Future Time Perspective, Socio-emotional Regulation, and Diurnal Cortisol Patterns

in Post-secondary Engineering Students

by

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ABSTRACT

Built upon Control Value Theory, this dissertation consists of two studies that examine university students’ future-oriented motivation, socio-emotional regulation, and diurnal cortisol patterns in understanding students’ well-being in the academic context. Study 1 examined the roles that Learning-related Hopelessness and Future Time Perspective Connectedness play in predicting students’ diurnal cortisol patterns, diurnal cortisol slope (DS) and cortisol awakening response (CAR). Self-reported surveys were collected ($N = 60$), and diurnal cortisol samples were provided over two waves, the week before a mid-term examination ($n = 46$), and the week during students’ mid-term ($n = 40$). Using multi-nominal logistic regression, results showed that Learning-related Hopelessness was not predictive of diurnal cortisol pattern change after adjusting for key covariates; and that Future Time Perspective Connectedness predicted higher likelihood for students to have low CAR across both waves of data collection. Study 2 examined students’ future-oriented motivation (Future Time Perspective Value) and socio-emotional regulation (Effortful Control and Social Support) in predicting diurnal cortisol patterns over the course of a semester. Self-reported surveys were collected ($N = 67$), and diurnal cortisol samples were provided over three waves of data collection, at the beginning of the semester ($n = 63$), during a stressful academic period ($n = 47$), and during a relaxation phase near the end of the semester ($n = 43$). Results from RM ANCOVA showed that Non-academic Social Support was negatively associated with CAR at the beginning of the semester. Multi-nominal logistics regression results indicated that Future Time Perspective Value and Academic Social Support jointly predicted CAR pattern.
change. Specifically, the interaction term marginally predicted a higher likelihood of students switching from having high CAR at the beginning or stressful times in the semester to having low CAR at the end the semester, compared to those who had low CAR over all three waves. The two studies have major limits in sample size, which restricted the full inclusion of all hypothesized covariates in statistical models, and compromised interpretability of the data. However, the methodology and theoretical implications are unique, providing contributions to educational research, specifically with regard to post-secondary students’ academic experience and well-being.
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INTRODUCTION

University life is comprised of more than the academic sector of experiences; within the university context, life includes social, personal, and emotional experiences that may shape one’s well-being. Although the main focus of higher education and related research has been on students’ learning, motivation, achievement, and academic performance (e.g., Copeland, 2015; Drew, 2015; Nelson, Shell, Husman, Fishman, & Soh, 2015), universities have focused more and more resources on the student well-being as a means to help students realize their full potential in higher education (e.g., Swaner, 2007). Well-being has been described in many ways, and there is no clear consensus on the definition so far. Some refer to well-being as the new definition of health, which encompasses not merely the absence of illness, but also positive functioning, such as having plenty of physical resources, being able to cope with normal life stresses, and the ability to work productively and contribute to the community, etc. (Herzlich, 1973, p. 60; World Health Organization, 2014). In motivation-related research, most refer to well-being as a psychological or subjective construct, which either is comprised of happiness, positive affect, low negative affect, and satisfaction of life (Diener & Suh, 1997; Headey, 2006; Sheldon & Kasser, 1995; Vansteenkiste, Lens, Soenens, & Luyckx, 2006), or highlights positive psychological functioning such as autonomy, environmental mastery, realization of potential, and positive relationships with others (Rogers, 1961; Ryff, 1989; Waterman, 1993). Dodge and colleagues argued that one’s psychological, social, and physical resources can help balance dips in the dynamic equilibrium of one’s well-being due to
environmental or life challenges (Dodge, Daly, Huyton, & Sanders, 2012). Their see-saw model suggests that moderate levels of life or environmental challenge could be optimal for one’s positive functioning and development; however, excessive amounts of challenge, in relation to one’s resources, could be disruptive for optimal well-being. Similarly, in the university context, academic challenges (for example class assignments, or examinations) could be beneficial for academic development (e.g., Flow Theory, Csikszentmihalyi, 2002); however, without adequate psychological, social, or physical resources, students’ well-being could be at stake. Examining the psychological and social antecedents to specific emotions and associated physiological markers in the university context, therefore, can be helpful to address well-being issues students may have in their university experience.

Notably, increasing amounts of literature emphasize the bio-psycho-social nature of subjective well-being (Dodge et al., 2012; World Health Organization, 2016). In recent decades, research in health psychology has been able to locate bio-psycho-social factors that are associated with well-being (Labbe & Kuczmierczyk, 2013; Sarafino & Smith, 2008). Studies examining social evaluative threat indicate that prolonged or repeated psychosocial stress could be harmful to one’s well-being via physiological stress pathways (Dickerson & Kemeny, 2004). Subjective well-being, or the lack thereof, has been associated with physiological stress dysregulation (e.g., Doane et al., 2013; Saxbe, Repetti, & Nishina, 2008). Interestingly, similar to the dynamic equilibrium nature of well-being (the resources vs. challenges see-saw as noted by Dodge et al., 2012; Heading & Wearing, 1991; 1992), a physiological stress
response is the body’s attempt to establish homeostasis in face of a stressor. Notably, although students do need a certain degree of pressure or level of challenge to achieve optimal learning and to develop deeper understanding of their course materials, if students face repeated or prolonged exposure to stress without adequate resources to cope, their well-being may be at stake. Socio-emotional support may help buffer or alleviate stress, and increase mental and physical well-being (e.g., Karb, Elliott, Dowd, & Morenoff, 2012), which is coherent to the concept of “resources” in the well-being literature. In the educational context, however, few have integrated this line of research on stress physiology in inspecting the bio-psycho-social aspects of student well-being. Building upon Control Value Theory, which explores the antecedents of specific academic emotions, and the multi-faceted nature of academic emotions (Pekrun, 2006), researchers in educational psychology have begun to examine physiological correlates of specific emotions in the educational context (Spangler, Pekrun, Kramer, & Hoffmann, 2012). Given that academic emotional experiences are a part of university life which may form students’ well-being alongside their resources and challenges, the goals of this dissertation are to investigate how students’ specific emotions, such as academic hopelessness, and students’ motivational and socio-emotional regulatory factors, may predict physiological stress dysregulation within the academic context (e.g., around examination) via diurnal cortisol assessments, to locate correlates of well-being in post-secondary education (see theoretical model in Figure 1).
Physiological Stress Pathways

A stress response is the body’s attempt to establish homeostasis in face of a stressor. The stressor that in ancient times was related to survival, such as escaping a predator, could in today’s environment be psychological or social, for example, taking an exam, or giving a presentation to an audience. Upon stress, two systems in our body are activated to produce a fight-or-flight response—the locus coeruleus-norepinephrine/sympathetic nervous system (LC-NE/SNS) and the hypothalamus-pituitary-adrenal (HPA) axis (*cf.* Nelson, 2011). The LC-NE/SNS often corresponds to stress in terms of a fight-or-flight reaction (imagine one’s bodily reactions when encountering intense threat: increased heart rate, fast-paced breathing, blood flows to muscles, sweaty palms, etc.), facilitating the body to react quickly to stress via the autonomous nervous system. The HPA axis reacts with a slightly slower pace; it is activated within minutes upon exposure to an environmental or psychosocial stressor, starting from the release of the corticotropin-releasing hormone (CRH) in the hypothalamus, which induces the release of the adrenocorticotropic hormone (ACTH) in the pituitary gland, in turn eliciting the release of corticosteroids (cortisol for humans) in the adrenal cortex. As an end product of the HPA axis, cortisol has been named a *stress hormone* in recent literature. Cortisol secretion is in general helpful for the body to adapt to social or environmental stressors (McEwen, 1998).

Notably, bodily reaction to a stressor is mediated by multiple interactive systems, including the autonomic nervous system, the HPA axis, the immune system, and metabolic hormones, etc. The coordination among these systems to achieve
stability over change is known as allostasis; it helps allocate bodily resources to systems in more immediate need. Allostatic overload, however, may occur when energy expenditure exceeds resources accessible (McEwen & Wingfield, 2003; McEwen & Wingfield, 2010). If a stressor continues to be present beyond one’s alarm reaction phase and resistance (coping) phase, it may produce dysregulation in systems’ coordination and exhaustion in the individual, which results in maladaptive consequences on behavior and health; this is known as the general adaptation syndrome (Seyle, 1950). In other words, if one is faced with repeated or prolonged psychosocial or environmental stress, such as experiencing repeated stressful coursework and examinations in post-secondary education, there may be failure in shutting down one’s stress response, and cortisol levels along with other products of the stress response (e.g., inflammatory cytokines) may become dysregulated.

For example, the neuroendocrine-immune system interaction contains a negative feedback loop between glucocorticoids and the immune system. Secretion of cortisol can down-regulate some cytokines (e.g., interleukin-1, IL-1) preventing local inflammation; increase in IL-1 can stimulate the release of CRH and ACTH, elevating cortisol levels (Wilder, 1995). Consequences from stress dysregulation in the neuroendocrine-immune system pertain to, but are not limited to, a subdued immune system, autoimmune diseases, and shorter survival from cancer; other maladaptive consequences include hippocampal neuronal damage, cardiovascular diseases, etc. (Kemeny, 2009; Sephton et al., 2013; Sephton, Sapolsky, Kraemer, & Spiegel, 2000).
Diurnal Cortisol Patterns

The aforementioned stress dysregulation and health consequences have been associated with abnormal diurnal cortisol patterns. Typically, cortisol levels follow a natural diurnal rhythm, with morning levels higher (peaking at around 30-minutes after awakening), and evening levels lower. The morning peak around 30-minutes after awakening has been called the cortisol awakening response (CAR); it indicates the body’s preparation to face the day. The natural decline of cortisol levels throughout the day has been called the diurnal cortisol slope (DS), which signifies cortisol recovery over the day. The diurnal rhythm has been found to show a flattened effect under repeated or prolonged stress, with less profound morning peaks and flattened evening recovery. The flattening of the diurnal rhythm signals that the body has reached saturation of the allostatic load (McEwen, 1998), with little resource to regulate cortisol levels back to diurnal normality (profound morning peaks and evening recovery). CAR and DS, therefore, can be appropriate candidates to indicate one’s allostatic profile, which is informative of one’s physiological stress regulation, and has important implications on one’s well-being, as the allostatic load is linked to other bodily systems important for daily functioning (such as the immune system, cardiovascular system, and the central nervous system, as stated above). As cortisol levels can be conveniently measured via assaying one’s saliva sample (cf., Granger et al., 2007), CAR and DS could be quick, non-invasive indicators for physiological stress regulation and enable researchers to gain objective insight into one’s well-being and health.
Specifically, the flattening of one’s DS has been found to be associated with factors that contribute to both mental and physical well-being, such as depression or immunal suppression (e.g., Doane et al., 2013; Sephton et al., 2013; Sephton, Sapolsky, Kraemer, & Spiegel, 2000). Flatter diurnal cortisol patterns were related to high levels of psychosocial risk factors (cynicism, depression, and vital exhaustion), whereas a steeper diurnal rhythm was related to psychosocial resources (social support and coping), positive general health, and well-being (Sjögren, Leanderson, & Kristenson, 2006). Notably, although CAR has been associated with one’s well-being (Chida & Steptoe, 2009), CAR has also been found to have substantial intraindividual variation over time, and has been found to be indicative of more momentary stress regulation that fluctuates on a daily basis (Stalder et al., 2015). Nonetheless, as Dodge and colleagues noted, the dynamic fluctuation of well-being is associated with recent life events, therefore, it is valuable to assess CAR as an indicator of well-being. In sum, the above literature suggests that diurnal cortisol patterns are related to one’s functioning and well-being.

**Theoretical Framework for the Educational Context: Control Value Theory**

Many areas in social sciences have used interdisciplinary methods to examine correlates of stress via both subjective (e.g., self-reports) and objective measures (e.g., physiological responses). In educational research, Control Value Theory suggests that academic emotional experiences can be multi-faceted as well. According to Control Value Theory, emotions can be represented by a hierarchically organized structure that includes four second-order factors: the affective, cognitive, motivational, and
physiological components (Pekrun, 2006). Built upon Expectancy-Value Theory (Vroom, 1964), Control Value Theory incorporates motivational, cognitive, and physiological aspects of emotions, and explores emotional experiences related to academic achievement (e.g., Pekrun, Goetz, Frenzel, Barchfeld, & Perry, 2011). However, only a small number of educational research studies have taken advantage of physiological measures to examine or describe students’ experiences in the academic context (Spangler et al., 2002).

According to Control Value Theory, academic achievement emotions are multi-faceted, suggesting that emotional experiences specific to the academic context are paired with physiological reactions. As noted previously, if students were to experience stressful academic events on a regular basis, students’ physiological stress responses could be activated repeatedly, and context-specific emotions could eventually either contribute to or become harmful for students’ health and well-being. For example, it is reasonable to posit that the feeling of Hopelessness in learning about a specific course could be associated with one’s saturated allostatic load (low well-being), which may in turn be reflected on one’s physiological stress responses in face of a mid-term examination of that course.

In line with Control Value Theory, I posit that motivational and affective factors as well as regulatory factors associated with one’s academic experience could help enhance or lower students’ well-being. Diurnal cortisol assessments may help illustrate current theory, and contribute to interdisciplinary research, giving us insight
to students’ psychological and physical well-being which could be crucial for academic persistence and success.

As Control Value Theory denotes, discrete academic achievement emotions include, but are not limited to, enjoyment, hope, pride, anxiety, hopelessness, shame, and anger, of which hopelessness is an under-examined emotion (Frenzel, Pekrun, & Goetz, 2007; Pekrun, Goetz, Titz, & Perry, 2002), but could be particularly related to students’ well-being. Research in psychology has discussed the associations between general hopelessness and depressive symptoms, as well as predictions from depressive symptoms to the flattening effect of diurnal cortisol (e.g., Pössel, Mitchell, Sjögren, & Kristenson, 2015). However, direct associations between academic-related hopelessness and students’ diurnal cortisol patterns in post-secondary educational settings are yet to be explored. As academic-related hopelessness is a prospective negative emotion, i.e., it is anticipatory in nature (Pekrun et al., 2002), although it is context specific, i.e., specific to the academic context, it would be reasonable to assume that in terms of temporal effects, the emotion could be related to dysregulated diurnal cortisol patterns due to prolonged or repeated academic stress.

**Inclusion of Future Time Perspective**

Control Value Theory suggests that academic achievement emotions are influenced by students’ appraisal antecedents, including *subjective control* over achievement activities, as well as *subjective outcome values* of these activities (Pekrun, 2006). In studying academic-related emotions, Control Value Theory has integrated theories such as Expectancy-Value Theory (e.g., Turner & Schallart, 2001),
theories of attribution in achievement (Weiner, 1985), theories on perceived control (Perry, 1991), etc.; however, albeit the burgeoning evidence that future-oriented motivation could be meaningful appraisal antecedents for academic-related emotions (e.g., Husman, Cheng, Puruhito, & Fishman, 2015), future time perspective theory has not yet been integrated into the Control Value Theory framework. According to future time perspective theory, future time perspective (FTP) is one’s perceptions about the future and ability to consider the future; it has been described as “the degree to which and the way in which the future is anticipated and integrated in the psychological present of an individual, … FTP is a cognitive-motivational personality characteristic that results from goal setting” (Lens, Paixao, Herrera, & Grobler, 2012). FTP has been found to be an important motivational construct that enhances learning experiences (Husman & Shell, 2008; Kauffman & Husman, 2004; Peetsma, 2000; Shell & Husman, 2001), promotes intrinsic motivation (Vansteenkiste, Simons, Soenens, & Lens, 2004), and supports active learning (Simons, Vansteenkiste, Lens, & Lacante, 2004). Studies in the time perspective literature show that FTP is a multidimensional construct (Husman & Lens, 1999; Simons et al., 2004; Stouthard & Peetsma, 1999), with sub-dimensions including: a) Connectedness, the tendency to anticipate future consequences, to make cognitive connections between the present and the future; b) Valence, or Value, the tendency to place value in future goals; c) Extension, how far thoughts are projected into the future; and d) Speed, how quick time seems to pass (Husman & Shell, 2008). Within these sub-dimensions, connectedness and valence have been positively linked with control beliefs (Shell & Husman, 2001). As potential
appraisal antecedents within the Control Value Theory framework, it is plausible that FTP Connectedness and FTP Value could contribute to one’s emotional experience and well-being via influencing the subjective control and subjective outcome value one has for academic activities.

In research regarding general FTP, King and Gaerlan (2014) found that FTP was positively associated with Filipino university students’ positive academic achievement emotions (hope, joy, and pride), and contrary to their hypothesis, positively associated with anxiety, linking FTP to academic achievement emotions. Qualitative analyses have, on the other hand, demonstrated that thoughts of future goals were helpful in recovering from present negative emotions, such as test-related shame, after an exam for college students, and acted as a means to protect goal-striving efforts (Turner & Husman, 2008).

**The Current Studies**

The current work, within the dimensional perspective of FTP, explored the specific roles that the sub-dimensions FTP Connectedness and FTP Value may have as appraisal antecedents, specifically in conjunction with the affective and physiological components of academic achievement emotions. This series of studies examined post-secondary Engineering students as participants of particular interest. Engineering students are a unique sample in that they encounter rigid curricula and problem-solving challenges on a regular basis. These challenges elicit repeated stress responses and frustration that may hinder their academic pursuit and program completion (Chang, Cerna, Han, & Sa'enz, 2008; Hsieh, Sullivan, Sass, & Guerra,
Engineering educational research has focused on the importance of motivational constructs in predicting students’ achievement and career plans (e.g., Jones, Paretti, Hien, & Knott, 2010). However, some research shows that for Engineering students, both motivation and institutional integration (e.g., beliefs of relationships with faculty and peers in college) play important roles in students’ persistence throughout their degree (French, Immekus, & Oakes, 2005). Motivation toward future goals helps students to progress and persevere through the degree; however, Engineering students do not necessarily acquire socio-emotional support in their learning environments (such as from faculty or peers) despite having course loads which may take heavy emotional tolls (e.g., Kötter et al., 2014). The nature of the academic environment of post-secondary Engineering students, i.e., high stress and low support, provides us with an opportunity to examine factors that may contribute to better well-being in students.

This dissertation consists of a series of two studies. In Study 1, the focus was on linking the negative achievement emotion hopelessness and FTP Connectedness to diurnal cortisol slopes surrounding a mid-term exam in university Engineering students. Firstly, I examined exam effects on diurnal cortisol slopes by comparing the diurnal slope differences between the week before a mid-term and the week during a mid-term in a sample of college engineering students (see Table 1 for timeline). From self-reported surveys obtained the week prior to the mid-term, I examined Learning-related Hopelessness, and its role as a risk factor for having flatter diurnal cortisol patterns as mid-term approaches, i.e., comparing diurnal patterns a week before
(Wave 1) and the week during mid-term examinations (Wave 2). I also examined FTP Connectedness as a protective factor in buffering the potential adverse effects that the mid-term exam could have on students’ diurnal cortisol patterns, i.e., whether FTP Connectedness relates to more fluctuation in diurnal cortisol patterns to cope with exam stress.

In Study 2, the focus was on exploring the roles of emotion regulation and social support in conjunction with FTP Value in predicting diurnal cortisol pattern change over time (see Table 2 for timeline). Valuing a future goal in itself may not be sufficient in goal pursuit or academic success. The striving that one undergoes in order to reach a future goal, however, is essential for goal attainment. For students to continuously move toward their future goals, it is crucial to have regulatory resources to maintain their emotional and physical well-being. Therefore, I posited that regulatory factors would also play a role in predicting students’ well-being in conjunction with FTP Value. Emotion regulation has been found to predict academic achievement in youth samples (Liew, 2012), and has been associated with lower momentary cortisol levels in an adolescent sample under a social-evaluative threat task (Oldehinkel, Hartman, Nederhof, Riese, & Ormel, 2011).

Moreover, perceived instructor affective support in college positively predicted students’ course-related enjoyment, and negatively predicted course-related hopelessness, which in turn resulted in higher academic motivation (Sakiz, 2012). Social support (from teachers, friends, and parents) in a youth sample predicted positive attitudes toward and higher sense of perceived ability on math and science subjects.
(Rice et al., 2013). In line with Control Value Theory, it is plausible that both emotion regulation and social support could provide students with more subjective control over their academic tasks, thus contributing to their emotional experience and physiological well-being. As these regulatory resources may influence students’ experiences through a more prolonged period of time, it made sense to link them with diurnal cortisol slope change over time. Although the above findings did not pertain to direct predictions in students’ diurnal cortisol slopes, it is plausible that both emotion regulation and social support could provide multiplicative value jointly with FTP Value in predicting students’ well-being over time.

For Study 2, I examined diurnal cortisol patterns (CAR & DS) at three time points over the course of a semester in a sample of post-secondary engineering students (including both upper-class undergraduate students and graduate students in the Engineering program); and I examined the moderating roles of emotion regulation and social support in predicting FTP Value to diurnal cortisol slope change over the three time points: beginning of semester, mid-term/major presentation week, and recovery phase.

