep quantity and quality, and 5-day rolling averages for the three stressor questions (social/academic/student-athlete) only asked on Thursday and Sunday were added.

Pearson correlation coefficients were calculated using R, and the linear regression models were computed and analyzed via R using a combination of forward and backward stepwise methods.

CHAPTER 4: RESULTS

Linear regression models were created using a bidirectional approach to the addition and elimination of variables. As a group, the 16 models had an average adjusted R^2 value of 0.57 with a range from 0.23 to 0.90 (see Table 1). When split into Match and Practice groups, Match players averaged an adjusted R^2 of 0.66 (range = 0.43 to 0.90), while Practice players averaged an adjusted R^2 of 0.44 (range = 0.23 to 0.70). In the Match group, seven of the nine models (78%) resulted in adjusted R^2 values above 0.60, while this was only true for two individuals in the Practice group (28.5%). Sleep duration metrics appeared with the highest frequency (eight) while RPE-based training load, locus of control, and physical fatigue metrics appeared in six, five, and four models, respectively. All Match player models (100%) were statistically significant at the $p < .05$ level, while all but one model of Practice players (14%) were significant at this same level.

Though sleep duration appeared at the highest frequency within the athletes' models, the signs of the coefficients were inconsistent amongst the eight players for which it was used. RPE-based training load metrics were also common in many models and while most coefficients were positive, this was not universal amongst models. The locus of control metric appeared with a positive coefficient in three models, indicating that less perceived control over one's day was associated with improved performance while in two others, a negative coefficient resulted (i.e., less perceived control associated with worse performance).

This pattern of inconsistency in the signs of the coefficients persisted for nearly every variable which appeared at least twice within the regression equations. While this may be affected by the use of both daily and rolling average scores, it is likely further evidence that each student-athlete is unique in how she responds to stressors at any point and the context of these stressors requires better understanding.

Table 1

Multiple Regression Equation Summaries Including adjusted- R^2 , Sigma, p -value, and Variables Used

Athlete	Adj- R^2	sigma	p-value	Var1	Var2	Var3	Var4	Var5	Var6	Var7	Performance
Athlete 5	0.90	0.30	0.00699159	(+) PhysFat	(+) R3 Control	(+) AC 7:28	(+) PhysFat*R3 Control				match
Athlete 13	0.87	0.38	0.01128622	(-) SleepD	(+) Sore	(-) R3 Control	(+) SleepD*Control				match
Athlete 3	0.77	0.50	0.00084323	(-) R3 ME Fat	(+) R5 Social	(+) R3 ME Fat*R5 Social					match
Athlete 10	0.63	0.69	0.03685286	(+) Control	(-) R3 Fuel	(+) SleepD	(+) R3 Diff				match
Athlete 2	0.62	0.64	0.05462947	(-) R3 Sore	(-) R3 Stress	(-) R3 PhysFat	(-) R3 Sore*R3 Stress	(-) R3 Sore*R3 PhysFat	(-) R3 Stress*R3 PhysFat	(-) R3 Sore*R3 Stress*R3 PhysFat	match
Athlete 7	0.62	0.65	0.00337991	(+) Diff	(+) Chronic 16						match
Athlete 16	0.61	0.64	0.00542063	(-) R3 HRV	(-) R3 SleepD	(-) R3 HRV*R3 SleepD					match
Athlete 1	0.51	0.75	0.03463949	(+) R3 How's	(+) R3 PhysFat	(+) R3 How's*R3 PhysFat					match
Athlete 11	0.43	0.79	0.04603862	(-) R3 PhysFat	(+) R3 Fuel	(+) R3 PhysFat*R3 Fuel					match
Athlete 14	0.70	0.57	0.00637734	(-) R5 Academic	(-) SleepD	(+) Control	(-) SleepD*Control				practice
Athlete 8	0.61	0.64	0.02775089	(+) AC 4:16	(+) SleepD	(-) ME Fat	(-) AC 4:21				practice
Athlete 15	0.42	0.79	0.04840174	(-) R3 HRV	(+) R2 SleepD	(-) R5 Social	(+) R3 HRV*R2 SleepD				practice
Athlete 4	0.41	0.79	0.05114379	(+) AC 4:16	(-) R3 Control	(-) R5 SA Stress	(+) AC 4:16*R3 Control				practice
Athlete 12	0.39	0.80	0.09357728	(-) Fuel	(+) R3 Fuel	(-) Chronic 21	(-) R3 Fuel*Chronic21				practice
Athlete 6	0.35	0.83	0.05244385	(+) Sore	(-) R3 SleepD	(-) Sore*R3 SleepD					practice
Athlete 9	0.23	0.91	0.04014246	(-) R2 SleepD							practice

Note: The Match ($n=9$) and Practice ($n=7$) groups are split and sorted by highest $adj-R^2$. R2, R3, and R5 indicate that a 2, 3, or 5-day rolling average was used, respectively. Variables without the R2/R3/R5 preface are the single day z-score values. Variables separated by an “” are interaction terms within the model. (+) indicates that the coefficient of this variable is positive. (-) indicates that the coefficient of this variable is negative.