In sum, this dissertation provides grounding for theory integration and expansion, and offers a framework for understanding university students’ well-being within the academic context via diurnal cortisol assessments. It takes into account the temporal aspects of emotions and motivation, as well as motivational and socio-emotional regulatory factors to understand correlates of health and well-being in students of post-secondary education.
Study 1: Future time perspective, hopelessness, and physiological stress
dysregulation indicated by diurnal cortisol patterns in college Engineering
students

Although attending college is an important steppingstone for preparing for the workforce, the process of completing one’s college degree may be overwhelming at times (Bland, Welle, Melton, & Bigham, 2012). College students’ mental and physical health and stamina are important for them to get through challenging academic environments. An indicator for physiological stress regulation is the diurnal cortisol pattern, which has been found to be associated with well-being (e.g., Dmitrieva, Almeida, Dmitrieva, & Pieper, 2013). Salivary cortisol is easy to obtain and non-intrusive, making it a convenient biomarker for stress and health (Doane, Chen, Sladek, van Lanten, & Granger, 2015). In the past several years, literature on the toll that continuous stress can play on one’s well-being has been well established (e.g., Kemeny, 2009). As educators, there is a need for us to understand the effects of stressors in academic settings and the possible moderators of that stress to pinpoint antecedents that may help enhance the well-being of students. There has been an exploration of emotions within the educational context; for example, Control Value Theory describes the antecedents and multi-faceted nature of emotions in the academic context (Pekrun, 2006). Physiological associations with specific emotions in the learning context, although posited in the theory, have not been examined much (Spangler et al., 2002). The current study investigates students’ physiological stress manifestations during their mid-term examination week by examining their diurnal
cortisol patterns; the study also assesses motivational and emotional factors that may contribute to differences in students’ physiological stress manifestation.

**Diurnal Cortisol Patterns**

Cortisol, a stress hormone, has received attention from psychological researchers because of its regulatory role in the central nervous system, the metabolic system, and the human immune system (Kemeny, 2009; Miller, Chen, & Zhou, 2007). Cortisol levels in the blood stream follow a diurnal rhythm — morning levels are highest (peaking at 30-minutes upon awakening, known as the cortisol awakening response, CAR), and gradually decline throughout the day (the recovery phase, known as the diurnal slope, DS). This daily rhythm is the so-called diurnal cortisol pattern.

Under acute stressful situations, momentary cortisol levels typically increase allowing the body to allocate resources to cope with the stressor (e.g., Dickerson & Kemeny, 2004; Lovell, Moss, & Wetherell, 2011). However, excess amounts of cortisol from repeated stress exposure may send negative feedback signals to the brain, causing a down-regulation in cortisol secretion, which has been termed hyporeactivity (e.g., Hankin, Badanes, Abela, & Watamura, 2010) or hypocortisolism (Gunnar & Vazquez, 2001; Heim, Ehlert, & Hellhammer, 2000). Chronic elevations in cortisol levels, may eventually cause dysregulation in the diurnal rhythm, i.e., the diurnal cortisol slope becomes flatter (e.g., Dmitrieva et al., 2013; Doane et al., 2015; Karb et al., 2012). A flatter diurnal cortisol slope, which implies a less profound boost of cortisol in the morning and lack of reduction in cortisol over the day, has been associated with lower well-being, including trait loneliness (Doane & Adam, 2010),
negative affectivity (Hoyt, Craske, Mineka, & Adam, 2015), depressive symptoms and anxiety (Pössel, Mitchell, Sjögren, & Kristenson, 2015, Saridjan et al., 2014), and suppressed immunity (Sephton et al., 2013). Given the negative mental and physiological consequences associated with flattened diurnal cortisol slopes, it is of interest to unravel potential risk factors and buffering factors to enhance students’ well-being when faced with adverse or stressful academic situations.

Biomarkers provide researchers with a valuable tool for understanding the physiological manifestations of stress, arousal, and well-being. These tools, however, have not yet provided us with insight into the particular emotional experiences of students within the academic setting, nor do they incorporate motivational correlates into the picture. Cortisol has been examined on different temporal levels, such as with regards to trait characteristics (e.g., trait loneliness predicting diurnal cortisol slopes), daily variations (e.g., loneliness of previous day predicting day-of cortisol awakening response), as well as momentary predictions (e.g., momentary loneliness predicting cortisol level; Doane & Adam, 2010).

The current study examined students’ well-being with respect to the occurrence of a mid-term. As students may anticipate the mid-term days, or even weeks, before the exam occurs, it was reasonable to posit that the mid-term examination of a specific course would have an effect on students’ physiological stress regulation over longer time frames, indicated by the cortisol parameters with a longer temporal implication, i.e., diurnal cortisol patterns (DS and CAR), instead of momentary pre-test or post-test cortisol levels. Notably, the current study examined
diurnal cortisol samples during the week before the mid-term exams (Wave 1) and the week during mid-term exams (Wave 2). Given that the mid-term is a stressful event, I posited that in general students would have a flatter DS and smaller CAR during Wave 2 compared to Wave 1. However, it is important to acknowledge that there could be individual differences in terms of diurnal cortisol patterns between waves; specifically, students who are low in psycho-social resources may have consistently flatter diurnal cortisol patterns across the two waves, signifying allostatic saturation and the inability for the body to respond to the stressful event. I posited that these individual differences in diurnal cortisol patterns could be predicted by correlates in the academic setting such as Learning-related Hopelessness specific to the class of said mid-term examination and students' future time perspective. As there were multiple factors that could influence the daily levels and fluctuation of cortisol secretion, such as differences in sleep duration, cigarette use, and medication use, these factors were proposed to be included as covariates to adjust for potential confounding effects they may have on the diurnal cortisol patterns (Dmitrieva et al., 2013; Granger et al., 2009; Mrug, Tyson, Turan, & Granger, 2015).

**Hopelessness as a Risk Factor**

Hopelessness specific to the academic setting is an under-studied emotion (Frenzel et al., 2007). Hopelessness, specific to the academic setting, is a negative prospective emotion, and has been linked to the anticipation of academic failure instead of success (Pekrun, 2006). For example, a student who reported more Learning-related Hopelessness (LHL) could feel helpless, less confident, more
resigned about a specific course, and would feel that they are unable to cope with specific class challenges. Importantly, the deactivating nature of LHL could be associated with physiological dysregulation in face of a challenge or stressful event, making a student unable to boost up required resources upon demand.

Although LHL is an understudied emotion, the antecedents and effects of general hopelessness are well established. Antecedents of general hopelessness for undergraduate students include perfectionism, poor problem-solving skills, and emotion dysregulation (O’Connor & O’Connor, 2003; Pössel et al., 2015; Rice, Leever, Christopher, & Porter, 2006; Vatan, Lester, & Gunn, 2014). The feeling of hopelessness has been associated with students’ decreased learning, disengagement in schooling, negative well-being, such as depression, poorer physical health, and even suicidality in college (e.g., Au, Watkins, & Hattie, 2010; Fellner-Rosenberg, 1989; McCarthy, 1992; Range & Penton, 1994). Clearly general hopelessness is negatively related to well-being. One question that still needs to be addressed is the possible magnitude of the effect of contextually specific LHL on students’ wellbeing.

Although the student may feel masterful in other domains in life, I argue that LHL may undermine one’s well-being due to events of a specific class (e.g., becoming more vulnerable to illness around an exam). As important as this emotion may be to students, few researchers explored LHL as a risk factor for well-being in academic settings (e.g., Burić, & Sorić, 2012; van Santen et al., 2011), specifically in post-secondary university students.
**Future Time Perspective as a Protective Factor**

In contrast to the prospective negative emotion Learning-related Hopelessness, it is reasonable to expect that students’ mental representations of their long-term personal futures may help release negative anticipations upon challenging life events. Future time perspective (FTP) is the study of one’s perceptions of the future. Specifically, FTP can be understood in the goal-setting and planning context. The longer or deeper one’s FTP, the further into the future one’s time perspective is extended, and the greater the number of goals one will possess (Simons, Vansteenkiste, Lens, & Lacante, 2004). Under the cognitive-motivational construct of FTP, four sub-dimensions have been found, including Valence, Connectedness, Extension, and Speed (Husman & Shell, 2008). Of the four FTP subscales, FTP Connectedness (FTPC) denotes the cognitive ability one has to make connections between present activities and future goals; those with high FTPC would have a general feeling of connectedness to and plan-fullness about the future.

FTPC has been found to predict students’ achievement in post-secondary educational settings (Shell & Husman, 2001). Most literature in motivational research suggests that intrinsic motivation is what makes tasks at hand enjoyable, whereas utility value, which denotes how a task at hand fits into one’s future plans (e.g., taking a class to fulfill degree requirement) has been linked with external motivation (Wigfield & Eccles, 2000). This line of motivational research suggests that intrinsic motivation supports students’ positive psychological well-being (Ryan & Deci, 1985). However, in future-oriented motivation research, it is found that FTP Connectedness
enables and individual to bring meaning to current academic tasks by connecting the present with the future (e.g., studying hard to pass an exam to graduate from the program and become an engineer). It is argued that such connectedness from the present to future goals enables one to experience intrinsic motivation for a current task, and in turn have positive emotional experiences from said task (Husman, Derryberry, Crowson, & Lomax, 2004). In past studies it has been found that individuals who are depressed and hopeless have an unrealistically negative attitude towards their future (Beck, Weissman, Lester, & Trexler, 1974); research also shows that individuals who are more hopeless tend to have greater gaps between their actual quality of life and their future (aspired) quality of life, indicating poor present well-being (Moore, Höfer, McGee, & Ring, 2005). It is plausible that FTPC could allow individuals to ruminate less on present negativity and divert more mental or physical resources on future goals, which could potentially lead to better well-being. The current study examined how FTPC, one’s ability to make meaning of present academic tasks with future goals in mind, played a role in protecting students’ well-being from stressful academic events, such as mid-term examinations.

Theoretical Framework

Control Value Theory posits that academic achievement emotions are those that are aroused due to achievement-related activities (Pekrun, 2006). Achievement emotions can be described in two dimensions, i.e., valence (positive vs. negative, pleasant vs. unpleasant), and activation (activating vs. deactivating, such as exuberant vs. relaxed), and hopelessness is a negative deactivating emotion that has been found
to be associated with performance-avoidant goals (Pekrun & Perry, 2014).

Hopelessness has been identified as a prospective emotion based on expectations of failure. In other words, it is anticipated that there will be a negative outcome, and subjective control over this outcome is low (Pekrun, 2006). Hopelessness comes from a cognitive focus on the non-attainability of success or the inevitability of failure (Pekrun, Frenzel, Goetz, & Perry, 2007). Such emotional experience could be quite frustrating for students, and certainly is not beneficial for students’ well-being. The focus of achievement-related emotional research, however, has been mostly on academic anxiety. Few studies have incorporated academic-specific hopelessness into investigation with regards to academic stress.

In addition, according to Control Value Theory (Pekrun, 2006), achievement emotions can be accounted for by multiple second-order facets—including the affective, motivational, physiological, and cognitive facets. Notably, although academic achievement emotions include the facet of physiological response, few studies examined physiological markers in relation to self-reported achievement emotions. In adult samples, a meta-analysis showed that emotions were predictive of cortisol responses to social evaluative threat in experimental settings; specifically, surprise, worry, and fear positively predicted cortisol levels in adults (Denson, Spanovic, & Miller, 2009). In the rare event of investigating associations between biomarkers and test-related emotions surrounding an *actual* test-taking event in university students, researchers found that high trait anxiety was associated with elevated cortisol levels following the exam, and low trait anxiety was associated with
decrease in cortisol after the exam (e.g., Spangler et al., 2002). Although different from hopelessness, research on anxiety informs us that academic-specific negative emotion does have associations with physiological stress responses. The hormonal underpinnings of negative deactivating emotions such as Learning-related Hopelessness, however, are yet to be explored. Given that Learning-related Hopelessness (LHL) is anticipatory in nature and could be associated with more prolonged physiological effects, albeit its academic specific nature, I posit that Learning-related Hopelessness would be associated with diurnal cortisol patterns surrounding an examination, which is indicative of a longer temporal effect, instead of around the traditionally experimentally investigated momentary cortisol levels collected right before, during, and after experimental stress tasks or examination events. Specifically, given that general hopelessness has been often associated with one’s poor well-being, it would be reasonable to suspect that LHL would be predictive of a flatter DS and a smaller CAR, and less fluctuation in diurnal cortisol patterns in face of stress, which indicates negative well-being due to stress dysregulation.

Moreover, Control Value Theory may provide insight into pinpointing paths to prevent the drastic downstream effects of academic stress. Control Value Theory is an integrated framework built upon the expectancy-value theory (Vroom, 1964), theories of attribution in achievement (Weiner, 1985), theories on perceived control (Perry, 1991), etc. The framework provides theoretical support for and empirical foundations for the motivational facet of emotional experiences (e.g., Pekrun, Goetz, Frenzel,
Barchfeld, & Perry, 2011). In particular, Control Value Theory suggests that achievement emotions are influenced by appraisal antecedents of the students, including subjective control over achievement activities, as well as subjective outcome values of these activities.

Research in future time perspective (FTP), one’s ability to consider the future, shows consistency with control-value theory. FTP been found to be important in enhancing learning experiences for university students (Husman & Shell, 2008; Kauffman & Husman, 2004; Shell & Husman, 2001). Specifically, FTP Connectedness has been found to predict endogenous perceptions of instrumentality, one’s perception of how gaining competence in a current task can help reach long-term future goals (Hilpert et al., 2012). Endogenous perceptions of instrumentality was found to be supportive of intrinsic motivation, which may in turn increase students’ positive emotions towards learning (Husman et al., 2004). I therefore suspect that students’ future orientation, specifically FTPC, may play a crucial role as an appraisal antecedent, protecting students against academic adversity, enhancing students’ well-being, and buffering the physiological stress responses surrounding students’ mid-term examination in post-secondary educational settings. As FTPC is a general cognitive-motivational tendency (I used a domain-general FTP measure; c.f. Hilpert et al., 2012) which is associated with long-term goal pursuits instead of momentary state affects, I expected to see FTPC’s association with students’ well-being as represented by diurnal cortisol patterns.
The Current Study

The aims of the current study included 1) to examine the mid-term examination effects for college students, i.e., the difference in diurnal cortisol a week before the exam (Wave 1), and the week during mid-term examination (Wave 2); 2) to examine Learning-related Hopelessness (LHL) as a risk factor in predicting exam effects for diurnal cortisol slopes (DS) and cortisol awakening responses (CAR) surrounding college students’ mid-term; 3) to examine FTPC as a protective factor in predicting exam effects for DS and CAR surrounding college students’ mid-term. Specifically, I hypothesized that H₁) there will be an overall exam-stress effect, namely, students in general will show a steeper DS and larger CAR at Wave 1 (week before mid-terms), and a flatter DS and smaller CAR at Wave 2 (day immediately before mid-term), as an indication of the stressful experience that mid-term examinations are for Engineering college students. H₂) students will vary in terms of physiological stress manifestations: specifically, I hypothesized that some students will have healthy patterns of diurnal cortisol (steep DS, large CAR) for both waves (Healthy group); some students will have lower well-being at Wave 2 as an adaptive response (a flatter DS and smaller CAR during Wave 2) to the mid-term exam stress (Exam-stress group); whereas some students with flatter DS and smaller CAR at Wave 1 will experience a non-response at Wave 2 (flat DS and small CAR for both waves) indicating poor well-being over time (Dysregulated group). H₃) Students with more LHL will have low DS and CAR and less fluctuation in diurnal cortisol patterns between the two waves indicating poor adaptation and stress dysregulation (predictive
of Dysregulated group). $H_{c2}$ FTPC would predict a steeper DS for both waves, or more fluctuation (from steep to flat) as an indicator of well-being or adaptive stress regulation before and during the week of exam (predictive of Health group & Exam-stress group).

The current study was innovative not only by allowing us to understand physiological correlates for hopelessness in post-secondary education, but also in that I examined students’ hopelessness in the academic, domain-specific context (i.e., Learning-related Hopelessness), instead of using traditionally constructed general hopelessness (such as the Beck Hopelessness Scale, e.g., Fellner-Rosenberg, 1989; Pompili et al., 2013) which has been under-examined in research that typically incorporates biomarkers into well-being investigation, such as in developmental psychology and social psychology research. More importantly, the current study weaves FTP theory with Control Value Theory, in suggesting FTPC as an appraisal antecedent construct in predicting the physiological correlates of academic-related emotions. I proposed that the current study would contribute theoretically to current literature, and that findings would be beneficial for educators and educational researchers to identify potential pathways of enhancing college students’ well-being.

**Methods**

**Participants**

Data were collected from two sections of a required engineering course. This course, Circuits, is one of the more challenging courses electrical engineering students take during their sophomore year. Among the sampled class sections, a total of
seventy-one students consented to participate in the survey part of the study, of which sixty students consented to participate in the saliva collection part of the study. The mean age of the sample was 21.31 years (SD = 2.95), and approximately 27% were female. In terms of race/ethnicity, there were approximately 52% White, 13% Asian, 13% Hispanic, 3% Black, and 8% mixed-race participants. Sixty students of all seventy-one participants provided valid surveys; for Wave 1 (week before mid-term), forty-eight participants provided valid saliva samples, and for Wave 2 (week of mid-term), forty-four participants completed the diurnal samples over the two waves of the study.

**Procedures**

All procedures were approved by the university institutional review board prior to data collection. Data collection for the current study spanned two consecutive weeks for each class. During Wave 1 participants consented, filled out the first online survey, and provided baseline diurnal salivary samples for two consecutive days (upon-awakening, 30-minutes after awakening, before lunch, before bed-time, with a total of 8 tubes). Wave 2 was the students’ mid-term examination week, and participants provided their second set of diurnal samples for two consecutive days (another 8 tubes) prior to their exam day. For both sets of diurnal saliva collection, participants were provided collection packets with detailed instructions about how to collect and store their sample tubes, as well as daily checksheets to record what they have consumed (high sugar, high sour contents, drugs/medicine, etc.), and whether or not they have experienced stressful events prior to sample collection.
**Diurnal Cortisol Sampling.** Procedures regarding saliva collection specifically followed rules written by the Institution of Interdisciplinary Salivary Bioscience Research (IISBR) at Arizona State University led by Dr. Douglas Granger. The suggested protocol of sample collection included rinsing the mount with water 10 minutes prior to collection, and to complete the checksheet items (including time of collection, medications, sleep time and sleep duration etc.) associated with each sample, to document if they had dairy, acidic or high sugar-content foods 20 minutes prior to sample collection, and report if they were ill or have oral health problems etc. Students were instructed to refrigerate or freeze their diurnal saliva samples immediately after collections, and put them in an ice-packet during transportation. The saliva samples were kept frozen in our research lab for less than two weeks before all samples were received and organized in grid boxes, and transported in an ice-chest to the IISBR at ASU and were stored in freezers prior to being assayed for cortisol (µg/dL); each sample was assayed for duplicates for assay reliability. The level of cortisol for each time point of each wave was an average between the two consecutive days of sample collection in each wave. Outliers were windsorized at 1.81 µg/dL for data analysis (equivalent to 50nmol/L; Nicolson, 2008).

**Measures**

**Academic achievement emotions.** Students completed self-reports on the Achievement Emotions Questionnaire (AEQ). The AEQ includes 53 learning-related emotions items, of which 11 items were on Learning-related Hopelessness (Pekrun et al., 2011). Sample items include "I'm resigned to the fact that I don't have the
capacity to master this material”, and “My hopelessness undermines all my energy”; items were situated before, during, and after studying/learning (Cronbach’s $\alpha = .64$; 5-point Likert scale from 1 = Strongly disagree to 5 = Strongly agree). The AEQ was surveyed at Wave 1, day 1. The Learning-related Hopelessness (LHL) composite was calculated by averaging the scores across the 11 items.

**Future time perspective – Connectedness.** Students completed self-reports on their Future Time Perspective – Connectedness subscale using the Future Time Perspective Scale (Husman & Shell, 2008). The Future Time Perspective scale Connectedness subscale (FTPC) includes 11 items (Cronbach’s $\alpha = .88$; 5-point Likert scale, from 1 = Strongly disagree to 5 = Strongly agree), such as, “One should be taking steps today to help realize future goals.”

**Diurnal cortisol patterns.** Mean cortisol levels of the two consecutive days for each wave were computed to create T1, T2, and T3 cortisol levels for each wave. Log transformations were performed for each time point before any calculation for indicators occurs if the data is positively skewed. Three samples, i.e., upon awakening (T1), 30-minute after awakening (T2), and before bed-time samples (T3) were used to create the diurnal cortisol slope (DS) and the cortisol awakening response (CAR) for each wave. The before lunch time sample was excluded from the diurnal cortisol pattern analysis, for two reasons, one being that students’ lunch times were extremely variable, second being that common practices for diurnal pattern calculation does not require this time point to be included for calculation.
DS was calculated by subtracting the before bedtime sample (T3) from the morning awakening sample (T1) after both are log transformed, and dividing this deviation by awake hours (DeSantis, Adam, Hawkley, Kudielka, & Cacioppo, 2015). The two morning samples were used to calculate the cortisol awakening response (CAR) for each wave. CAR was calculated by subtracting wake level T1 from peak level T2, also after both are log transformed.

**Covariates.** Gender and race/ethnicity were included as covariates, as they have been found to be associated with diurnal cortisol patterns (e.g., DeSantis et al., 2015). From checksheet data, I included sleep duration as a covariate, and dichotomized variables cigarette use and medication use of any of the following six types of prescription and over-the-counter medicines that have been shown to influence cortisol levels: steroid inhalers, other types of steroid medications, medications or creams containing cortisone, birth control pills, and anti-depressant or anti-anxiety medications (Dmitrieva et al., 2013; Granger et al., 2009), and included them as covariates.

**Plan of Analysis**

Descriptive statistics and bivariate correlations were performed in SPSS, including means, standard deviations, and zero-order bivariate correlations on Learning-related Hopelessness, FTPC, and diurnal cortisol levels. First, I used repeated measures ANCOVA to examine exam-stress effects between the two waves of diurnal cortisol patterns for both DS and CAR (regardless of grouping but taking into account the covariates). This step was meant to test whether there are general
trends in students’ physiological responses to the mid-term exam. Next, I used regression models to examine relations between Wave 1 variables, and predictions from Wave 1 LHL and FTPC to DS and CAR patterns (comparing the groups) across the waves. I examined my hypotheses using the following analysis:

I examined $H_a$) there will be an overall exam-stress effect, namely, students in general will show a steeper DS and larger CAR at Wave 1 (week before mid-terms), and a flatter DS and smaller CAR at Wave 2 (day immediately before mid-term), as an indication of the stressful experience that mid-term examinations are for Engineering college students by using repeated measures one-way ANCOVA between Wave 1 and Wave 2 data for both DS and CAR; covariates (e.g., sleep hours) was included in the model. This provided support for the exam-stress effects the mid-term has on students’ physiological stress regulation. Large negative values from contrasting Wave 2 diurnal cortisol patterns to Wave 1 diurnal cortisol patterns would be able to support this hypothesis, indicating flattened diurnal cortisol patterns.

Hypothesis $H_b$) students will vary in terms of physiological stress manifestations: specifically, some students will have healthy patterns of diurnal cortisol (steep DS, large CAR) for both waves (Healthy group); some students will have lower well-being at Wave 2 as an adaptive response (a flatter DS and smaller CAR during Wave 2) to the mid-term exam stress (Exam-stress group); whereas some students with flatter DS and smaller CAR at Wave 1 will experience a non-response at Wave 2 (flat DS and small CAR for both waves) indicating poor well-being over time (Dysregulated group) was examined by assigning groups via investigating the diurnal
cortisol pattern change in each student. I proposed to form groups using the following criteria: one standard deviation above the mean as high, one standard deviation below the mean as low, and between these two points as medium. Students who showed high-high patterns of diurnal cortisol (DS and/or CAR) for both waves would be assigned to the Healthy group. Students who showed a flattening effect of diurnal cortisol patterns from Wave 1 to Wave 2 (for example high-medium, high-low, or medium-low) would be assigned to the Exam-stress group. Students who showed flat diurnal cortisol patterns for both waves (low-low DS and/or CAR) would be assigned to the Dysregulated group. It was possible that there would be students who would not fit into any of the three groups, for example those who showed a steeper diurnal cortisol pattern at Wave 2 (e.g., medium-high, low-medium); I proposed to further investigate whether or not, and how, they would be incorporated in the analysis.

I examined \( H_{c,i} \) Students with more LHL at Wave 1 will have low DS and CAR and less fluctuation in diurnal cortisol patterns between the two waves indicating poor adaptation and stress dysregulation (predictive of Dysregulated group) by using multinominal logistic regression models to predict group status for DS and CAR patterns as the dependent variables (the Healthy group, Exam-stress group, and Dysregulated group). The independent variable was LHL at Wave 1. Covariates such as gender, race/ethnicity, cigarette use, medicine use, and sleep hours were proposed to be included in the model. The proposed criteria to support this hypothesis was that odds ratio of LHL for the Dysregulated group compared to the Healthy and Exam-stress group should be greater than 1, indicating increased probability for more
Hopelessness in the Dysregulated group, which would be supportive of LHL being a risk factor for well-being.

I examined $H_{c,2}$ FTPC would predict a steeper DS for both waves, or more fluctuation (from steep to flat) as an indicator of well-being or adaptive stress regulation before and during the week of exam (predictive of Healthy group & Exam-stress group) by using multinomial logistic regression models to predict group status for DS and CAR patterns as the dependent variables (the three groups would be dummy coded). The independent variable was FTPC at Wave 1. Covariates such as gender, race/ethnicity, cigarette use, medicine use, and sleep hours were proposed to be included in the model. The proposed criteria to support this hypothesis was that odds ratio of FTPC for the Healthy and Exam-stress group compared to the Dysregulated group should be greater than 1, indicating the probability for more future time perspective (Connectedness) in the Healthy group and Exam-stress group compared to the Dysregulated group, which would be supportive of FTPC being a protective factor for well-being.

**Results**

**Participant Demographics**

A total of 71 students enrolled in Study 1, and out of these participants, 60 completed their surveys. Out of all the participants who completed surveys for Study 1 ($N = 60$), 72% were male students ($n = 41$) and 28% were female students ($n = 16$); with regards to race/ethnicity, 2% were American Indian, 15% were Asian, 15% were Hispanic, 3% were Black, 53% were White, 0% were Pacific Islanders, and 8% were
of mixed racial background. Three students out of the 60 participants had missing
gender data (5%), and two had missing race/ethnicity data (3%). The participants had
a mean age of 21.36 years ($SD = 2.95$).

**Attrition analysis.** Of the 60 participants who completed their survey data, 23
students attrited between survey collection and Wave 1 cortisol collection (a total of
46 students participated in Wave 1 cortisol collection); another six students attrited
between Wave 1 and Wave 2 data collection (a total of 40 students participated in
both Wave 1 and Wave 2 cortisol collection). Table 1 shows participants’
demographic information with regards to study participation and attrition over time,
comparing those who completed survey data, participated in Wave 1 cortisol
collection, and participated in Wave 2 cortisol collection. According to cross
(tabulation analysis and $t$-test results performed in SPSS v.22, no significant
association between attrition over time and gender or age was found. However, using
cross tabulation, Pearson Chi-square results showed that if the race/ethnicity variable
was recoded, to avoid low cell count, into White vs. Minority, there was a significant
association between attrition and minority status, $\chi^2(2, N = 58) = 6.19$ ($p = .045$),
indicating that attrition was significantly higher in ethnic minorities. Notably,
recoding race/ethnicity into Under-represented Minority vs. Others, with Under-
represented Minority consisting of American Indian, Hispanic, Black, and Mixed
Race groups, the association between attrition over time and Under-represented
Minority status was also significant ($\chi^2(2, N = 58) = 7.46, p = .024$). When examining the
attrition from Wave 1 cortisol collection to Wave 2 cortisol collection, gender and age
again showed no significant association with attrition. Both minority status coding systems were found to be significantly associated with attrition between waves, i.e., White vs. Minority ($\chi^2(1, N=44) = 5.17, p = .023$) and Under-represented Minority vs. Others ($\chi^2(1, N=44) = 6.43, p = .011$), were found to be significantly associated with between-wave attrition.

**Covariate Data**

Participants reported to have slept for an average of 7.93 hours ($SD = 1.34$; range = 4.87 to 10.50) during the nights before two consecutive days of Wave 1 cortisol collection, and slept for an average of 7.93 ($SD = 1.81$; range = 4.50 to 12.50) during the nights before two consecutive days of Wave 2 cortisol collection. Check-sheet data from the diurnal cortisol saliva kits indicated that during Wave 1, 25 students reported to have experienced a stressful event within the 24 hours prior to their saliva sample collection; three students reported smoking within 12 hours of saliva collection; and 20 students reported have taken medication (a dichotomized variable for intake of allergies medication, pain killers, contraceptives, medication for a chronic health concern, or other) within 24 hours of saliva collection. During Wave 2, 22 students reported to have experienced a stressful event within the 24 hours prior to their saliva sample collection; one student reported smoking within 12 hours of saliva collection; and 13 students reported have taken medication within 24 hours of saliva collection.
Preliminary Analysis

Raw cortisol data were examined, and one participant had an outlier data point greater than 1.81 µg/dL (equivalent to 50 nmol/L, approximately the highest non-stimulated salivary cortisol level for healthy subjects; Nicolson, 2008) at 30-minutes upon wakening during Wave 1 Day 2 which was windsorized at 1.81 µg/dL. All other cortisol data were within the bounds of 1.81 µg/dL. One case was excluded from cortisol data analysis due to staying up all night during both Wave 1 and Wave 2 data collection.

After the exclusion, 45 participants had cortisol data for Wave 1, and 39 participants had cortisol data for Wave 2. For Wave 1 data collection, one participant only submitted their Day 1 samples. During Wave 2 data collection, for Wake level cortisol (samples collected upon awakening), two participants only submitted their Day 1 samples, and two participants only submitted their Day 2 samples; for Peak level cortisol (collected 30-minutes upon awakening), one participant only submitted their Day 1 sample, and two participants only submitted their Day 2 samples; for Bedtime cortisol, two participants only submitted Day 2 samples (Table 2).

The cortisol values were then averaged between the two consecutive days at each time point for each wave. As noted, some participants were missing one or both days of cortisol samples, however, one day of missingness was allowed for the averaged cortisol levels at each time point to maximize retention of cortisol data (see Table 2).
Descriptive statistical analysis (Table 3) indicated that there were excess skewness and kurtosis in the mean cortisol values (skewness range = -0.03 to 5.07; kurtosis range = -1.04 to 28.55) therefore the mean cortisol values were log-transformed to approximate normality. For each wave, a composite to represent the diurnal cortisol slope (DS) was then calculated by subtracting mean bedtime cortisol (Bed) from mean awakening cortisol (Wake) and dividing the score by awake hours for each participant; a composite to represent the cortisol awakening response (CAR) was calculated by subtracting mean awakening cortisol from mean 30-minute upon awakening cortisol (Peak) for each wave (see Table 4).

Bivariate correlations between the diurnal cortisol parameters were examined (Table 5). Results showed that Wave 1 DS and Wave 2 DS were significantly positively correlated ($r = .59, p < .001$), Wave 1 DS and Wave 1 CAR were significantly negatively correlated ($r = -.45, p < .01$), and Wave 1 CAR and Wave 2 CAR were significantly positively correlated ($r = .74, p < .001$). As a preliminary examination with regard to diurnal cortisol parameter’s relation with Study 1 main predictors, Wave 1 DS was significantly negatively correlated with Learning-related Hopelessness ($r = -.33, p < .05$); and Wave 2 CAR was marginally negatively correlated with Future Time Perspective Connectedness ($r = -.28, p < .10$).

Gender differences for mean-level cortisol and diurnal cortisol parameters were also examined (Table 6). Results showed that there were no significant differences between males and females with regards to mean-level cortisol. A marginally significant difference in Wave 1 DS was found between males ($M = .11$,
and females (\(M = .07, SD = .04\)), with male students having higher DS at Wave 1 than their female counterparts (\(t = 1.74, p < .10\)). The effect size for this analysis (\(d = .70\)) was found to exceed Cohen’s (1988) convention for a medium effect size (\(d = .50\)). There were no significant gender differences in all other diurnal cortisol parameters, though notably effect sizes for DS at Wave 1 (\(d = .61\)) and CAR at Wave 1 (\(d = .56\)) also exceeded the convention for a medium effect size (\(d = .50\)); and effect size for CAR at Wave 2 (\(d = .49\)) approached the medium effect size.

Minority status differences for mean-level cortisol and diurnal cortisol parameters were also examined (Table 7). Results showed that a significant difference was found in Wave 1 Wake level cortisol, between Minorities including American Indian, Asian, Hispanic, Black, Mixed Race students (\(M = -1.29, SD = .44\)) and White students (\(M = -.94, SD = .42\)), with Minorities having a significant lower mean Wake level cortisol (log-transformed) than their White peers (\(t = 2.61, p < .05\)). The effect size for this analysis (\(d = .81\)) exceeded Cohen’s (1988) convention for a large effect size (\(d = .80\)). Wave 1 CAR was found to be significantly higher in Minorities (\(M = .63, SD = .62\)) and White (\(M = .22, SD = .43\)), with Minority students having higher CAR at Wave 1 than their White peers (\(t =-2.51, p < .05\)). The effect size for this analysis (\(d = .77\)) exceeded Cohen’s (1988) convention for a medium effect size (\(d = .50\)). Statistically significant differences (\(t\)-tests) were not found when the minority status included Underrepresented Minorities only. However, effect sizes comparing Underrepresented Minorities vs. Others for log-transformed Wave 1 Wake level cortisol (\(d = .56\)), Wave 1 Bedtime cortisol (\(d = .59\)), Wave 2 Bedtime cortisol (\(d = .62\))
= .53), and Wave 1 CAR (d = .52) exceeded Cohen’s convention for a medium effect size (d = .50).

**Missing Data Analysis**

For Wave 1 cortisol, 14 participants out of the total valid participants (N = 59) had missing data on both days of data collection (23.7%). For Wave 2 cortisol, 20 participants out of the total valid participants had missing data on both days of data collection (33.9%).

Using logistic regression, it was found that Minority status (all racial/ethnic minorities) significantly predicted missingness in Wave 2 DS ($\chi^2(1, N = 57) = 4.815, p = .028$), explaining 10.9% (Nagelkerke $R^2$) of the variance in Wave 2 DS missingness and correctly classifying 64.9% of cases. White students were 3.33 times more likely to have data for Wave 2 DS than their Minority peers ($B = 1.20, SE = .56, p = .032$).

Minority status also significantly predicted missingness in Wave 2 CAR ($\chi^2(1, N = 57) = 4.709, p = .030$), again, explaining 10.9% (Nagelkerke $R^2$) of the variance in Wave 2 CAR missingness and correctly classifying 64.9% of cases. White students were 3.43 times more likely to have data for Wave 2 CAR than their minority counterparts ($B = 1.23, SE = .58, p = .034$).

Similarly (see Figure 1), under-represented Minority status (American Indian, Hispanic, Black, and Mixed Race) significantly predicted missingness in Wave 2 DS ($\chi^2(1, N = 57) = 5.071, p = .024$), explaining 11.4% (Nagelkerke $R^2$) of the variance in Wave 2 DS missingness and correctly classifying 66.7% of cases. Under-represented Minorities were 3.81 times more likely to exhibit missingness in Wave 2 DS than
their counterparts \((B = 1.34, SE = .61, p = .028)\). Under-represented Minority status also significantly predicted missingness in Wave 2 CAR \(\chi^2(1, N = 57) = 5.849, p = .016)\), explaining 13.4\% (Nagelkerke \(R^2\)) of the variance in Wave 2 CAR missingness and correctly classifying 70.2\% of cases. Under-represented Minorities were 4.29 times more likely to exhibit missingness in Wave 2 CAR than their counterparts \((B = 1.46, SE = .61, p = .018)\).

Experience of stressful life events 24 hours within cortisol collection (dichotomized variable, 0 = no events experienced, 1 = at least one event was experienced) at Wave 1 marginally predicted missingness in Wave 2 DS \(\chi^2(1, N = 40) = 4.968, p = .026)\), explaining 17.3\% (Nagelkerke \(R^2\)) of the variance in Wave 2 DS missingness and correctly classifying 75.0\% of cases. Those who were stressed within 24 hours of data collection during Wave 1 were 7.88 times more likely to have missing data in DS at Wave 2 \((B = 2.06, SE = 1.12, p = .064)\). Stressful life events, did not significantly predict missingness in Wave 2 CAR. All other demographic variables (gender, age) and covariates (sleep hours, smoking, and medication use) did not significantly predict missingness in diurnal cortisol parameters.

Some Wave 1 survey variables that were outside of the substantive interest of this project were included in missing data analysis as auxiliary variables to address missingness, but were outside of the substantive interest of this project, such as Learning-related Pride and Self-efficacy. Learning-related Pride marginally predicted missingness in Wave 1 CAR \(\chi^2(1, N = 59) = 3.802, p = .051)\), explaining 9.4\% (Nagelkerke \(R^2\)) of the variance in Wave 1 CAR missingness and correctly classifying
76.3% of cases. Those who reported more Learning-related Pride in their survey were .273 times less likely to have data for CAR at Wave 1 ($B = 1.30, SE = .72, p = .071$). Self-efficacy significantly predicted missingness in Wave 2 DS ($\chi^2_{(1, N = 59)} = 4.674, p = .031$), explaining 10.2% (Nagelkerke $R^2$) of the variance in Wave 2 DS missingness and correctly classifying 57.6% of cases. Those who reported more Self-efficacy in their survey were .622 times less likely to have data for DS at Wave 2 ($B = -.48, SE = .23, p = .040$). Self-efficacy marginally predicted missingness in Wave 2 CAR ($\chi^2_{(1, N = 59)} = 3.773, p = .057$), explaining 8.6% (Nagelkerke $R^2$) of the variance in Wave 2 CAR missingness and correctly classifying 64.4% of cases. Those who reported more Self-efficacy in their survey were .642 times less likely to have data for CAR at Wave 2 ($B = -.44, SE = .24, p = .064$).

The above analyses on missing data suggested that further steps to address missingness should take place for Study 1. Therefore, Full Information Maximum Likelihood (FIML) was performed in Mplus v.7 and variables that were related to missingness were used as auxiliary variables to adjust for missing data (Enders, 2010).

**Comparing Wave 1 and Wave 2 Diurnal Cortisol Patterns**

To examine hypothesis $H_0$ that there will be an overall exam-stress effect, namely, students in general will show a steeper DS and larger CAR at Wave 1 (week before mid-terms), and a flatter DS and smaller CAR at Wave 2 (day immediately before mid-term), as an indication of the stressful experience, models mimicking $t$-tests and Repeated-Measures Analysis of Covariance (RM ANCOVA) were used.
Typical $t$-tests and RM ANCOVAs were not used because of the need to address missing data and include auxiliary variables. Models were instead estimated in Mplus such that the diurnal cortisol parameters between Waves 1 and 2 were compared via Wald tests, adjusting for missingness using FIML and auxiliary variables. In one set of models, covariates were not included and differences in diurnal cortisol parameter means were assessed with Wald tests constraining means equal over time. In another set of models covariates were included. Diurnal cortisol parameters were predicted by mean-centered time-invariant covariates and wave-corresponding time-variant covariates. Differences in adjusted means across the two waves of data were assessed with Wald tests examining differences in intercepts of the diurnal cortisol parameters.

**Wald tests: Wave 1 and Wave 2 differences in DS and CAR.** Wald tests and FIML were used in Mplus to mimic $t$-tests in assessing the mean-level differences between waves for both cortisol parameters DS and CAR. For DS differences between waves, Wave 1 Learning-related Pride and Self-efficacy were entered as Auxiliary variables; model fit was good overall, $\chi^2 (1, N = 60) = .21 (p = .65)$, RMSEA = .00 (95% CI: [.00, .26]), CFI = 1.00, and SRMR = .05. The Wald test with parameter constraint of equal means for Diurnal Slopes was non-significant ($\chi^2 (1, N = 60) = .79, p = .37$), indicating that no significant mean-level difference was found between the two waves of data. For CAR differences between waves, Wave 1 Self-efficacy was entered as Auxiliary variable; model fit yielded fair to poor fit, $\chi^2 (1, N = 60) = 2.87 (p = .09)$, RMSEA = .18 (95% CI: [.00, .43]), CFI = .94, and SRMR = .12. The Wald test with the parameter constraint of equal means for CAR was non-significant.
(\chi^2_{(1, N=60)} = 1.08, p = .30), indicating that no significant mean-level difference was found between the two waves of data. See Table 8 for estimated descriptive statistics of DS and CAR. Wave 1 DS was slightly higher than Wave 2 DS, and Wave 1 CAR was slightly lower than CAR at W2. The bivariate correlation between Wave 1 DS and Wave 2 DS was \( r = .59 \) \((p < .001)\). The bivariate correlation between Wave 1 CAR and Wave 2 CAR was \( r = .74 \) \((p < .001)\).