PhysFat = Physical Fatigue
 Control = Who's in control of your day?
 AC X:Y = Acute:Chronic ratio using X days
 as the acute and Y days as the chronic
 SleepD = Sleep Duration

Sore = Morning Soreness
 ME Fat = Mental/Emotional Fatigue
 Social = Social Stress
 Academic = Academic Stress
 SA Stress = Student-Athlete Stress

Stress = Pre-Volleyball Stress
 Chronic 16 = RPE-based training load over
 the last 16 days
 HRV = HRV4Training Score
 Fuel = Optimal Fueling

* See Appendix B for full set of questions on each portion of the survey

CHAPTER 5: DISCUSSION

Combination of Physical and Cognitive Variables

The majority of research into the relationship between stressors and performance has focused on either the physical or mental load the athlete is under, but has failed to take a holistic perspective. Twelve of the 16 (75%) regression models created in the present study resulted in both physical-leaning and cognitive-leaning equations to provide the best account of athlete performance. In nine of the 16 (56%), interaction terms between a “physical” and “cognitive” variable existed, highlighting the need to understand not just the combination, but the interaction of these commonly isolated variables.

Sleep duration, RPE-based training load measures, locus of control, and physical fatigue appeared within the models with the greatest frequencies, both validating previous research while raising novel questions. The locus of control variable, asked immediately before practice and matches, appeared in five of the 16 models (31%). Previous research into locus of control has primarily focused on a trait-level analysis rather than daily evaluation, yet the results from this study suggest that whether or not an athlete feels in control of her day may provide an insightful look into sport performance itself. The coefficients within the models using locus of control were not uniform, however. Two of the three which used a rolling 3-day average were negative, while the two using the same day Z-score were both positive. While again supporting the notion that each athlete is unique in her profile of what impacts performance, the negative coefficients indicated that a lack of control over their day was negatively correlated with performance. On the other hand, the positive coefficients suggest that this feeling of being less in control was associated with improved performance. For some athletes, this sense of control may lead to an anxious state in which they are worried about the results that they perceive having control over. For other athletes, having a sense that their day is out of their control may provide a sense of comfort and relinquish them from the pressures of decision-making.

Physical fatigue as a variable, as well RPE-based training load metrics, appeared several times in multiple models. As with other variables, both positive and negative coefficients existed for different athletes in a non-uniform sense. For some athletes, increased physical fatigue was associated with improved performance while the opposite was true for other athletes. The acute to chronic workload ratio metrics were primarily positive, though variation did exist. This suggests that for most athletes, a higher level of load encountered in the acute phase relative to the chronic phase was associated with better sport performance.

Sleep Metrics

Sleep was hypothesized to play a significant role in athlete performance such that more sleep would result in improved outcomes. While sleep duration appears in 50% of all the performance models (the highest frequency of all variables), the sign of the coefficient was inconsistent. For some participants, more sleep led to better performance, while the opposite was true for others. This suggests that an underlying mediator may be at work. In this case, overtraining may manifest in a similar fashion to depression in terms of excessive sleep and/or constant fatigue. For others, less sleep may be a side effect of increased emotional arousal and anxiety which is perhaps conducive to better performance. While sleep is hailed as the most cost-effective method to improve performance, professionals should use sleep metrics in combination with other tools to help create a more complete picture of athlete wellness and performance.

Sleep quality, as previously mentioned, has shown value through its association with mood states and other wellness scores (Pilcher, Ginter & Sadowsky, 1997). However, in this study this metric did not appear in any of the athlete models. While there were several medium to strong correlations between sleep quality and performance for some athletes, those specific models do not include sleep quality. This is likely due to the strong correlation between sleep quality and sleep duration for those athletes and the inclusion of both decreased overall model performance in terms of explained variance.

Heart Rate Variability (HRV) Metrics

Another frequently discussed metric in athlete monitoring is HRV and its suggested ability to indicate an athlete's readiness to adapt to stressors. While extremely popular in the field, HRV appeared in only two of the sixteen models (12.5%) – interestingly, with a negative coefficient in both. This would suggest that for these two individuals, higher HRV was associated with lower performance outcomes. Paralleling the trend of mainly positive coefficients in the acute to chronic metrics, this may indicate that slight fatigue might actually benefit athlete performance. While full rest and recovery may sound logically optimal, these findings suggest that perhaps being partially fatigued keeps an athlete in the proper mindset of competition and performance. Additional research is needed to investigate competitive performance under varying levels of fatigue as indexed via HRV and RPE-based workload metrics.