Wald tests: diurnal cortisol differences between waves adjusting for covariates. Wald tests using FIML were performed in Mplus to examine differences in adjusted means between waves for both DS and CAR, adjusting for missingness and covariates, to mimic RM ANCOVAs. All covariates were mean centered, creating an interpretable intercept that represented adjusted means of the outcome variables. The adjusted means were compared via a Wald test which constrained intercepts to be equal. To assess DS and CAR respectively, two models were run to assess the between-wave differences.

In the first model, W1 DS and W2 DS were regressed on time-invariant covariates Gender, Age, Minority Status, as well as corresponding time-variant covariates Medication, Sleep Hours, Smoking, and Stressful Events (prior to saliva sampling); Wave 1 Learning-related Pride and Self-efficacy were entered as Auxiliary variables. Given that the full model was not identified, I had to probe a more parsimonious model, with select covariates. As a result, in the final model for DS, Wave 1 DS was regressed on Gender, Minority Status, W1 Sleep Hours, and W1 Smoking; Wave 2 DS was regressed on Gender, Minority Status, W2 Sleep Hours,
W2 Stress Events, and W2 Smoking. The model yielded fair fit, $\chi^2_{(6, N=60)} = 9.70$ ($p = .14$), RMSEA = .10 (95% CI: [.00, .21]), CFI = .87, and SRMR = .09. According to the Wald test comparing the adjusted means (intercepts), no significant difference was found between DS at W1 and DS at W2 ($\chi^2_{(1, N=60)} = .77, p = .38$). Model estimates of covariates predicting DS showed that Gender significantly predicted DS at W1, with female students exhibiting .046 units lower in DS at W1 than their male counterparts ($p = .047$). Sleep Hours at W1 marginally predicted DS at W1, with each hour increase in sleep yielding a .012 unit increase in W1 DS ($p = .075$). Smoking at W1 also marginally predicted W1 DS, with smoking at Wave 1 associated with a .067-unit decrease in DS at Wave 1 than non-smokers ($p = .060$). The total variance explained for DS at W1 was 19.6% ($p = .075$). For Wave 2 DS, covariate model estimates indicated that experiences of Stressful Event(s) within 24 hours of saliva collection at W2 significantly predicted a .040-unit decrease in DS at W2 than those who did not experience a Stressful Event ($p = .024$). The total variance explained for DS at W2 was 25.1% ($p = .038$). All other covariates did not significantly predict DS at W1 or W2.

In the second model, W1 CAR and W2 CAR were regressed on time-invariant covariates Gender, Age, Minority Status, as well as corresponding time-variant covariates Medication, Sleep Hours, Smoking, and Stressful Events; Wave 1 Self-efficacy was entered as Auxiliary variable. Given that the full model was not identified, I had to probe a more parsimonious model, with select covariates. As a result, in the final model for CAR, Wave 1 CAR was regressed on Gender, Minority
Wave 2 DS was regressed on Gender, Minority Status, W2 Sleep Hours, W2 Stress Events, and W2 Smoking. The model yielded good fit, $\chi^2(5, N=60) = 5.02 (p = .41)$, RMSEA = .009 (95% CI: [.00, .18]), CFI = .999, and SRMR = .06. According to the Wald test comparing the adjusted means (intercepts), a significant difference was found between CAR at W1 and CAR at W2 ($\chi^2(1, N=60) = 13.99, p < .001$). Model estimates of covariates predicting CAR at Wave 1 showed that experience of any Stressful Event during Wave 1 marginally predicted .23 units lower of CAR at W1 than those who did not experience a Stressful Event ($p = .061$). The total variance explained for CAR at W1 was 19.7% ($p = .049$).

For Wave 2 CAR, covariate model estimates indicated that each unit increase in Age significantly predicted .056 units lower of CAR at W2 ($p = .030$); and each hour increase in sleep prior to the exam at W2 significantly predicted .15 units lower of CAR at W2 ($p < .001$). The total variance explained for CAR at W2 was 28.9% ($p = .006$). All other covariates did not significantly predict CAR at W1 or W2.

**Grouping: Patterns in Diurnal Cortisol Change**

To examine hypothesis $H_0$, that students will vary in terms of physiological stress manifestations: specifically, some students will have healthy patterns of diurnal cortisol (steep DS, large CAR) for both waves and that some students will have decreased well-being at Wave 2, grouping of participants who showed similar diurnal cortisol pattern change over time was performed in SPSS. Diurnal cortisol parameters were split by the median (see Table 4) to create a boundary defining “low” (i.e.,
below the median) and “high” (i.e., above the median) levels for each parameter at each wave.

**Individual differences in diurnal cortisol change over time.** In support of hypothesis $H_b$, students showed individual differences in diurnal cortisol pattern change over time. Specifically, four patterns for diurnal slope (DS) change over time were created in students between W1 and W2: low-low ($n = 11$), low-high ($n = 3$), high-high ($n = 13$) and high-low ($n = 5$). Four patterns for cortisol awakening response (CAR) change over time were created in students between W1 and W2: low-low ($n = 17$), low-high ($n = 2$), high-high ($n = 17$) and high-low ($n = 2$). Cross tabulation for DS group status and CAR group status was assessed and reported in Table 9.

**Predicting Group Status: Multinomial Logistic Regression Models**

To examine hypotheses $H_{c1}$, that students with more LHL at Wave 1 will have low DS and CAR and less fluctuation in diurnal cortisol patterns between the two waves indicating poor adaptation and stress dysregulation and $H_{c2}$ that FTPC would predict a steeper DS for both waves, or more fluctuation (from steep to flat) as an indicator of well-being or adaptive stress regulation before and during the week of exam, multinomial logistic regression models in *Mplus* (using FIML) were estimated to predict group status for DS and CAR patterns as the dependent variables. In order to build predictive multinomial logistic regression models that would efficiently work for the sample size in this study, I examined the covariates in predicting group status
prior to including key variables of the study into the models for DS and CAR respectively.

**Predicting DS groups.** First, each covariate was entered into the covariates-only multinomial logistic regression model separately. Among all covariates, results showed that only Gender marginally predicted a higher likelihood of being in the Low-high group compared to the High-high group for DS change over time. Specifically, female students were 22.53 times more likely to be in the Low-high group compared to the High-high group ($B = 3.12, SE = 1.60, p = .052$) for DS change over time. All other covariates did not predict DS group status. The marginal association between Gender and DS group status remained ($B = 3.82, SE = 2.26, p = .091$) when adding covariates that showed the next lowest $p$-values in their group status predictions, such as W1 Stress Event, W2 Medication, and W2 Sleep Hours, in an identified model. In this final base model ($n = 59$), female students were 45.38 times more likely to be in the Low-high group compared to the High-high group.

The main hypothesized variables were then entered into the final base model. Results from a multinomial logistic regression model with FTP Connectedness at W1 as a predictor and Gender, W1 Stress Events, W2 Medication, and W2 Sleep Hours as covariates ($N = 60$) showed that FTPC at W1 did not significantly predict group status of DS change over time. Results from a multinomial logistic regression model with Learning-related Hopelessness (LHL) at W1 as a predictor and Gender, Smoking at W1, and Stressful Events at W2 as covariates ($N = 60$) showed that LHL at W1 also did not significantly predict group status of DS change over time.
Predicting CAR groups. First, each covariate was entered into the covariates-only multinomial logistic regression model separately. Among all covariates, results showed that Gender significantly predicted a lower likelihood of being in the Low-low group compared to the High-high group for CAR change over time. Specifically, female students were .17 times less likely to be in the Low-low group compared to the High-high group ($B = -1.80, SE = .90, p = .045$) for CAR change over time. Wave 2 Sleep Hours significantly predicted a higher likelihood of being in the Low-low group compared to the High-High group for CAR change over time. Specifically, with each hour increase in sleep right before the mid-term, it was 2.75 times more likely for students to be in the Low-low group compared to the High-high group ($B = 1.01, SE = .37, p = .006$) for CAR change over time. Wave 2 Stress Events significantly predicted a higher likelihood of being in the Low-low group compared to the High-High group for CAR change over time. The experience of stressful events prior to the midterm was associated with 7.39 times more likely for students to be in the Low-low group compared to the High-high group ($B = 2.00, SE = .90, p = .026$) for CAR change over time. The association between W2 Sleep Hours and CAR group status ($B = 1.14, SE = .51, p = .025$) remained significant, and that of W2 Stress Events and CAR group status ($B = 2.40, SE = 1.23, p = .052$) remained marginally significant, when adding covariates that showed the next lowest $p$-values in their group status predictions along with Gender, such as W2 Medication, in an identified model. In this final base model ($n = 59$), students were 3.12 times more likely to be in the Low-low group compared to the High-high group with each hour
increase in sleep, holding other covariates constant; and with stressful experiences before the exam, they were 11.03 times more likely to be in the Low-low group compared to the High-high group, holding other covariates constant.

The hypothesized main variables were then entered into the final base model. In order to achieve model identification and proper fit, only W2 Sleep Hours was retained as a covariate. Results from a multinomial logistic regression model with FTP Connectedness (FTPC) at W1 as a predictor and W2 Sleep Hours as a covariate \((N = 60)\) indicated that FTPC at W1 significantly predicted group status of CAR change over time \((B = 3.14, SE = 1.41, p = .025)\). Each unit increase in FTPC was associated with students being 23.05 times more likely of being in the Low-low CAR group compared to the High-high CAR group. Results from a multinomial logistic regression model with Learning-related Hopelessness (LHL) at W1 as main predictor and Stressful Events and Sleep Hours at W2 as covariates showed that LHL at W1 did not significantly predict group status of CAR change over time.

**Discussion**

The overall objective for this study was to examine exam effects on students’ well-being circa a mid-term examination, and whether stress effects on students’ diurnal stress physiological responses would be associated with a context-specific negative academic emotion (Learning-related Hopelessness), and students’ future-oriented motivation (Future Time Perspective Connectedness).
Exam Stress Effects for Diurnal Cortisol Parameters

The first main goal of this study was to examine whether students would show a mean-level difference in diurnal cortisol parameters such as the diurnal cortisol slope (DS) or cortisol awakening response (CAR) the week before and the week during a mid-term examination. It was proposed that both DS and CAR would represent student’s physiological well-being and would be lower during the week of the exam, as a manifestation of students’ well-being being compromised the week of mid-term exams ($H_0$). Findings indicated that students showed no difference in DS between the two weeks. However, there was a significant CAR difference between waves. CAR was on average higher during the week of mid-terms, immediately prior to the mid-term, compared to the week prior to mid-terms. Although the direction of this finding is inconsistent with the hypothesis (i.e., study results showed that CAR increased rather than decreased), the finding is supported by previous literature, indicating that normative undergraduate students showed increased CAR in response to an academic exam period (Hewig et al., 2008). These findings imply that, compared to DS, CAR may be a diurnal cortisol parameter that is more susceptible to daily stress for college students, and is positively associated with the stressful academic events. Findings support the argument made by previous literature that CAR could be representative of day-to-day stress (Almeida, Piazza, & Stawski, 2009), acting as a marker of anticipatory stress of the day, instead of chronic stress (Fries, Dettenborn, & Kirschbaum, 2009).
Patterns of Diurnal Cortisol Change circa a Mid-term Exam

The second main goal of this study was to examine whether students will vary in terms of physiological stress manifestations, specifically, whether students would exhibit differences in diurnal cortisol pattern change circa a mid-term examination ($H_6$). It was hypothesized that some students would show steep DS and large CAR for both waves (Healthy group); some students will have lower well-being at Wave 2 as an adaptive response (a flatter DS and smaller CAR during Wave 2) to the mid-term exam stress (Exam-stress group); whereas some students would exhibit flat DS and small CAR for both waves, indicating poor well-being over time (Dysregulated group).

Results showed that four distinct patterns of diurnal cortisol change over the two waves of data collection (Week before mid-term, and Week of mid-term) were formed. Some students had relatively high DS or CAR over the two weeks; some students had relatively low DS or CAR over the two weeks; some students switched from having low DS or CAR during the first week to having high DS or CAR during mid-term; remaining students switched from having high DS or CAR to having low DS or CAR over the two weeks. These findings were supportive of the hypothesis in that individual differences in stress physiology could be found when students experience an academic stressful experience such as a mid-term exam (Weekes et al., 2006). However, inconsistent with the study hypothesis, many students had a different DS pattern in relation to their CAR pattern (see Table 11). The finding supports the competing argument that DS and CAR may have differential implications with regard
to a stressful experience (Fries et al., 2009), which was consistent with the first main finding of this study.

**Predicting Diurnal Cortisol Patterns over Time**

The third main goal of the study was to further examine predictors of well-being, manifested by diurnal cortisol pattern change over time. Specifically, the role of context-specific negative emotion, Learning-related Hopelessness as a risk factor of having low or decreased well-being over time ($H_{c1}$), and the role of Future Time Perspective Connectedness as a protective factor ($H_{c2}$) for sustained well-being over time were examined. Findings indicated that after adjusting for covariates, Future Time perspective Connectedness significantly predicted a higher likelihood of having a stable low value of Cortisol Awakening Response circa a mid-term examination compared to having a stable high value of CAR over time. The direction of this prediction was not supportive of the theory and hypothesis (it was hypothesized that FTPC would predict higher CAR over time as an indication of sustained well-being). However, given that CAR may be indicative of the anticipation of a same-day stressful experience, or momentary well-being, rather than a more long-term well-being (Fries et al., 2009), this finding is consistent with the hypothesis in that FTPC could be a protective factor for students’ daily well-being in response to anticipatory academic stress. In other words, the negative relationship between CAR and FTPC may be evidence that students’ ability to feel connected to a future goal is associated with the anticipation of a manageable, instead of stressful, academic experience (Turner & Husman, 2008).
**Strengths and Implications**

The current study examined Learning-related Hopelessness and Future Time Perspective Connectedness and their predictions for diurnal cortisol pattern change circa a mid-term examination in university students. The study was designed to explore students’ emotional and motivational experiences in an academic context, and examine how these components may predict students’ well-being given a stressful academic experience. In the past, researchers have examined cortisol levels during low vs. high examination stress periods (e.g., Weekes et al., 2006) in an academic environment. However, very few have explored diurnal cortisol patterns during an ecological exam stress period, in relation to learning-related emotional (i.e., Learning-related Hopelessness) and motivational constructs (i.e., Future Time Perspective Connectedness), which makes the current study unique and additive to current literature.

Given the known relations between heightened CAR and decreased psychological well-being and health (Nelemans et al, 2014; Ulrike, Reinhold, & Dirk, 2013; Vrshek-Schallhorn, Doane, Mineka, & Zinbarg, 2013; Adam et al., 2014; Chida & Steptoe, 2009), this study contributes to current literature via its innovative revelation that students’ future-oriented motivation (e.g., FTPC) may be useful in keeping CAR low at a stressful period within an academic semester. The finding sheds light to future educational intervention research, as educational interventions that address students’ future-oriented motivation may become helpful in sustaining their physiological and psychological well-being.
Limitations and Future Directions

The study was limited by the sample size. Specifically, the statistical models for hypotheses $H_a$, $H_{c1}$, and $H_{c2}$ were compromised as the models could not withhold the inclusion of all hypothesized time-variant and time-invariant covariates. Instead, only the most potent covariates were included to examine these models. The lack of a larger sample restricted the interpretability of the data. Future studies should be conducted with a larger sample size to better address and support the research hypotheses and generalize to the university population.

An additional limitation of this study is the lack of inclusion of detailed sleep information. Literature has shown that sleep problems may affect cortisol levels as well (Mrug, Tyson, Turan, & Granger, 2015). It is possible that dysregulation in students’ sleep patterns (e.g., sleep-wake problems, parasomnias, etc.) could have an influence on their diurnal cortisol patterns. To rule out the implications of poor quality of sleep, future research should include a sleep problem questionnaire, in addition to a record of the number of hours slept, in their diurnal cortisol sampling kit to adjust for sleep quality and quantity.

In future studies, it would be meaningful to address other discrete academic-related emotions that could also be related to students’ well-being, such as anger, enjoyment, hope, anxiety, and shame. It is plausible that the academic emotional experience can be associated with students’ chronic or momentary well-being via many channels. It would also be important for future studies to clarify the influences of domain-specific academic experiences (e.g., class-related, learning-related, or test-
related experiences) on students’ chronic or momentary well-being (Goetz, Frenzel, Pekrun, & Hall, 2006), to better foster students’ health and success in post-secondary education.
Study 2: Future time perspective (value), emotion regulation, and social support predicting diurnal cortisol slope change over the course of a semester

As described by Dodge and colleagues (2012), one’s well-being is a dynamic equilibrium between psychological, social, and physical resources and the life challenges one faces. This idea of dynamic well-being emphasizes that the attempts an individual makes to return to a stable point of well-being is a part of the definition of well-being. Similarly, physiological stress manifestations are known to have daily fluctuations and have tendencies for homeostasis (Smyth, Hucklebridge, Thorn, Evans, & Clow, 2013); however, while studies have discussed the links from the physiological stress pathways to one’s well-being (e.g., Doane & Adam, 2010; Hoyt et al., 2015), few studies have focused on examining the patterns of the diurnal fluctuations of stress hormones over multiple time points where individuals would have different levels of life stress.

The current study attempts to address well-being change over time in university Engineering students by examining diurnal cortisol patterns over the course of an academic semester. The study explores motivational and regulatory factors that may contribute to a healthy fluctuation of well-being, and what predicts exhaustion at the end of the semester in the university context. Specifically, the tendency student has to assign value to their future goals and the socio-emotional regulatory resources that a student has in the university context are examined as predictors for the fluctuation of well-being over time in this study.
Diurnal cortisol patterns

Research in cortisol, an end product of the hypothalamas-pituitary-adrenal axis (HPA-axis), has spurred much attention in the recent decade or two, as researchers have found many psychological and social factors associated with this physiological stress hormone. Reactivity upon acute stress could cause an increase in cortisol secretion; repeated psychosocial stress exposure, e.g., chronic stress, could result in saturation of the allostatic load (Susman, 2006), and was found to be related to dysregulation in cortisol secretion. In other words, excess amounts of cortisol from repeated stress exposure may send negative feedback signals to the brain, causing a down-regulation in cortisol secretion, which has been termed hyporeactivity (e.g. Hankin et al., 2010) or hypocortisolism (Gunnar & Vazquez, 2001; Heim et al., 2000). The study of the daily fluctuation in cortisol levels, i.e., diurnal cortisol patterns, reflects such attenuated physiological effects from repeated stress, and has been consistently associated with the well-being of both youth and adult samples (see Figure 1). Steeper diurnal cortisol slopes (DS, i.e., the reclining of cortisol levels from morning to bedtime), and larger cortisol awakening responses (CAR, i.e., the morning peak after awakening), representing good regulation with high cortisol levels in the morning and decreased levels throughout the day, has been found to be related to positive well-being such as positive affectivity and social support (Hoyt et al., 2015; Sladek & Doane, 2015; Slatcher, Selcuk, & Ong, 2015). Flatter diurnal cortisol slopes, with an attenuated recovery slope throughout the day, have been associated with less optimal factors, such as trait loneliness (or chronic loneliness), depression,
anxiety, and suppressed immunity (Doane & Adam, 2010; Hoyt et al., 2015; Pössel et al., 2015; Saridjan et al., 2014). Smaller CAR has been found to be associated with job stress, general life stress, fatigue, and burnout (Chida, & Steptoe, 2009). Notably, Sjögren and colleagues (2006) found that steeper diurnal rhythm was related to social support, general health, and well-being.

**Diurnal Cortisol over Time**

Although the diurnal cortisol patterns seem to be consistently associated with physiological correlates in health and well-being, not many studies have examined diurnal cortisol patterns over time, i.e., the change in diurnal cortisol over multiple time-points. Several studies have used longitudinal modeling to examine within-day diurnal cortisol fluctuation over a single wave of data collection, and the association between the diurnal slope and predictors or outcomes that preceded or followed the saliva collection (e.g., Hoyt et al., 2015; Slatcher et al., 2015). Few studies have examined the change in DS or CAR over multiple time-points, and the mechanisms associated with longitudinal change in diurnal cortisol patterns. Singh-Manoux and colleagues (2014) examined DS longitudinally, however, they only used two waves of data over a period of five years. As an extension of Study 1, the current study proposes to examine diurnal cortisol patterns over three waves of data in the course of one academic semester.

**Diurnal Cortisol in Educational Settings.** In addition, much of the literature that has examined diurnal cortisol and its correlates has been embedded in developmental or social psychology contexts (e.g., Slatcher & Robles, 2013; Saxbe,
Repetti, & Nishina, 2008). However, few studies in educational research have considered using diurnal cortisol, or physiological markers of any kind, to help locate motivational and psychological correlates that could be associated with students’ well-being, which could be crucial for optimizing students’ performance and persistence in school.

**Future Time Perspective**

Future time perspective (FTP) is “the degree to which and the way in which the future is anticipated and integrated in the psychological present of an individual, … FTP is a cognitive-motivational personality characteristic that results from goal setting” (Lens et al., 2012). From a goal-setting perspective, FTP can be defined as the present anticipation of goals in the near future, where people with longer or deeper FTP formulate relatively more long-terms goals (Nuttin & Lens, 1985).

**FTP–Value.** According to the Future Time Perspective Theory, the value of a goal or reward decreases as the length of the temporal delay increases. However, for those with long FTP, the decrease in value would become less steep than those with shorter FTP. In other words, the incentive value of an anticipated future goal is higher for individuals with longer FTP (Rachlin, 1995; Lens et al., 2012). Individuals who have longer FTP may be more motivated towards goals precisely because the incentive value of delayed goals would be higher (Husman & Shell, 2008). Of the four dimensions found in the FTP construct, including Value, Extension, Speed, and Connectedness, the current study focused on FTP Value (FTPV, or FTP Valence), which denotes the importance one places on goals attainable in the future (Simons et
al., 2004; Husman & Shell, 2008). In a study on young adults conducted at the University of Helsinki (Salmela-Aro & Nurmi, 1997), university students who had future goals that were “age-graded developmental tasks” (tasks relevant to their developmental stage and life situation, such as family goals or achievement goals) showed better well-being two years later (lower depression and higher self-esteem). In line with these findings, it is plausible that individuals who have high value in certain future goals may exhibit higher levels of well-being (e.g., university students who have achievement future goals), given that they are able to attain these goals. However, anticipation does not warrant goal attainment; high FTPV would not necessarily warrant the much needed regulatory abilities to strive for and continue to work towards, despite repeated frustration, said future goals. I therefore posited that high FTPV would be beneficial for individuals’ well-being and would stabilize students’ diurnal cortisol slopes across time, given that they have the regulatory resources (including emotional regulation and social support) to face the adversity that comes with rigid course-work in post-secondary studies. Specifically, students who were high on FTPV and had good regulation would be more likely to have healthy physiological responses to stress, either having steep diurnal patterns throughout the semester (able to remain healthy and resilient), or an adaptive response (i.e., being able to recover after the mid-term even though their diurnal patterns flattened during mid-term). On the other hand, students who had high FTPV, yet lacked the emotion regulation or social support to attain future goals, could experience higher levels of frustration, which could be reflected in their well-being
represented by diurnal cortisol patterns, i.e., flatter diurnal cortisol slopes. In other words, I suspected that emotion regulation and social support would interact with FTPV in predicting well-being as represented by healthy diurnal cortisol patterns over time, which, in the current study, was over the course of one semester.

**Emotion-related Regulation**

Emotion regulation, broadly defined as the changes associated with activated emotions (Cole, Martin, & Dennis, 2004) has been linked to well-being quite often in recent literature. For adult samples, multiple constructs have been used to examine emotion regulation and its relation to well-being. Such regulation constructs include but are not limited to cognitive reappraisal and executive functioning. Cognitive reappraisal, i.e., cognitively changing how one thinks about an emotion-eliciting situation has been found to predict positive emotions, better social functioning, and psychological well-being (Gross & John, 2003). Executive functioning, the regulating strategies focused on mental shifting, information updating, and monitoring, was found to be associated with heart rate variability, a physiological marker which indicates self-regulatory processes and goal-directed behavior and adaptation. Thus far, there is no consensus on a definition of emotion regulation, nor is there a singular construct used to measure emotion regulation. Rather than to focus on searching for a unified definition, it is helpful to focus on processes involved by examining emotion-related regulation.

Emotion-related regulation has been defined as “processes used to manage and change if, when, and how one experiences emotions and emotion-related motivational
and physiological states, as well as how emotions are expressed behaviorally” (Gross, 2007, p. 288). Emotion-related regulation therefore includes both the regulation of emotion reactivity and the regulation of behavior associated with an emotion. For the current study, I focus on one of the emotion-related regulation constructs, effortful control.

**Effortful Control.** In line with the field of developmental psychology, effortful control has been found to be one of the dimensions that encompass one’s temperament, and has been identified as a construct that facilitates one’s emotion-related and behavior-related self-regulation (Eisenberg et al., 2012; Eisenberg & Spinrad, 2004; Liew, 2012; Valiente, Swanson, & Lemery-Chalfant, 2009). Effortful control (EC) denotes one’s ability to inhibit a dominant response and/or activate a subdominant response according to individual needs or in face of environmental demands (Rothbart & Bates, 2006).

In educational settings, EC has been found to be related to school readiness for preschoolers (Blair, 2002), and predicted academic achievement in children (Blair & Razza, 2007; Liew, McTigue, Barrois, & Hughes, 2008; Swanson, Valiente, & Lemery-Chalfant, 2012; Valiente et al., 2013). However, despite evidence of EC predicting positive school outcomes in children, the role of EC in higher education has not been examined as much. Given that the scales used to measure effortful control extend from infancy to adulthood across developmental stages (Rothbart & Bates, 2006), using EC as an emotion-related regulation construct gives educational
researchers an opportunity to address this phenomenon across multiple stages of
development.

So far, EC in adolescence and emerging adulthood has been discussed in
literature pertaining to well-being. For example, higher levels of effortful control in
adolescence were related to lower levels of problematic substance use in early
adulthood (Piehler, Veronneau, & Dishion, 2012); EC also moderated the associations
between temperamental positive affectivity and negative affectivity and depressive
symptoms, where low positive affectivity and high negative affectivity predicted
depressive symptoms only when EC was low (Verstraeten, Vasey, Raes, & Bijttebier,
2009). Although predictions from EC to the diurnal cortisol slope are unclear, EC has
negatively predicted depressive symptoms, additionally, depressive symptoms have
been linked to flatter diurnal slopes in multiple studies (e.g., Doane et al., 2013;
Doane et al., 2011).

With these findings in mind, it made sense to examine EC as an emotion
regulation construct for university students within the educational context, in
predicting their well-being. In particular, EC may be an important regulatory resource
for post-secondary students to strive for their future goals, especially when rigid
university course work demands more attentional focus and self-regulation. The
current study thus proposes to examine not only the association between EC and well-
being in a post-secondary education sample, but also the moderating role of EC in
predicting diurnal cortisol slopes over time (representing well-being) from FTPV
(representing the valence one puts on future goals) in the current study. Specifically, I
posited that individuals high on both FTPV and EC would have an easier time envisioning future goals, and regulating themselves to achieve their future goals, and thus would have better-regulated and stabilized diurnal cortisol patterns, i.e., a steeper diurnal slope over time, or indication of recovery from the mid-terms; whereas individuals high on FTPV but low on EC may experience a flattening of diurnal cortisol slope over time, with no sign of recovery during Wave 3.

Social Support

In general, social support has been found to be a stress buffer (Cohen & Wills, 1985). General social support was found to be significantly positively related to university students’ subjective well-being, i.e., happiness and life satisfaction (Lonnqvist & Deters, 2016). Specifically, social connections or lack thereof (i.e., loneliness) have been associated with diurnal cortisol patterns. For example, Doane and Adam (2010) found that university students with higher trait loneliness showed flatter diurnal cortisol slopes. Academic-specific social support in the educational setting, however, has not been studied much. From a developmental standpoint, social functioning predicted academic achievement in elementary school students (kids high on both were positively viewed by teachers and peers, e.g., Valiente et al., 2011). However, social networking may be less beneficial for students’ academic achievement in middle or high school, as students may be shifting their focus in life to peer affiliation or popularity instead of course work (e.g., Peetsma, 2000). Nonetheless, in post-secondary educational settings, students may already have been stratified to have certain future goals in mind, and could benefit from social
interactions for their academic success. For example, college students may form study groups to help each other digest heavy course material, or motivate each other to do well in various academic settings. In a Swedish study, findings showed that in university students, optimism in achievement goals was positively related to social optimism, and negatively associated with social withdrawal; in addition, longitudinally, university students who had postponed life transitions (to career or to romantic partnership) had more depression and task avoidance, and less optimism in both social and academic situations (Salmena-Aro, Kiuru, Nurmi, & Eerola, 2014). Given such evidence, it was logical to posit that social support within the academic context, for example via peer or faculty support, could be crucial to post-secondary students’ well-being. As a result, in the current study I posited that academic social support would be associated with students’ well-being as represented by a healthy diurnal cortisol slope at baseline (Wave 1). In addition, for individuals with high FTPV, social support may be beneficial in providing additional resources for students to work toward their future goals; students without adequate academic social support may find themselves struggling more in achieving their goals. Therefore, I posited that social support will interact with FTPV in predicting students’ well-being over time, specifically, individuals high on both composites would have steeper and more stable diurnal cortisol slopes over time, or would show better recovery from stress over time; whereas individuals high on FTPV but low on social support may experience a flattening of diurnal cortisol slope over time and no recovery from stress (see Table 2).
The Current Study

In sum, the aims of this study included, 1) to examine the interactive effects between how students’ FTPV and their effortful control predict well-being represented by diurnal cortisol patterns and pattern change over the course of a semester; 2) to examine post-secondary engineering students’ social support in their academic environment, and whether students’ social support would moderate the effects that FTP Value has in predicting their well-being represented by diurnal cortisol patterns over the semester. I proposed that I will see different groups of students showing differential diurnal cortisol patterns over time, such as: 1) healthy group (steep DS, large CAR, across three waves), 2) exam-stress group (flattened during Wave 2 but recovered during Wave 3, showing adaptive stress responses), and 3) exhaustion group (continual flattening over the semester). I posited that correlates proposed in the current study will be able to predict group classification.

The study hypotheses thus included: **Hypothesis a)** Students’ effortful control and social support would be positively associated with steeper cortisol slopes (DS) and larger cortisol awakening responses (CAR) at Wave 1 (baseline). **Hypothesis b)** Students’ effortful control and social support would predict less flattening in diurnal cortisol patterns across the semester (over three waves of data collection), or would predict a recovery during Wave 3 from Wave 2 exam-stress (healthy group and exam-stress group). **Hypothesis c)** Given that students have high effortful control, high FTPV would predict a healthier pattern of diurnal cortisol change over time, e.g., steep at Wave 1, flatter at Wave 2, and steep at Wave3, or steep across all three waves.
(healthy group and exam-stress group); whereas high FTPV and low EC would be associated with non-recovery in diurnal cortisol patterns over the semester, specifically smaller CAR and DS at Wave 3 (exhaustion group). Hypothesis d) Given that students have high social support, high FTPV would predict a healthier pattern of diurnal cortisol change over time, e.g., steep at Wave 1, flatter at Wave 2, and steep at Wave 3, or steep across all three waves (healthy group and exam-stress group); whereas high FTPV and low social support would be associated with non-recovery in diurnal cortisol patterns over the semester, specifically smaller CAR and DS at Wave 3 (exhaustion group).

Method

Participants

A total of 80 post-secondary engineering students were enrolled in this study, including both upper-level undergraduate students and graduate students at a large public university in the southwest of the US. The proposed sample of participants in this study was to have approximately 10-15% of students with Hispanic/Latino ethnicity background, and approximately 10-15% female students, which would be representative of the populations of ASU engineering students in terms of diversity. The proposed sample of participants was to have approximately half of the students recruited from the School of Engineering who were in an Engineering program, and half of the students affiliated with an Engineering Research Center at the university. No ethnic/racial or gender group was excluded. Participants were proposed to have an
age range of 20-30 years of age. Exclusion criteria was students below 18 years of age.

**Design**

This project employed a longitudinal design with multiple data collection time points throughout the course of one semester (see Table 2). I examined engineering students’ survey data and the change in diurnal cortisol slopes throughout the semester. The first wave of data collection was at the beginning of the semester (Wave 1, W1, circa week three); second wave was in the middle of the semester during a stressful academic event (Wave 2, W2, the stressful phase); and the third wave was at the end of the semester during a time of relatively less stress (Wave 3, W3, serving as a recovery/relaxation phase). During each wave, students provided diurnal saliva samples over two consecutive days, and I examined students’ future time perspective, their emotional regulation, and social support via self-reported surveys (see below for measures).

**Procedures**

Participant recruitment started during week two of the spring semester—which entailed study introduction and student consent—and data collection began during the third week of the academic semester (W1). For recruitment, the research team entered engineering research labs and engineering classrooms to hand out fliers, and ask students to complete consent forms via hard-copy or online in order to participate in the study. Students visited a central location for a short training for cortisol sample collections (this was implemented by trained RAs) upon enrollment. Students filled
out all self-reports online (they were given the option of hard-copy surveys if preferred), and were given a saliva collection kit to collect their saliva samples for two consecutive days, three times per day for each wave (see below for cortisol collection). The survey took less than 30 minutes to complete. They turned in their samples (and surveys if hard-copy) upon collection completion, and were compensated $10, $15, and $25 per wave to encourage continual participation. The second wave of data collection was at mid-semester (W2), and also included both student self-reports and diurnal salivary cortisol collection. The third wave of data collection was near the end of the semester (W3), again including self-reports and diurnal saliva collection. Researchers only entered the classrooms and labs during participant recruitment week. All other communications, including contacting students for reminders, scheduling saliva kit drop-offs, and providing participation incentives were over email communication and text messaging if the students opted in to receive text message reminders. The research team held research office hours for saliva kit drop-offs and to provide students their incentives.

Measures

Future time perspective. Students provided self-reported responses on the Future Time Perspective – Value subscale (FTPV; Cronbach’s $\alpha = .72$; Husman & Shell, 2008), which includes seven items, on a Likert scale of 1 to 5 ($1 = \text{Strongly disagree}$ to $5 = \text{Strongly agree}$). Sample items included “Given the choice, it is better to get something you want in the future than something you want today,” or “The most important thing in life is how one feels in the long run.”
**Effortful control.** Effortful Control Scale (EC; short form from the Adult Temperament Questionnaire; from previous literature, EC subscales had Cronbach’s $\alpha = .66 - .88$; Evans & Rothbart, 2007) included a total of 19 items on three subscales, including Activation Control (e.g., “I can keep performing a task even when I would rather not do it”), Attentional Control (e.g., “It’s often hard for me to alternate between two different tasks”), and Inhibitory Control (e.g., “Even when I feel energized, I can usually sit still without much trouble if it’s necessary), reported on a scale of 1 to 7 (1 = Extremely untrue of you, 7 = Extremely true of you). I used an EC composite score for emotion regulation by averaging students’ scores on the three EC subscales.

**Social support.** Quality of Relationships Inventory (Pierce, Sarason, & Sarason, 1991; revised for engineering students), and the Social Network Questionnaire (revised for engineering students). A context-specific Social Support composite variable was created to evaluate students’ overall social support in the engineering program. The items were standardized and averaged to from a composite. Both the Quality of Relationships Inventory and Social Network Questionnaire was also adapted to include relationships with both peer and faculty within the engineering academic context. Two subscales of social support were calculated, including an Academic Social Support subscale, and Non-academic Social Support Subscale (which included items pertaining to family, friends, and co-workers, from the original items).
**Self-reported health.** Students’ self-reported health was measured by a 12-item short form health survey (SF-12 Health Survey; Ware, Kosinski, & Keller, 1996). Self-reported health served as an additional indicator for students’ well-being.

**Salivary cortisol.** Diurnal samples along with a checklist of items regarding salivary sampling was collected for two consecutive days for each wave. Diurnal samples were collected sublingually three times per day, i.e., upon awakening, 30-minutes after awakening (for the cortisol awakening response), and before bedtime (for recovery). Each sample took two minutes to complete. In addition, each sample had a corresponding check-sheet that students completed when taking each saliva sample that records the time of collection, sleep hours, and food/drink/drug consumption before taking the sample. For this study, a sleep problem survey (see covariates section below) was also included in the checksheet packets for each wave of saliva data. The samples were kept in ice-packets or the refrigerator before and during transportation. The packets were sent in the research lab for low temperature storage for each wave.

The saliva samples were then shipped to the Cortisol Lab at the University of Trier in Germany for low temperature storage and cortisol analyte assays, as the assay costs and assay schedule at Trier were most suitable for the study’s budgets and timeline. The saliva samples were stored at -20 °C until analysis at Trier. After thawing, saliva samples were centrifuged at 2000 g for 10 minutes, which resulted in a clear supernatant of low viscosity. 100ul of saliva were used for duplicate analysis. Cortisol levels were determined employing a competitive solid phase time-resolved
fluorescence immunoassay with fluromeric end point detection (DELFIA). 96-well-Maxisorb microtiterplates were coated with polyclonal swine anti-rabbit immunoglobulin. After an incubation period of 24h at 4°C plates were washed three times with washbuffer (pH=7.4). In the next step the plates were coated with a rabbit anti-cortisol antibody and were incubated for 48h at 4°C. Synthetic saliva mixed with cortisol in a range from 0-100nmol/l served as standards. Standards, controls (saliva pools) and samples were given in duplicate wells. 50µl of biotin-conjugated cortisol were added and after 30min of incubation the non-binding cortisol / biotin-conjugated cortisol would be removed by washing (3x). 200µl europium-streptavidin (Perkin Elmer, Liefe science Turku, Finnland) was added to each well and after 30 minutes and 6 times of washing 200µl enhancement solution was added (Pharmacia, Freiburg, Germany). Within 15 min on a shaker the enhancement solution induced the fluorescence, which could be detected with VICTOR™ X4 Multilabel Plate Reader (Perkin Elmer, Massachusetts, USA). With a computer-controlled program a standard curve was generated and the cortisol concentration of the samples were calculated. The intra-assay coefficient of variation was between 4.0% and 6.7%, and the corresponding inter-assay coefficients of variation was between 7.1% -9.0%. Outliers that were three standard deviations away from the mean of each sample were excluded or windsorized for statistical analyses. Data was windsorized at 1.81 µg/dL (equivalent to 50nmol/L; Nicolson, 2008).

**Diurnal cortisol patterns.** Mean cortisol levels of the two consecutive days for each wave were computed to create T1, T2, and T3 cortisol levels for each wave.
Log transformations was performed for each time point before any calculation for indicators occurs if the data is positively skewed. Three samples, i.e., upon awakening (T1), 30-minute after awakening (T2), and before bed-time samples (T3) were used to create the diurnal cortisol slope (DS) and the cortisol awakening response (CAR) for each wave. DS was calculated by subtracting the before bedtime sample (T3) from the morning awakening sample (T1) after both are log transformed, and dividing this deviation by awake hours (DeSantis, Adam, Hawkley, Kudielka, & Cacioppo, 2015). The two morning samples were used to calculate the cortisol awakening response (CAR) for each wave. CAR was calculated by subtracting wake level T1 from peak level T2, also after both are log transformed.

**Covariates.** Demographic information for each wave of survey was collected for covariates in the models, including gender, race/ethnicity, and age. For each wave, students also reported their sleep duration in the saliva checksheets, and well as their sleep problems in a Sleep Questionnaire (see Mrug et al., 2015) along with their checksheets, allowing for sleep duration and sleep problems to be included as covariates in the models. I included Learning-related Hopelessness as a covariate as it has been found to be correlated with diurnal cortisol patterns in Study 1 in preliminary analyses. In addition, I dichotomized variables for both cigarette use and medication use of any of the following six types of prescription and over-the-counter medicines that have been shown to influence cortisol levels: steroid inhalers, other types of steroid medications, medications or creams containing cortisone, birth control pills,
and anti-depressant or anti-anxiety medications (Dmitrieva et al., 2013; Granger et al., 2009), and included them as covariates.

**Statistical Analysis**

Descriptive statistics and bivariate correlations were performed in SPSS, including means, standard deviations, and zero-order bivariate correlations on all key variables and diurnal cortisol levels. Multiple regression analyses allowed me to address **Hypothesis a)** Students’ effortful control and social support would be positively associated with steeper cortisol slopes (DS) and larger cortisol awakening responses (CAR) at Wave 1 (baseline), with covariates (e.g., sleep hours) included, which provided support for concurrent associations between stress regulation and socio-emotional-related regulation in the baseline measures.

Prior to examining diurnal cortisol patterns over time for Hypotheses b), c), and d), I used repeated measures ANCOVA as preliminary analysis to examine whether there are wave differences for both CAR and DS, regardless of predictors, and I used post-hoc comparisons to examine between wave differences to look at overall diurnal cortisol patterns over the semester.

I examined Hypotheses b), c) and d) using multinomial logistic regression models, with three groups for classification. I proposed to form the groups by using the following criteria: one standard deviation above the mean as high, one standard deviation below the mean as low, and between these two points as medium. The flattening effect of diurnal cortisol patterns from exam stress would be determined if an individual has high DS or CAR at Wave 1, and medium DS or CAR Wave 2; or if
an individual has high/medium DS or CAR at Wave 1 and low DS or CAR at Wave 2. Recovery from stress would be determined if an individual had low/medium DS or CAR at Wave 2, but high DS or CAR at Wave 3; or from low DS or CAR at Wave 2 and medium DS or CAR at Wave 3. I proposed that if an individual remained high across three waves they would be assigned to the healthy group; if an individual showed a pattern of flattening and then recovery, for example if they have high-low-medium or medium-low-medium, they would be assigned to the exam-stress group; if an individual showed a pattern of flattening from Wave 1 to Wave 2 and does not recover at Wave 3, or if they remained low in all three waves, they would be assigned to the exhaustion group. Each individual had a group assignment for DS and CAR, and I examined both parameters for the following models. For people not assigned to the above groups, I investigated further to see if another group should be formed, or whether/how they should be included into the analyses.