Compliance with the HRV testing each morning did reduce the number of athletes for which the HRV variable was a possibility (i.e., too few entries). While not completed as a part of this research, a more detailed analysis into the component pieces of HRV [e.g., low frequency power (LF); high frequency power (HF); ratio of low:high frequency power (LF:HF); standard deviation of R-R intervals (SDNN); root mean square of successive differences (RMSSD)] may be necessary to uncover significant relationships with athlete performance. As with previous work, it should be noted that HRV may best serve as a complementary tool in monitoring athletes rather than the sole data source.

Practical Applications, Implications, and Issues

While further research is needed to better encapsulate the stressors athletes face, this study serves to further the conversation and bridge the divide between the physical and cognitive loads previously examined. While the dataset is arguably too small to be relied on from a statistically predictive standpoint, athlete buy-in may be increased through the use of their own subjective ratings for these metrics. The ability to take athlete data and show them the

relationships between self-rated performance and two or three relevant health/wellness variables may reinforce good habits, especially those conducive to overall student-athlete wellness.

Knowledge of key metrics on a per-athlete basis may also benefit the coaching and support staffs in how they adjust training loads and initiate conversations with each athlete. A current failure within athlete monitoring is that, without a specific outcome variable, checking in at the appropriate time with an athlete can be primarily guesswork. But the awareness of declining trends in an athlete's performance indicators may clearly indicate the need for minor interventions before major decrements are realized.

There are several limitations with the current study. Athlete compliance with completing surveys during the day proved challenging. For this reason, some variables were excluded (such as HRV) for a few individuals who failed to submit routine measurements. Along this same line, because the regression models used variables from different surveys given at different times during the day, if an athlete did not have an entry for a variable in her equation, that day's performance outcome could not be included in the final model; this is why some athletes differed in the number of performance ratings included (i.e., some days needed to be excluded). An issue with using primarily subjectively rated information is that once athletes understand the key metrics, they can provide the answers in a way to shape the outcomes they desire. In this same manner, a self-fulfilling prophecy situation may occur in which athletes who understand that longer sleep duration is critical to their sport performance see their low score in the morning and actually perform worse because they have this preconceived notion that they will fail.

A final hurdle for implementation of this information is persuading coaching and support staffs to utilize it. A common complaint from the athletes was that they felt action was lacking after they provided this information. As Saw (2015) indicates clearly, if the athletes do not see action resulting from their efforts, both compliance and buy-in drop sharply. From this

standpoint, better predictive models may need to be constructed, from larger datasets, such that staff members will feel confident applying the results in meaningful, actionable ways. At present, the dataset is too small to provide small enough predictive intervals such that a head coach would likely feel comfortable making decisive changes. However, with that in mind, the range of explained variance for the models clearly highlights the range of success this study had in modelling performance. For some players the models account for much of the variance in the performance outcome; for others, the models perform very poorly. Further research into overlooked stressors and other factors this study failed to include may help to better encapsulate the components that contribute to performance. Variables such as self-efficacy, travel hardships, and daily academic/social stressors may provide additional insight into the fluctuations of athlete performance in future studies.