I looked at main effects for EC and social support (SS) in the predictions, to examine Hypothesis b) Students' effortful control and social support would predict less flattening (healthy group) in diurnal cortisol patterns across the semester (over three waves of data collection), or would predict a recovery during Wave 3 from Wave 2 exam-stress (exam-stress group) compared to the exhaustion group. I examined the two-way interaction term between FTPV and EC to address Hypothesis c) Given that students have high effortful control, high FTPV would predict a healthier pattern of diurnal cortisol change over time, e.g., steep at Wave 1, flatter at Wave 2, and steep at Wave 3, or steep across all three waves (healthy group and
exam-stress group compared to the exhaustion group; whereas high FTPV and low EC would be associated with non-recovery in diurnal cortisol patterns over the semester, specifically smaller CAR and DS at Wave 3 (exhaustion group). Lastly, I examined the two-way interaction term between FTPV and SS to address \textit{Hypothesis d}). Given that students have high social support, high FTPV would predict a healthier pattern of diurnal cortisol change over time, e.g., steep at Wave 1, flatter at Wave 2, and steep at Wave 3, or steep across all three waves (healthy group and exam-stress group); whereas high FTPV and low social support would be associated with non-recovery in diurnal cortisol patterns over the semester, specifically smaller CAR and DS at Wave 3 (exhaustion group). For each logistic regression model, I looked at the significance of the predictors, and the significance of the interaction terms. I examined the odds ratio for each coefficient to compare the predictions of the groups. I proposed that if the interaction term for either FTPVxEC or FTPVxSS were significant, I would expect to see the odds ratio of the interaction term for the Healthy and Exam-stress group to be greater than 1 compared to the Exhaustion group, which would be supportive of my hypothesis.

\textbf{Power analysis.} Power analyses were used to determine the sample size necessary to detect effects if they are present. The power of a logistic regression model can be estimated using the statistical program G*Power (Faul, Erdfelder, Lang, & Buchner, 2007; Faul, Erdfelder, Buchner, & Lang, 2009). For the current project, assuming that I had a medium effect size (odds ratio) of 3.5, alpha of .05 for my model, and would like to achieve a power of .95, I would need a total sample size of
66 participants. If I had an effect size of 3.5, alpha of .05, and would like to achieve a power of .80, I would need a total sample size of at least 44 participants.

According to the estimations, in order to achieve adequate power (i.e., power above .80), the study would at least need 44 participants, and ideally more than 66 participants. Considering the budget of our study, and the implementation difficulty and typical small samples of bioscience interdisciplinary research, I considered a total of 44 and above participants adequate for this project given an odds ratio of 3.5.

Results

Participant Demographics

Out of the total of 80 students who enrolled to participate in Study 2, 67 students completed Wave 1 Survey collection; out of these students, 55% were male ($n = 37$) and 43% were female ($n = 29$). With regards to race/ethnicity, 2% were American Indian, 35% were Asian, 6% were Hispanic, 2% were Black, 50% were White, 0% were Pacific Islanders, and 6% were of mixed racial/ethnic background. One student (2%) of the 67 participants who completed Wave 1 Survey had missing gender, race, and age data. All participants were 18 years or older, and had a mean age of 23.05 years ($SD = 4.92; Median = 22$). See Table 10 for Study 2 participants’ demographic information.

Attrition Analysis. Of the 67 participants who completed their survey data, 63 students submitted any Wave 1 cortisol samples, 47 students submitted any Wave 2 cortisol samples, and 43 students submitted any Wave 3 cortisol samples (Table 10). Of the 67 participants, 40 students had cortisol data for all three waves; four students
submitted no cortisol data at all; 13 students only submitted Wave 1 cortisol samples, and attrited during Wave 2 and Wave 3 cortisol collection; seven students only submitted cortisol samples for Wave 1 and Wave 2, and attrited during Wave 3 data collection; three students only submitted cortisol samples for Wave 1 and Wave 3, and did not submit their cortisol samples during Wave 2. According to cross tabulation analysis performed in SPSS v.22, Pearson Chi-square results showed a significant association between all data (survey and cortisol) attrition over time and gender, $\chi^2(4, N = 66) = 11.72$ ($p = .020$), with Male students’ attrition rate higher than Females. Further, examining cortisol data attrition over time, Male students showed higher attrition in cortisol data than their Female counterparts, with a Pearson Chi-square of $\chi^2(2, N = 62) = 6.26$ ($p = .044$). In addition, Pearson Chi-square results showed that if the race/ethnicity variable was recoded, to avoid low cell count, into White vs. Minority, there was a marginal significant association between cortisol data attrition and minority status, $\chi^2(2, N = 62) = 5.34$ ($p = .069$), indicating that attrition was marginally higher in ethnic minorities. A one-way ANOVA examining whether age was associated with attrition in cortisol data showed that there was a marginal significant difference in age for those who had no attrition in cortisol data compared to those who attrited for one or two waves ($F_{(13,48)} = 1.91$, $p = .052$), indicating that attrition in cortisol data was marginally higher in older students.

**Covariate Data**

Participants reported to have slept for an average of 7.16 hours ($SD = 1.16$; range = 3.75 to 10.00) during the nights before the two consecutive days of Wave 1
cortisol collection, slept for an average of 7.18 hours ($SD = 1.42$; range = 2.42 to 10.00) during the nights of Wave 2 cortisol collection, and slept for an average of 7.57 hours ($SD = 1.50$; range = 2.75 to 11.50) during the nights of Wave 3 cortisol collection. Participants reported to have an average of 1.99 ($SD = .40$) Sleep Problems (on a scale of 1 = Never to 5 = Everyday) during Wave 1, an average of 2.01 ($SD = .33$) Sleep Problems during Wave 2, and an average of 1.97 ($SD = .34$) Sleep Problems during Wave 3. Check-sheet data from the diurnal cortisol saliva kits indicated that during Wave 1, 18 students reported to have experienced a stressful event within the 24 hours prior to their saliva sample collection; five students reported smoking within 12 hours of saliva collection; and 20 students reported have taken medication (a dichotomized variable for intake of allergies medication, pain killers, contraceptives, medication for a chronic health concern, or other) within 24 hours of saliva collection. During Wave 2, 20 students reported to have experienced a stressful event within the 24 hours prior to their saliva sample collection; two students reported smoking within 12 hours of saliva collection; and 15 students reported have taken medication within 24 hours of saliva collection. During Wave 3, 11 students reported to have experienced a stressful event within the 24 hours prior to their saliva sample collection; no students reported smoking within 12 hours of saliva collection; and 11 students reported have taken medication within 24 hours of saliva collection.

**Preliminary Analyses**

**Cortisol samples.** Raw cortisol data were examined, and values that were higher than 50 nmol/L (approximately the highest non-stimulated salivary cortisol
level for healthy subjects; Nicolson, 2008) were windsorized at 50 nmol/L; including two samples at Wave 1 Day 1 Wake-time, three samples at Wave 1 Day 1 Peak-time, one sample at Wave 1 Day 2 Wake-time, one sample at Wave 1 Day 1 Peak-time, and two samples at Wave 1 Day 2 Bedtime. No Wave 2 or Wave 3 raw cortisol data were higher than 50 nmol/L.

During Wave 1 data collection, for Wave-level cortisol collection (samples collected upon awakening), 61 participants submitted samples for both consecutive days of saliva collection, one participant submitted Day 1 sample only, and one participant submitted Day 2 sample only. For Wave 1 Peak-level cortisol collection (collected 30-minutes upon awakening), 61 participants submitted samples for both consecutive days of saliva collection, one participant submitted Day 1 sample only, and one participant submitted Day 2 sample only. For Wave 1 Bedtime cortisol collection, 60 participants submitted samples for both consecutive days of saliva collection, and three participants only submitted their Day 2 samples. During Wave 2 data collection, for Wave-level cortisol collection, 43 participants submitted samples for both consecutive days, two participants only submitted their Day 1 samples, and three participants only submitted Day 2 samples. For Wave 2 Peak-level cortisol collection, 43 participants submitted samples for both consecutive days, one participant submitted Day 1 sample only, and three participants only submitted their Day 2 samples. For Wave 2 Bedtime cortisol collection, 43 participants submitted samples for both consecutive days, one participant submitted Day 1 sample only, and two participants only submitted their Day 2 samples. During Wave 3 data collection,
for Wave-level cortisol collection, 41 participants submitted samples for both consecutive days, and two participants only submitted their Day 1 samples. For Wave 3 Peak-level cortisol collection, 41 participants submitted samples for both consecutive days, and two participants only submitted their Day 1 samples. For Wave 3 Bedtime cortisol collection, 42 participants submitted samples for both consecutive days, and one participant submitted Day 1 sample only (Table 11).

The cortisol values were then averaged between the two consecutive days at each time point for each wave. As noted, some participants were missing one or both days of cortisol samples, however, one day of missingness was allowed for the averaged cortisol levels at each time point to maximize retention of cortisol data (see Table 11).

Descriptive statistical analysis (Table 12) indicated that there were excess skewness and kurtosis in the mean cortisol values (skewness range = -0.03 to 5.07; kurtosis range = -1.04 to 28.55) therefore the mean cortisol values were log-transformed to approximate normality. For each wave, a composite to represent the diurnal cortisol slope (DS) was then calculated by subtracting log-transformed mean bedtime cortisol (Bed) from log-transformed mean awakening cortisol (Wake) and dividing the score by awake hours for each participant; a composite to represent the cortisol awakening response (CAR) was calculated by subtracting log-transformed mean awakening cortisol from log-transformed mean 30-minute upon awakening cortisol (Peak) for each wave. Wave 1 CAR and Wave 2 CAR contained outliers that were three standard deviations below the mean, and both cases were windsorized at
the -3SD level (-1.69 for Wave 1 CAR, and -1.53 for Wave 2 CAR). Descriptive statistics for the diurnal cortisol parameters DS and CAR post-windsorization can be found in Table 13, with all skewness and kurtosis within normal bounds.

Bivariate correlations between the diurnal cortisol parameters were examined (Table 14). Results showed that Wave 1 DS and Wave 2 DS were significantly positively correlated ($r = .54, p < .001$), Wave 1 DS and Wave 3 DS were marginally positively correlated ($r = .28, p = .095$), Wave 1 CAR and Wave 3 CAR were marginally positively correlated ($r = .28, p = .071$), Wave 2 DS and Wave 2 CAR were marginally negatively correlated ($r = -.28, p = .086$), Wave 1 DS and Wave 3 CAR were significantly positively correlated ($r = .31, p = .049$).

Gender differences for mean-level cortisol and diurnal cortisol parameters were also examined (Table 15). Results showed that there was a significant difference between males ($M = 2.26, SD = .61$) and females ($M = 2.75, SD = .66$) with regards to Peak-level cortisol at Wave 1 ($t = -3.01, p = .004, 95\% CI [-.82, -.16]$), with female students having higher W1 Peak-level cortisol. The effect size for this analysis ($d = .77$) was found to exceed Cohen’s (1988) convention for a medium effect size ($d = .50$) and approached a large effect size ($d = .80$). A significant difference between males ($M = 2.20, SD = .44$) and females ($M = 2.58, SD = .64$) with regards to Wave 3 Peak-level cortisol ($t = -2.26, p = .029, 95\% CI [-.72, -.04]$) was found, with female students having higher W3 Peak-level cortisol. The effect size for this analysis ($d = .69$) was found to exceed the medium effect size ($d = .50$). A marginally significant difference in Wave 1 CAR was found between males ($M = .17, SD = .58$) and females
(M = .41, SD = .44), with female students having higher CAR at Wave 1 than their male counterparts (t = -1.74, p = .087, 95% CI [-.51, .04]), with the Cohen’s d approaching medium effect size (d = .47). A significant difference in Wave 3 CAR was found between males (M = -.08, SD = .49) and females (M = .34, SD = .49), again, with female students having higher CAR at Wave 3 than their male counterparts (t = -2.80, p = .008, 95% CI [-.73, -.12]). The effect size for this analysis (d = .86) was found to exceed Cohen’s (1988) convention for a large effect size (d = .80). There were no significant gender differences in all other diurnal cortisol parameters, though notably the effect size for the differences in DS at Wave 2 (d = .39) exceeded a small effect size (d = .20), and approached a medium effect size.

Minority status differences for mean-level cortisol and diurnal cortisol parameters were also examined (Table 16). Results showed that a significant difference was found in Wave 2 Peak-level cortisol, between Minorities, including American Indian, Asian, Hispanic, Black, Mixed Race students (M = 2.70, SD = .46), and White students (M = 2.24, SD = .64), with Minority students having significantly higher Peak level cortisol (log-transformed) than their White peers (t = -2.75, p = .009, 95% CI [-.80, -.12]). The effect size for this analysis (d = .83) exceeded that of a large effect size (d = .80). A significant difference between Minorities (M = .34, SD = .49) and White students (M = -.01, SD = .54) with regards to Wave 2 CAR was found, with Minorities having a larger CAR than their White peer (t = -2.30, p = .026, 95% CI [-.66, -.04]). The effect size for this analysis (d = .69) exceeded a medium effect size (d = .50). Statistically significant differences (t-tests) were not found when
the minority status included Under-represented Minorities only. However, effect sizes for the \( t \)-tests comparing Under-represented Minorities vs. Others were notable (Table 17), including W2 Peak level cortisol \( (d = .58) \), W3 Peak level cortisol \( (d = .55) \), W3 DS \( (d = .69) \), and W3 CAR \( (d = .59) \), all of which exceeded a medium effect size \( (d = .50) \).

**Missing Data Analysis**

For Wave 1 cortisol, four participants out of the total valid participants \( (N = 67) \) had missing data on both days of data collection (6.0%). Four participants had missing data for W1 CAR, and nine participants had missing data for W1 DS. For Wave 2 cortisol, 20 participants out of the total valid participants had missing data on both days of data collection (29.9%). Twenty participants had missing data for W2 CAR, and 28 participants had missing data for W2 DS. For Wave 3 cortisol, 24 participants out of the total valid participants had missing data on both days of data collection (35.8%). Twenty-four participants had missing data for W3 CAR, and 27 participants had missing data for W3 DS.

Using logistic regression, it was found that among the time-variant covariates, Wave 1 Stress Events significantly predicted missingness in Wave 2 DS \( (\chi^2_{(1, N = 60)} = 3.874, p = .049) \), explaining 8.5% (Nagelkerke \( R^2 \)) of the variance in Wave 2 DS missingness and correctly classifying 66.7% of cases. Experiencing Stress Events prior to data collection during Wave 1 was associated with participants being 3.13 times more likely to have missing data in Wave 2 DS \( (p = .051) \). Wave 1 Stress Events also significantly predicted missingness in Wave 2 CAR \( (\chi^2_{(1, N = 60)} = 4.902, p \)
=.027), explaining 11.6% (Nagelkerke $R^2$) of the variance in Wave 2 CAR missingness and correctly classifying 75.0% of cases. Experiencing Stress Events prior to data collection during Wave 1 was associated with participants being 4.00 times more likely to have missing data in Wave 2 CAR ($p = .028$). Wave 1 Smoking significantly predicted missingness in Wave 3 DS ($\chi^2(1, N=60) = 4.669, p = .031$), explaining 10.3% (Nagelkerke $R^2$) of the variance in Wave 3 DS missingness and correctly classifying 70.0% of cases. Smoking prior to data collection during Wave 1 was marginally associated with participants being 8.94 times more likely to have missing data in Wave 3 DS ($p = .058$). Wave 1 Medication marginally significantly predicted missingness in Wave 2 DS ($\chi^2(1, N=60) = 3.792, p = .052$), explaining 8.4% (Nagelkerke $R^2$) of the variance in Wave 2 DS missingness and correctly classifying 63.3% of cases. Taking medication prior to data collection during Wave 1 was associated with participants being .306 times less likely to have missing data in Wave 2 DS ($p = .065$). Wave 1 Medication significantly predicted missingness in Wave 2 CAR ($\chi^2(1, N=60) = 4.030, p = .045$), explaining 9.6% (Nagelkerke $R^2$) of the variance in Wave 2 CAR missingness and correctly classifying 75.0% of cases. Taking medication prior to data collection during Wave 1 was associated with participants being .231 times less likely to have missing data in Wave 2 CAR ($p = .073$).

Wave 2 Sleep Duration (hours slept night before cortisol collection) significantly predicted missingness in Wave 3 DS ($\chi^2(1, N=46) = 4.452, p = .035$), explaining 14.7% (Nagelkerke $R^2$) of the variance in Wave 3 DS missingness and correctly classifying 80.4% of cases. Each hour increase in Sleep Duration was
associated with participants being 1.76 times more likely to have data for Wave 3 DS ($p = .051$). Wave 2 Sleep Problems significantly predicted missingness in Wave 3 DS ($\chi^2_{(1, N = 46)} = 4.042, p = .044$), explaining 13.4% (Nagelkerke $R^2$) of the variance in Wave 3 DS missingness and correctly classifying 80.4% of cases. Each unit increase in W2 Sleep Problems was associated with participants being 13.16 times more likely to have data for Wave 3 DS ($p = .068$). Wave 2 Sleep Problems significantly predicted missingness in Wave 3 CAR as well ($\chi^2_{(1, N = 46)} = 4.152, p = .042$), explaining 15.0% (Nagelkerke $R^2$) of the variance in Wave 3 CAR missingness and correctly classifying 84.8% of cases. Each unit increase in Sleep Problems was associated with participants being 19.80 times more likely to have data for Wave 3 CAR ($p = .071$). None of the time-invariant covariates (Gender, Minority Status, Under-represented Minority Status, or Age) predicted missingness in the diurnal cortisol parameters.

Some Wave 1 survey variables that were outside of the substantive interest of this project were included in missing data analysis as potential auxiliary variables to address missingness, such as Emotion Regulation Reappraisal and Emotion Regulation Suppression. Emotion Regulation Reappraisal marginally predicted missingness in Wave 2 DS ($\chi^2_{(1, N = 60)} = 3.759, p = .053$), explaining 7.5% (Nagelkerke $R^2$) of the variance in Wave 2 DS missingness and correctly classifying 76.3% of cases. Those who reported more Emotion Regulation Reappraisal in their survey were 2.104 times more likely to have data for DS at Wave 2 ($p = .067$). Emotion Regulation Suppression significantly predicted missingness in Wave 2 DS
(\chi^2_{(1, N=60)} = 5.382, p = .020), explaining 10.6% (Nagelkerke \textit{R}^2) of the variance in Wave 2 DS missingness and correctly classifying 65.2% of cases. Those who reported more Emotion Regulation Suppression in their survey were 2.014 times more likely to have data for DS at Wave 2 (\(p = .027\)). Emotion Regulation Suppression significantly predicted missingness in Wave 2 CAR (\(\chi^2_{(1, N=60)} = 3.946, p = .048\), explaining 8.2% (Nagelkerke \textit{R}^2) of the variance in Wave 2 CAR missingness and correctly classifying 74.2% of cases. Those who reported more Emotion Regulation Suppression in their survey were 1.877 times more likely to have data for CAR at Wave 2 (\(p = .055\)).

Emotion Regulation Suppression also significantly predicted missingness in Wave 3 DS (\(\chi^2_{(1, N=60)} = 5.489, p = .019\), explaining 10.8% (Nagelkerke \textit{R}^2) of the variance in Wave 3 DS missingness and correctly classifying 69.7% of cases. Those who reported more Emotion Regulation Suppression in their survey were 2.037 times more likely to have data for DS at Wave 3 (\(p = .026\)). Lastly, Emotion Regulation Suppression significantly predicted missingness in Wave 3 CAR (\(\chi^2_{(1, N=60)} = 8.211, p = .004\), explaining 16.0% (Nagelkerke \textit{R}^2) of the variance in Wave 3 CAR missingness and correctly classifying 72.7% of cases. Those who reported more Emotion Regulation Suppression in their survey were 2.474 times more likely to have data for CAR at Wave 3 (\(p = .008\)).

The above missing data analyses suggested that further steps to address missingness should take place for Study 2. Therefore, Full Information Maximum Likelihood (FIML) was performed in \textit{Mplus} v.7 and variables that were related to
missingness were used as auxiliary variables to help adjust for missing data (Enders, 2010).

**Examining Associations at Wave 1**

The first main goal of this study was to investigate whether baseline (Wave 1) socio-emotional regulatory factors would be associated with concurrent physiological stress regulation, represented by diurnal cortisol parameters DS and CAR. The proposed hypothesis (*Hypothesis a*) was that students’ effortful control and social support (academic and non-academic) would be positively associated with steeper cortisol slopes (DS) and larger cortisol awakening responses (CAR). To examine this hypothesis, multiple regression models predicting Wave 1 DS and Wave 1 CAR were estimated in *Mplus* to adjust for missing data using FIML estimation, and covariates were included in the models to adjust for the diurnal parameter predictions. Covariates for baseline multiple regressions included Wave 1 Sleep Hours, Sleep Problems, Medication, Smoking, Stress Events (within 24 hours of saliva collection), Future Time Perspective Connectedness, Learning-related Hopelessness, Gender, Minority Status, and Age. A total of six multiple regression analyses were estimated, one regression model for each main predictor variable (Effortful Control, Academic Social Support, and Non-academic Social Support) with all covariates included, to predict Wave 1 DS and Wave 1 CAR respectively.

**Multiple regression predicting Wave 1 DS.** In a multiple regression model predicting Wave 1 DS with all hypothesized covariates mean-centered and included, it was found that holding all covariates constant, Effortful Control did not significantly
predict DS at W1 \((B = .009, SE = .010, p = .35)\). In a second multiple regression model predicting Wave 1 DS, with all hypothesized covariates mean-centered and included, it was found that holding all covariates constant, Academic Social Support did not significantly predict DS at Wave 1 \((B = .008, SE = .007, p = .28)\). In this model, among the covariates, Sleep Hours marginally positively predicted DS at W1, with each hour increase in Sleep Hour predicting a .008 unit increase in W1 DS \((B = .008, SE = .005, p = .056)\). In a third multiple regression model predicting Wave 1 DS, with all hypothesized covariates mean-centered and included, it was found that holding all covariates constant, Non-academic Social Support did not significantly predict DS at Wave 1 \((B = .006, SE = .011, p = .58)\). Results did not support the hypothesis for concurrent Social Support and Effortful Control’s positive association with DS at Wave 1.

**Multiple regression predicting Wave 1 CAR.** In a multiple regression model predicting Wave 1 CAR with all hypothesized covariates mean-centered and included, it was found that holding all covariates constant, Effortful Control did not significantly predict CAR at W1 \((B = -.15, SE = .12, p = .22)\). In a second multiple regression model predicting Wave 1 CAR, with all hypothesized covariates mean-centered and included, it was found that holding all covariates constant, Academic Social Support did not significantly predict CAR at Wave 1 \((B = .001, SE = .093, p = .99)\). In a third multiple regression model predicting Wave 1 CAR, with all hypothesized covariates mean-centered and included, it was found that holding all covariates constant, Non-academic Social Support marginally negatively predicted
CAR at Wave 1 ($B = -.23, SE = .13, p = .091$), indicating that higher Non-academic social support was associated with lower CAR at W1. The same model also showed that Gender marginally positively predicted W1 CAR ($B = .23, SE = .14, p = .098$), indicating that female students on average had higher trend of CAR at W1 than their male counterparts. Results did not support the hypothesis for the positive association between concurrent Effortful Control and Academic Social Support with CAR at W1; however, results indicated that Non-academic Social Support was marginally associated with having lower CAR at W1.

**Examining Diurnal Cortisol Patterns Over time**

The second main goal of this study was to examine whether the socio-emotional regulatory factors could predict the fluctuation of well-being, represented by diurnal cortisol parameters (DS and CAR) over time. Prior to assessing Hypotheses b) to d), within-individual wave differences across the three waves for CAR and DS were examined. In order to examine mean-level differences, models mimicking Repeated-Measures Analysis of Covariance (RM ANCOVA) were used. Typical RM ANCOVAs were not used because of the need to address missing data and include Auxiliary variables. In one set of models, covariates were not included and omnibus differences in diurnal cortisol parameter means over Waves 1-3 were assessed with Wald tests constraining means equal over time. In another set of models, covariates were included. Time-invariant covariates included Gender, Race, and Age; time-variant covariates included Smoking, Medication, Sleep Problems, Sleep Hours, Stress Events (prior to saliva collections); and Study 1 key variables Wave 1 FTP
Connectedness, and Learning-related Hopelessness were also included as covariates. Auxiliary variables that were not main variables of the study but were found to be associated with missingness in cortisol data were included in the models, such as Emotion Regulation Reappraisal and Emotion Regulation Suppression. Mean-level differences across the three waves were assessed with an omnibus test of differences in intercepts (means adjusted for covariates) by Wald tests, constraining the intercepts to be equal. Post-hoc comparisons with Wald tests were used to examine between wave differences.

Notably, due to limited sample size ($N = 67$), the full models for DS and CAR repeated measures assessment resulted in model non-identification. Taking the sample size and number of parameters into consideration, I excluded covariates that had the highest $p$-values from the models to achieve model identification and improve fit. As a result, only select covariates were included in the final models for DS and CAR respectively, specified below.

**Diurnal cortisol slope differences over time.** Diurnal Cortisol Slope (DS) differences across waves were examined, with Wave 1 DS regressed on mean-centered covariates Wave 1 Sleep Hours and Wave 1 Medication, Wave 2 DS regressed on Gender and Learning-related Hopelessness, and Wave 3 DS regressed on Future Time Perspective Connectedness and Learning-related Hopelessness. Auxiliary variables were included (i.e., Wave 1 Emotion Regulation Reappraisal, Wave 1 Emotion Regulation Suppression, Wave 1 Sleep Problems, Wave 2 Sleep Problems, Wave 1 Smoking, and Wave 1 Stress Events).
The final model yielded good model fit, $\chi^2(17, N=67) = 13.76 (p = .68)$, RMSEA = .00 (95% CI: [.00, .09]), CFI = 1.00, and SRMR = .086. The Wald test with parameter constraints of equal adjusted means (intercepts) for Diurnal Slopes across all three waves was non-significant ($\chi^2(2, N=67) = 1.14, p = .57$), indicating that no significant mean-level difference was found across the three waves of data. Among the covariates, Wave 1 Sleep Hours marginally predicted Wave 1 DS, with each hour increase in sleep resulting in a trend of .006-unit increase in DS ($B = .006, SE = .003, p = .085$); Learning-related Hopelessness (LHL) significantly predicted Wave 2 DS, with each unit increase in LHL yielding a .015-unit decrease in Wave 2 DS ($B = -.015, SE = .007, p = .034$); Gender marginally predicted Wave 2 DS, with female students having a slightly higher Wave 2 DS than males ($B = .020, SE = .011, p = .057$); Wave 2 Sleep Hours significantly predicted Wave 2 DS, with each hour increase in sleep yielding a .008-unit increase in DS at Wave 2 ($B = .008, SE = .004, p = .031$); Wave 2 Smoking significantly predicted Wave 2 DS, with smokers having a lower DS at Wave 2 ($B = -.076, SE = .022, p = .001$). The total variance explained for Wave 1 DS was $R^2 = .06 (p = .28)$, for Wave 2 DS was $R^2 = .38 (p < .001)$, and for Wave 3 DS was $R^2 = .06 (p = .37)$.

**Cortisol awakening response differences over time.** Cortisol Awakening Response (CAR) differences between waves were examined, with Wave 1 CAR regressed on mean-centered covariates Wave 1 Sleep Hours and Gender, Wave 2 CAR regressed on Wave 2 Sleep Problems, Sleep Hours, Medication and Minority Status, and Wave 3 CAR regressed on Gender and Age. Auxiliary variables were
included (i.e., Wave 1 Emotion Regulation Suppression, Wave 1 Stress Events, Wave 2 Stress Events, and Wave 1 Smoking).

The final model yielded fair fit, $\chi^2_{(15, N=67)} = 22.94 (p = .085)$, RMSEA = .09 (95% CI: [.00, .16]), CFI = .76, and SRMR = .10. The Wald test with parameter constraints of equal adjusted means (intercepts) for Diurnal Slopes across all three waves was significant ($\chi^2_{(2, N=67)} = 7.94, p = .019$), indicating that a significant mean-level difference was found across the three waves of data. Among the covariates, Gender significantly predicted both Wave 1 and Wave 3 CAR, with female students having higher Wave 1 CAR than male students ($B = .29, SE = .13, p = .025$), and again having higher Wave 3 CAR than males ($B = .56, SE = .16, p < .001$); Wave 1 Sleep Hours significantly predicted Wave 1 CAR, with each hour increase in sleep resulting in a .12-unit decrease in CAR ($B = -.12, SE = .06, p = .035$); Minority Status significantly predicted Wave 2 CAR, with minority students having higher Wave 2 CAR than their White peer ($B = .73, SE = .18, p < .001$); Wave 2 Sleep Hours marginally predicted Wave 2 CAR, with each hour increase in sleep resulting in a trend of .09-unit decrease in CAR ($B = -.09, SE = .05, p = .086$); Wave 2 Sleep Problems significantly predicted Wave 2 CAR, with each unit increase in sleep problems resulting in a .57-unit decrease in CAR ($B = -.57, SE = .27, p = .037$); Wave 2 Medication significantly predicted Wave 2 CAR, with those who medicated having a higher CAR at Wave 2 ($B = .58, SE = .20, p = .004$); and Age significantly predicted Wave 3 CAR, with each year increase in age associated with an increase in Wave 3 CAR ($B = .03, SE = .01, p = .03$). The total variance explained for Wave 1 CAR was

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\[ R^2 = .14 \ (p = .099), \] for Wave 2 CAR was \( R^2 = .28 \ (p = .008) \), and for Wave 3 CAR was \( R^2 = .21 \ (p = .033) \).

Post hoc analyses also using Wald tests showed that on average, adjusting for covariates and missingness, there was no significant difference \( (\chi^2 (1, N=67) = 2.28, p = .13) \) between the estimated CAR at W1 \( (M = .29, SD = .06) \) and CAR at W2 \( (M = .16, SD = .08) \). Post hoc Wald test comparing Wave 1 CAR and Wave 3 CAR \( (M = .05, SD = .08) \) showed that a significant mean-level difference between Wave 1 and Wave 3 CAR \( (\chi^2 (1, N=67) = 7.90, p = .005) \) was found, with CAR at W1 being significantly greater than that of W3. Lastly, no significant difference was found between Wave 2 CAR and Wave 3 CAR \( (\chi^2 (1, N=67) = 1.66, p = .20) \).

**Grouping: Patterns in Diurnal Cortisol over Time**

Next, individuals were assigned to groups, according to their diurnal cortisol patterns over time, and group status was predicted using multinomial logistic regressions to assess overall diurnal cortisol patterns over the semester in examination of Hypotheses b) to d). Grouping of participants who showed similar diurnal cortisol pattern change over time was performed in SPSS. Diurnal cortisol parameters were split by the median (see Table 13) to create a boundary defining “low” (i.e., below the median) and “high” (i.e., above the median) levels for each parameter at each wave.

**Patterns for diurnal slope over time.** The total number of valid participants assigned for DS groups was 30 out of all 67 participants. Missing group assignments were largely due to attrition over time, lack of bedtime samples or lack of documentation of hours awake to complete the DS composite calculation. Among the
valid participants, eight patterns were found with regards to the high or low levels of DS across the three waves, including high-high-high \((n = 5)\), high-high-low \((n = 5)\), high-low-low \((n = 3)\), high-low-high \((n = 3)\), low-high-high \((n = 3)\), low-low-high \((n = 5)\), low-high-low \((n = 1)\), and low-low-low \((n = 5)\).

**Patterns for cortisol awakening response.** The total number of valid participants assigned for CAR groups was 40 out of all 67 participants. Missing group assignments were mostly due to attrition over time. Among the valid participants, eight patterns were found with regards to the high or low levels of CAR across the three waves, including high-high-high \((n = 9)\), high-high-low \((n = 5)\), high-low-low \((n = 5)\), high-low-high \((n = 3)\), low-high-high \((n = 2)\), low-low-high \((n = 5)\), low-high-low \((n = 4)\), and low-low-low \((n = 7)\).

**Group status for diurnal cortisol patterns.** In order to reduce pattern groups to maximize the participant number in each group for prediction of patterns over time, patterns high-high-low, high-low-low, and low-high-low were combined as one group to represent a flattening effect of diurnal cortisol over the semester, specifically towards the end of the semester. Patterns high-low-high, low-high-high, and low-low-high were combined as one group to represent recovery in diurnal cortisol levels over the semester, specifically towards the end of the semester. High-high-high and low-low-low were kept as individual groups to represent stably high and stably low patterns respectively.

Notably, as can be seen by the frequencies cross tabulated in Table 18, there was no significant association between patterns for DS over time and patterns for
CAR over time, $\chi^2_{(49, n=30)} = 43.97, p = .68$. Given this information, in addition to the overall non-positive relations between concurrent DS and CAR (see Table 14), it was indicative that DS and CAR levels likely characterized stress regulation in a different manner. Consequently, the hypothesized group names (e.g., healthy, exam-stress, exhausted groups) for this study that were rather rigid across DS and CAR, and that were suggestive of positive or negative well-being according to how the patterns fluctuated for both DS and CAR, were not assigned to the groups. Instead, I referred to the groups as **Chronic-high, Recovery, Flattening**, and **Chronic-low** groups for both DS patterns over time and CAR patterns over time, which depicted the fluctuation of the levels over time for each diurnal cortisol parameter, rather than associating positive or negative denotation for well-being according to the direction of fluctuation.

As a result, for DS patterns over time ($n = 30$), five participants were in the Chronic-high group (16.7%), 11 participants were in the Recovery group (36.7%), nine participants were in the Flattening group (30.0%), and five participants were in the Chronic-low group (16.7%). CAR patterns over time ($n = 40$) resulted in nine participants in the Chronic-high group (22.5%), 10 participants in the Recovery group (25.0%), 14 participants in the Flattening group (35.0%), and seven participants in the Chronic-low group (17.5%).

**Predicting Diurnal Cortisol Patterns over Time**

**Covariates.** In order to build predictive multinomial logistic regression models that would efficiently work for the sample size in this study, I examined the
covariates in predicting group status prior to including key variables of the study into the models. A full model with all covariates was assessed.

For DS group status \((n = 30)\), among the time-invariant variables, Gender marginally predicted DS group status, with female students having a 4.17 increase in the relative log odds of being in the Recovery group vs. Chronic-low group, indicating that it was 64.77 times more likely for female students compared to male students to be in the Recovery group compared to the Chronic-low group \((p = .078)\) for DS patterns over time. In addition, female students had a 3.87 increase in the relative log odds of being in the Flattening group vs. Chronic-low group, indicating that it was 48.10 times more likely for female students compared to male students to be in the Flattening group compared to the Chronic-low group \((p = .092)\) for DS patterns over time. Wave 1 Future Time Perspective Connectedness (FTPC) marginally predicted DS group status, with FTPC associated with a 3.16 decrease in the relative log odds of being in the Recovery group vs. the Chronic-low group, indicating that it was 4.2% less likely for students to be in the Recovery group vs. the Chronic-low group with each unit increase in FTPC at Wave 1 \((p = .085)\) for DS patterns over time.

With regard to CAR group status \((n = 40)\), adjusting for all covariates, Gender significantly predicted CAR group status, with female students having a 5.25 increase in the relative log odds of being in the Recovery group vs. the Chronic-low group, indicating that it was 190.31 times more likely for female students compared to male students to be in the Recovery group compared to the Chronic-low group \((p = .019)\).
Wave 1 FTPC marginally predicted CAR group status, with FTPC associated with a
6.54 increase in the relative log odds of being in the Chronic-high group vs. the
Chronic-low group, indicating that it was 691.70 times more likely for students to be
in the Chronic-high group vs. the Chronic-low group with each unit increase in FTPC
at Wave 1 ($p = .095$) for CAR patterns over time. Wave 1 Sleep Hours marginally
predicted CAR group status, with Sleep Hours associated with a 2.92 increase in the
relative log odds of being in the Recovery group vs. the Chronic-low group,
indicating that it was 18.44 times more likely for students to be in the Recovery group
vs. the Chronic-low group with each hour increase in Sleep Hours at Wave 1 ($p
= .068$) for CAR patterns over time.

All covariates that were significant or marginally significant in predicting
group statuses were entered in multinomial logistic regressions for DS and CAR
group respectively. Covariates that yielded $p$-values > .10 in predicting group statuses
were excluded from the multinomial logistic regression models to accommodate for a
balance between number of estimated parameters and the small sample sizes of this
study.

**Regulatory factors: Effortful Control and Social Support.** To examine
*Hypothesis b*, that students’ socio-emotional regulation such as effortful control and
social support (academic and non-academic) would predict a healthier or more
adaptive diurnal cortisol pattern over time, multinomial logistic regressions were
performed to predict group status for DS ($n = 30$) and CAR ($n = 40$) in *Mplus*, and
FIML was used to adjust for missing data.
**Effortful Control.** In a model with only the main variable Effortful Control as the predictor variable (no covariates), results showed that Effortful Control did not significantly predict DS group status, with non-significance for Chronic-high vs. Chronic-low ($B = 1.40, SE = 1.43, p = .33$), Recovery vs. Chronic-low ($B = -1.20, SE = 1.00, p = .23$), and Flattening vs. Chronic-low ($B = -.46, SE = 1.03, p = .65$). In a model adjusting for covariates Gender and FTP Connectedness, results again showed that Effortful Control did not significantly predict DS group status, with non-significance for Chronic-high vs. Chronic-low ($B = 1.71, SE = 1.67, p = .31$), Recovery vs. Chronic-low ($B = -.98, SE = 1.15, p = .39$), and Flattening vs. Chronic-low ($B = -.29, SE = 1.21, p = .81$).

In a model with only the main variable Effortful Control as the predictor variable (no covariates), results showed that Effortful Control did not significantly predict CAR group status, with non-significance for Chronic-high vs. Chronic-low ($B = .112, SE = .90, p = .90$), Recovery vs. Chronic-low ($B = .95, SE = .92, p = .30$), and Flattening vs. Chronic-low ($B = .37, SE = .82, p = .65$). In a model adjusting for covariates Gender, FTP Connectedness, and Wave 1 Sleep Hours, results again showed that Effortful Control did not significantly predict CAR group status, with non-significance for Chronic-high vs. Chronic-low ($B = .49, SE = 1.16, p = .67$), Recovery vs. Chronic-low ($B = 1.37, SE = 1.11, p = .22$), and Flattening vs. Chronic-low ($B = .69, SE = .87, p = .42$).

**Academic Social Support.** In a model with only the main variable Academic Social Support as the predictor variable (no covariates), results showed that Academic
Social Support did not significantly predict DS group status, with non-significance for Chronic-high vs. Chronic-low ($B = .37, SE = 1.02, p = .72$), Recovery vs. Chronic-low ($B = -.28, SE = .84, p = .74$), and Flattening vs. Chronic-low ($B = -.19, SE = .87, p = .83$). In a model adjusting for covariates Gender and FTP Connectedness, results again showed that Academic Social Support did not significantly predict DS group status, with non-significance for Chronic-high vs. Chronic-low ($B = .42, SE = 1.05, p = .69$), Recovery vs. Chronic-low ($B = -.22, SE = .88, p = .81$), and Flattening vs. Chronic-low ($B = -.18, SE = .92, p = .84$).

In a model with only the main variable Academic Social Support as the predictor variable (no covariates), results showed that Academic Social Support did not significantly predict CAR group status, with non-significance for Chronic-high vs. Chronic-low ($B = -.36, SE = .86, p = .67$), Recovery vs. Chronic-low ($B = -.66, SE = .83, p = .43$), and Flattening vs. Chronic-low ($B = -.53, SE = .79, p = .50$). In a model adjusting for covariates Gender, FTP Connectedness, and Wave 1 Sleep Hours, results again showed that Academic Social Support did not significantly predict CAR group status, with non-significance for Chronic-high vs. Chronic-low ($B = -.25, SE = .98, p = .80$), Recovery vs. Chronic-low ($B = -.43, SE = .99, p = .66$), and Flattening vs. Chronic-low ($B = -.46, SE = .82, p = .58$).

**Non-academic Social Support.** In a model with only the main variable Non-academic Social Support as the predictor variable (no covariates), results showed that Non-academic Social Support did not significantly predict DS group status, with non-significance for Chronic-high vs. Chronic-low ($B = 1.22, SE = 1.74, p = .48$),
Recovery vs. Chronic-low \((B = 2.59, SE = 1.73, p = .14)\), and Flattening vs. Chronic-low \((B = .02, SE = 1.34, p = .99)\). In a model adjusting for covariates Gender and FTP Connectedness, results again showed that Non-academic Social Support did not significantly predict DS group status, with non-significance for Chronic-high vs. Chronic-low \((B = 1.17, SE = 1.84, p = .53)\), Recovery vs. Chronic-low \((B = 2.29, SE = 1.80, p = .20)\), and Flattening vs. Chronic-low \((B = -.08, SE = 1.53, p = .96)\).