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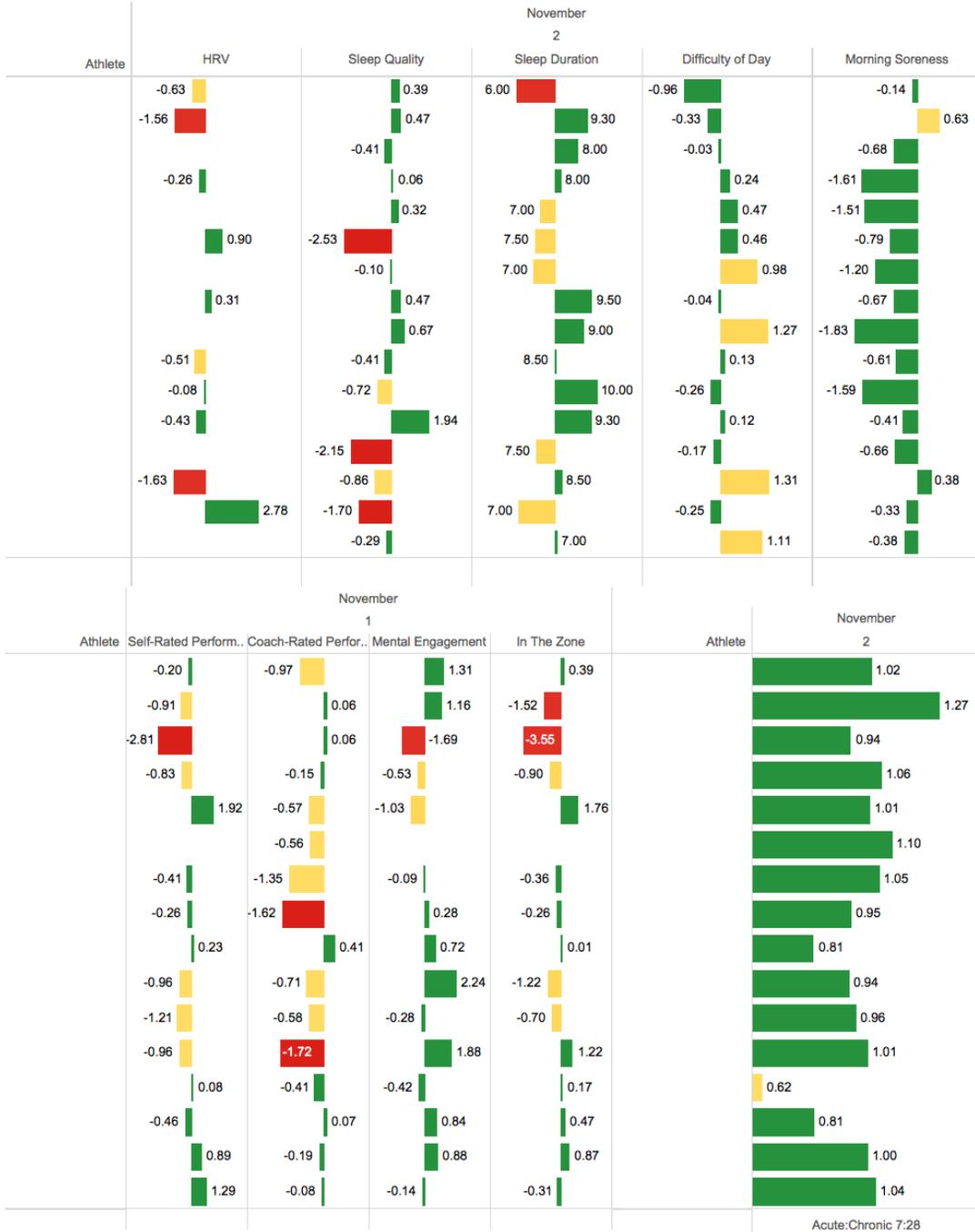
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APPENDIX A: Daily Wellness Report Sample

11/2/16 12:38:39 PM



Sample report given to coaches and support staff members on a daily basis with information from the AM Wellness from the morning and Post-Sport surveys from the previous day.

APPENDIX B: Summary of Survey Questions

Survey	Question	Bottom Anchor (0)	Top Anchor (100)
AM Wellness	HRV4Training Score - please leave blank if you've had breakfast, caffeine, or have done anything beyond getting ready for class	n/a	n/a
AM Wellness	Sleep Duration - in hours (eg. 8.75)	n/a	n/a
AM Wellness	Quality of Sleep	Extremely Bad	Extremely Good
AM Wellness	How is your soreness right now?	No Soreness	Extremely Bad
AM Wellness	How difficult is your day today?	Extremely Easy	Extremely Difficult
AM Wellness *only Thursday/Sunday	In the last 5 days, how has your <u>friends/family/social</u> stress been?	Minimal	Maximal
AM Wellness *only Thursday/Sunday	In the last 5 days, how has your <u>academic</u> stress been?	Minimal	Maximal
AM Wellness *only Thursday/Sunday	In the last 5 days, how has your <u>student-athlete</u> stress been?	Minimal	Maximal
Pre-Volley	How mentally/emotionally fatigued are you right now?	None at all	Max Fatigue
Pre-Volley	How physically fatigued are you right now?	None at all	Max Fatigue
Pre-Volley	How is your day going so far?	Terrible	Excellent
Pre-Volley	How's your stress level right now?	No Stress	Max Stress
Pre-Volley	Who is in control of your day today?	Myself	Others
Pre-Volley	Have you fueled optimally for this upcoming session?	Absolutely not	Absolutely yes
Post-Volley	How did you play today?	My worst performance	My best performance
Post-Volley	Rating of Perceived Exertion & Duration	n/a	n/a

Survey column denotes which questions belong to which survey. Bottom anchor on the visual sliding scale corresponded to a score of 0 while the top anchor corresponded to a score of 100. HRV, Sleep Duration, and RPE questions did not use a sliding scale.