In a model with only the main variable Non-academic Social Support as the predictor variable (no covariates), results showed that Non-academic Social Support did not significantly predict CAR group status, with non-significance for Chronic-high vs. Chronic-low \((B = -.73, SE = 1.76, p = .68)\), Recovery vs. Chronic-low \((B = -1.50, SE = 1.64, p = .36)\), and Flattening vs. Chronic-low \((B = -2.14, SE = 1.58, p = .18)\). In a model adjusting for covariates Gender, FTP Connectedness, and Wave 1 Sleep Hours, results again showed that Non-academic Social Support did not significantly predict CAR group status, with non-significance for Chronic-high vs. Chronic-low \((B = -1.00, SE = 2.48, p = .69)\), Recovery vs. Chronic-low \((B = -2.37, SE = 2.36, p = .32)\), and Flattening vs. Chronic-low \((B = -3.23, SE = 2.27, p = .16)\).

**Future Time Perspective Value and Effortful Control.** To examine \textit{Hypothesis c)}, that students who have high effortful control (EC) and high future time perspective value (FTPV) would display healthier patterns of diurnal cortisol change over time, whereas high FTPV and low EC would be associated with less than ideal patterns in diurnal cortisol over the semester, multinomial logistic regressions with an
interaction term of the two main variables were performed to predict group status of DS ($n = 30$) and CAR ($n = 40$), and FIML was used to adjust for missing data.

**Interaction effect predicting DS groups.** No significant interaction effect was found between FTPV and Effortful Control in predicting DS group status. In a model with main variables only (FTPV, EC, and their interaction term [formed by mean-centering and multiplying the two main variables]), results showed non-significance in the interaction term coefficient for Chronic-high vs. Chronic-low ($B = 2.72, SE = 2.64, p = .34$), Recovery vs. Chronic-low ($B = .88, SE = 1.81, p = .63$), and Flattening vs. Chronic-low ($B = .29, SE = 1.80, p = .87$). After adjusting for covariates Gender and FTP Connectedness, results again showed non-significance in the interaction term coefficient for Chronic-high vs. Chronic-low ($B = 3.75, SE = 3.20, p = .24$), Recovery vs. Chronic-low ($B = .63, SE = 2.06, p = .69$), and Flattening vs. Chronic-low ($B = -.27, SE = 2.15, p = .90$).

**Interaction effect predicting CAR groups.** No significant interaction effect was found between FTP Value and Effortful Control in predicting CAR group status. In a model with main variables only (FTPV, EC, and their interaction term), results showed non-significance in the interaction term coefficient for Chronic-high vs. Chronic-low ($B = -.28, SE = 1.70, p = .87$), Recovery vs. Chronic-low ($B = .67, SE = 1.67, p = .69$), and Flattening vs. Chronic-low ($B = .30, SE = 1.48, p = .84$). After adjusting for covariates Gender, FTP Connectedness, and Wave 1 Sleep Hours, results again showed non-significance in the interaction term coefficient for Chronic-high vs.
Chronic-low ($B = -.88, SE = 2.21, p = .69$), Recovery vs. Chronic-low ($B = .40, SE = 1.85, p = .83$), and Flattening vs. Chronic-low ($B = .057, SE = 1.54, p = .97$).

**Future Time Perspective Value and Social Support.** To examine *Hypothesis d*, that students who have high social support and high FTPV would display healthier patterns of diurnal cortisol change over time, whereas high FTPV and low social support would be associated with less than ideal patterns in diurnal cortisol over the semester, multinomial logistic regressions with interaction terms of the main variables were performed to predict group status of DS ($n = 30$) and CAR ($n = 40$), and FIML was used to adjust for missing data.

*Interaction effect predicting DS groups.* No significant interaction effect was found between FTP Value and Academic Social Support in predicting DS group status. In a model with main variables only (FTPV, Academic Social Support, and their interaction term [formed by mean-centering and multiplying the two main variables]), results showed non-significance in the interaction term coefficient for Chronic-high vs. Chronic-low ($B = 2.72, SE = 2.64, p = .34$), Recovery vs. Chronic-low ($B = .88, SE = 1.81, p = .63$), and Flattening vs. Chronic-low ($B = .29, SE = 1.80, p = .87$). After adjusting for covariates Gender and FTP Connectedness, results again showed non-significance in the interaction term coefficient for Chronic-high vs. Chronic-low ($B = .069, SE = 2.17, p = .98$), Recovery vs. Chronic-low ($B = -1.32, SE = 1.79, p = .46$), and Flattening vs. Chronic-low ($B = -1.92, SE = 1.81, p = .29$).

No significant interaction effect was found between FTP Value and Non-academic Social Support in predicting DS group status. In a model with main
variables only (FTPV, Non-academic Social Support, and their interaction term),
results showed non-significance in the interaction term coefficient for Chronic-high vs. Chronic-low ($B = -.91, SE = 3.49, p = .80$), Recovery vs. Chronic-low ($B = 10.87, SE = 7.96, p = .17$), and Flattening vs. Chronic-low ($B = .12, SE = 2.87, p = .97$).

After adjusting for covariates Gender and FTP Connectedness, results again showed non-significance in the interaction term coefficient for Chronic-high vs. Chronic-low ($B = -1.16, SE = 3.50, p = .74$), Recovery vs. Chronic-low ($B = 11.13, SE = 8.83, p = .21$), and Flattening vs. Chronic-low ($B = -.31, SE = 3.14, p = .92$).

**Interaction effect predicting CAR groups.** In a model with main variables only (FTP Value, Academic Social Support, and their interaction term), results indicated that there was a marginally significant interaction effect between FTP Value and Academic Social Support in predicting CAR group status when comparing the Flattening group and the Chronic-low group in CAR patterns over time. The main effects for FTP Value ($B = -1.87, SE = 1.36, p = .17$) and Academic Social Support ($B = -1.33, SE = 1.06, p = .21$) were not statistically significant; however, the marginally positive interaction effect ($B = 3.25, SE = 1.82, p = .073$) indicated that there was a trend in those who were high in both FTP Value and Academic Social Support being 25.86 times more likely to be in the Flattening group vs. the Chronic-low group for CAR patterns over time. After adjusting for covariates Gender, FTP Connectedness, and Wave 1 Sleep Hours, results showed that the a marginally significant interaction effect between FTP Value and Academic Social Support in predicting CAR group status remained. Again, when comparing the Flattening group and the Chronic-low
group, the main effects for FTP Value ($B = -2.07, SE = 1.59, p = .19$) and Academic Social Support ($B = -1.71, SE = 1.31, p = .19$) were not statistically significant; however, the marginally positive interaction effect ($B = 3.71, SE = 2.21, p = .094$) indicated that there was a trend in those who were high in both FTP Value and Academic Social Support being 40.72 times more likely to be in the Flattening group vs. the Chronic-low group for CAR patterns over time.

No significant interaction effect was found between FTP Value and Non-academic Social Support in predicting CAR group status (interaction term formed by mean-centering and multiplying the two variables). Results showed non-significance in the interaction term coefficient for Chronic-high vs. Chronic-low ($B = -.95, SE = 3.85, p = .81$), Recovery vs. Chronic-low ($B = 3.32, SE = 3.89, p = .39$), and Flattening vs. Chronic-low ($B = 1.87, SE = 3.46, p = .59$). After adjusting for covariates Gender, FTP Connectedness, and Wave 1 Sleep Hours, results again showed non-significance in the interaction term coefficient for Chronic-high vs. Chronic-low ($B = -2.05, SE = 4.66, p = .66$), Recovery vs. Chronic-low ($B = 3.41, SE = 4.63, p = .46$), and Flattening vs. Chronic-low ($B = 1.32, SE = 4.02, p = .74$).

Discussion

The overall objective of this study was to better understand changes in students’ diurnal cortisol pattern over the course of a semester. Specifically, I worked to explore the roles of socio-emotional regulatory variables, such as emotion-related self-regulation Effortful Control (Evans & Rothbart, 2007), and social support, including Academic and Non-academic Social Support (Pierce et al., 1991), in
conjunction with the value a student puts in a future goal (Future Time Perspective Value; Husman & Shell, 2008), in predicting changes in students’ diurnal cortisol over the course of a semester. According to previous studies (e.g., McGregor, Murphy, Albano, & Ceballos, 2016) and the hypotheses of this study, diurnal cortisol slope (DS) and cortisol awakening response (CAR) decreases over time for those who experience chronic stress. This study tested whether future-oriented motivation and socio-emotional regulatory factors could jointly predict the status of students’ well-being represented by a sustained or flattened diurnal cortisol pattern.

**Baseline Associations at the Beginning of the Semester**

The first aim of this study was to examine whether baseline (Wave 1) socio-emotional regulatory factors (Effortful Control, Academic Social Support, and Non-academic Social Support) would be associated with concurrent physiological stress regulation, represented by diurnal cortisol parameters – DS and CAR, at the beginning of a semester. The study hypothesis was that baseline DS and CAR would be positively associated with Effortful Control, Academic Social Support, and Non-academic Social Support ($H_a$). Findings indicated that Non-academic Social Support was marginally associated with baseline CAR, with Non-academic Social Support negatively associated with CAR at the beginning of the semester. The direction of this finding was not consistent with the original hypothesis or previous literature that delineates the positive relation between social support or social connection with higher CAR (e.g., Pinto et al., 2016; Sladek & Doane, 2015; Stetler & Miller, 2005). However, the direction of the finding is consistent with Study 1 findings, as well as
previous literature that suggest the day-of anticipatory stress (Fries et al., 2009) and perceived stress (Pruessner et al., 1999) implications of CAR. In other words, according to past literature that investigated in normative samples, i.e., samples that did not have clinical conditions (such as depressive or anxiety disorders, e.g., Stetler & Miller, 2005) or traumatic life experiences (such as early adversity or inter-partner violence, e.g., Pinto et al., 2016), CAR can be representative of day-to-day anticipatory stress, or a more momentary excerpt of one’s well-being.

The current finding thus is implicative that Non-academic Social Support, the support students obtain from social friends, coworkers, family, or their romantic partner is helpful in lowering anticipatory academic stress; and those who have lower Non-academic Social Support may experience higher anticipatory academic stress. This speculation is supported by a meta-analysis conducted by Chida and Steptoe (2009), delineating that increased CAR has been associated with general life stress, which consisted of low social support.

The study, however, did not show support for the positive associations between baseline diurnal cortisol parameters (DS or CAR) and the proposed socio-emotional regulatory factors Effortful Control and Academic Social Support. Previous studies have shown that steeper DS (awakening and evening difference) was related to concurrent social support, general health, and well-being (Sjögren et al., 2006). Current findings did not support this line of research.
Socio-emotional Regulatory Factors and Diurnal Cortisol Patterns

The second aim of this study was to examine whether socio-emotional regulation such as Effortful Control (an emotion-related regulatory construct) and Social Support (academic and non-academic) would predict a healthier or more adaptive diurnal cortisol pattern over time. It was hypothesized that constructs such as Effortful Control (EC) and Social Support (SS) would be beneficial in sustaining a steep DS and large CAR in post-secondary university students over the three waves of data collection throughout a semester ($H_b$). Findings indicated that groups of students with differential diurnal cortisol pattern change over time could be formed, indicating presence of individual differences in students’ diurnal cortisol profiles over the course of a semester. Overall, students were placed in Chronic-high, Recovery, Flattening, and Chronic-low groups. However, both EC and SS did not uniquely predict the groups that students were in. Given the complexity and costliness of diurnal cortisol research, past literature has provided scare evidence with regard to multiple-wave assessments of diurnal cortisol patterns over time.

Predicting Diurnal Cortisol Patterns: FPT Value and Effortful Control

The next aim of the study was to examine whether Future Time Perspective Value interacted with Effortful Control in predicting diurnal cortisol pattern change over time. It was hypothesized that if students place high value in a future goal with regards to the class they are taking, Effortful Control (an emotion-related self-regulatory construct) may be important for one to continue to strive and maintain well-being (indicated by DS and CAR) until the end of the semester ($H_c$). Results
showed that FTPV and Effortful Control did not jointly predict diurnal cortisol pattern change over time. This study is the first to examine FTPV and Effortful Control’s joint prediction in well-being.

**Predicting Diurnal Cortisol Patterns: FTP Value and Social Support**

The last aim of the study was to examine whether Future Time Perspective Value interacted with the socio-emotional regulatory factors in predicting diurnal cortisol pattern change over time. It was hypothesized that if students place high value in a future goal with regards to the class they are taking, Social Support (both Academic and Non-academic) may be important for one to continue to strive and maintain well-being (indicated by DS and CAR) until the end of the semester ($H_d$). Results showed that FTPV and Academic Social Support had a trend in jointly predicting CAR patterns over a semester. High on both FTPV and Academic Social Support predicted higher likelihood in having a pattern of switching from high to low CAR towards the end of the semester, compared to those who had low CAR throughout the semester. There was no evidence of Non-academic Social Support and FTPV jointly predicting DS or CAR pattern change over the semester.

The findings are unique in examining the joint effects of FTPV and Academic Social Support in predicting CAR. Notably, it is important to recognize the interpretation of CAR of this study, which plausibly represents anticipatory stress of the day and short-term well-being. Given this understanding, the joint effect of Academic Social Support and FTPV predicting the higher likelihood of students being the Chronic-low CAR group, compared to the group that had higher CAR at the end
of the semester, indicates that both future-oriented motivation and domain-specific social support were helpful for students to regulate their daily stress and well-being over the course of a semester.

**Strengths and Implications**

This study is consistent with Study 1 in its interpretation of CAR as an anticipatory (or daily) stress indicator in the post-secondary educational context. Moreover, the study is an extension of Study 1 by two-folds. First of all, it goes beyond the scope of Study 1 in terms of time span. The study contributes to the scarce literature of research on longitudinal assessments of multiple-wave diurnal cortisol patterns within the educational context.

Secondly, the study emphasizes the role of regulatory resources in predicting diurnal cortisol pattern change over time, in conjunction with future-oriented motivation. It provides support for Dodge and colleagues’ (2012) model for well-being, in that dynamic well-being is balance by psychological, physical and social resources.

Lastly, this study provides theoretical implications in expansion of Control Value Theory. In line with Control Value Theory, the current findings suggest that Future Time Perspective Value could be provide students with the subjective value for completing academic tasks, whereas regulatory resources such as Academic Social Support could supply students with more subjective control over their academic tasks, thus jointly contributing to their emotional experience and physiological well-being.
Limitations, and Directions for Future Research

The study was limited in sample size. The lack of a larger sample has impacted the power and interpretability of the data. Future studies should be conducted with a larger sample size to better generalize to the university population. Specifically, to support theory and hypotheses of this study, many of the statistical models would require a larger sample to include and adjust for all hypothesized covariates that could potentially influence the cortisol data. Without a sufficient sample size, the final statistical models were limited to adjusting for only the most potent covariates. Moreover, a larger sample size would allow for analytic methods that more fully explore the longitudinal changes in well-being.

It may be helpful to examine other constructs pertaining to emotion regulation in predicting diurnal cortisol patterns, such as emotion reappraisal and emotion suppression (Gross & John, 2003). Constructs that directly assess strategies used for emotion regulation may be more relevant for predicting diurnal cortisol patterns, that are often indicative of one’s emotional and physiological well-being (Lam, 2012), and potentially better measures of the emotional-regulatory resource that this study was designed to examine.

With regard to salivary cortisol data, it would be useful for future studies to adjust the cortisol windsorizing value from an absolute value of 1.81 µg/dL to a cutting point of 2.5 or 3 SDs away from the mean (Granger et al., 2007; Marceau et al., 2013; Miller et al., 2017; Saridjan et al., 2014; Schlotz, 2011), since recent studies show that there have been many cases of participants having levels of cortisol that are
greater than 1.81 µg/dL (e.g., Harden et al., 2016; Kim et al., 2014). This method could help retain data points, and increase the accountable variability in cortisol data.

Future studies could also explore relations between socio-emotional factors and diurnal cortisol area under the curve (AUC, which captures the overall secretion of cortisol over a day), in addition to the diurnal cortisol parameters DS and CAR. By including AUC alongside DS and CAR in assessing diurnal cortisol over time, researchers can have a more comprehensive picture of the properties of each diurnal cortisol parameter in terms of temporal meaning and better locate relevant socio-emotional factors in predicting students’ well-being (Granger et al., 2012).

Finally, it would be meaningful for future research to address gender and minority status differences with regard to the predictions of student well-being. The current study found that there are differential responses in cortisol levels and diurnal cortisol patterns, and slightly differential attrition rates in cortisol data for students of different demographic backgrounds. Future studies (with a sufficient sample size and reduced attrition rate) that examine the precursors of these differences in well-being research could be beneficial for post-secondary university students of diverse backgrounds.
GENERAL DISCUSSION

Built upon Control Value Theory, the overarching goals of this dissertation were to strengthen well-being research in the educational context with the support of diurnal cortisol parameters, and to provide empirical evidence that could be informative to current educational theory. Students in the post-secondary educational context are undergoing crucial stages of their lives. A good portion of literature in post-secondary education has been focused on learning and cognitive processes. Not until recent decades has the field begun to acknowledge the importance of university students’ socio-emotional experience and the important role of well-being in students’ academic journey (Nelson et al., 2015; Swaner, 2007).

Findings from Study 1 suggest that future-oriented motivation (Future Time Perspective Connectedness) is associated with lower anticipatory stress represented by the cortisol awakening response (CAR) around university students’ mid-term examination. Findings from Study 2 suggest that Non-academic Social Support is associated with lower anticipatory stress (represented by CAR) at the beginning of a semester; and that Academic Social Support and future-oriented motivation (Future Time Perspective Value) jointly predict a higher likelihood in having decreased anticipatory stress (represented by CAR) toward the end of a semester.

Both studies included findings of FTP Connectedness, an operationalization of student’s tendency of planning for and thinking about the future, in relation to diurnal cortisol parameters. In Study 1, FTP Connectedness, was helpful in the recovery of momentary well-being represented by CAR; in Study 2, FTP Connectedness was
associated with the non-recovery of the diurnal cortisol slope (DS), which was a relatively stable construct, arguably indicative of chronic well-being.

The two distinct but complementary studies in this dissertation contribute to the field in two major ways. First of all, the studies link Future Time Perspective with the experience of academic stress. Secondly, results suggest that socio-emotional regulatory factors such as Social Support may be important to help the recovery of well-being, given high future-oriented motivation within the academic context.

The findings of this dissertation were inconsistent with initially proposed study hypotheses, with regard to lack of significance in the predictions for diurnal cortisol slope, and with regard to the directionality of predictions for cortisol awakening response over time. However, given the scope of the studies, the main findings jointly contribute to current literature, and are informative of research in the future, with both theoretical and practical implications.

**Theoretical Implications**

**Future Time Perspective and well-being.** So far, few studies have explored the role Future Time Perspective (FTP) has with regard to well-being in the educational context. Webster and Ma (2013) found that having a balanced time perspective, i.e., having positive thoughts and feeling about both the past and future, was predictive of subjective well-being in adults, assessed by their happiness and satisfaction with life. Notably, this line of research (Webster & Ma, 2013) focused on the cognitive components of well-being and did not address affective or physiological components of well-being.
The current dissertation examines the roles future-oriented motivation subscales, Future Time Perspective Connectedness and Future Time Perspective Value (Husman & Shell, 2008), play in predicting students’ well-being. The two studies emphasize the cognitive-motivational features of future time perspective, and is innovative in associating the anticipatory functions of FTP with anticipatory stress represented by cortisol awakening responses.

Notably, in Study 1, FTP Connectedness was associated with the recovery of momentary stress represented by CAR; and in Study 2, findings indicated that FTP Connectedness was associated with the non-recovery of DS over the course of a semester, which could be associated with chronic stress. Given these different temporal implications of the diurnal cortisol parameters, it may be important for future research to explore the temporal specificity of how FTP constructs are associated with stress physiology and well-being. It is plausible that DS recovery over a course of the semester would also require regulatory resources, given high FTP Connectedness, to sustain one’s well-being over time.

**Expansion of Control Value Theory.** Drawing from Control Value Theory (Pekrun, 2006), the two studies in this dissertation examine university students’ well-being within the academic context, addressing cognitive, affective, motivational, and physiological components of students’ experiences. The findings from the two studies explore constructs that have not been addressed in Control Value Theory before. In particular, the current studies examine students’ future-oriented motivation and regulatory resources in predicting their academic-related experiences on multiple
facets, including all four components suggested by Control Value Theory that are related to students’ academic-related emotional experience.

Specifically, reduced CAR predicted by future-oriented motivational constructs and social-regulatory constructs imply that these predictors are useful in regulating students’ academic stress and their HPA axis for them to continue pursuing their academic goals. Particularly, the anticipatory nature of future time perspective could drive students’ emotional experiences that are also anticipatory in nature (Pekrun et al., 2014), in turn affecting students’ physiological responses. It is plausible that 1) Future Time Perspective Value is important in contributing to students’ subjective value in academic-related tasks, motivating students to regard future goals as meaningful and valuable, and to strive for these goals; 2) Future Time Perspective Connectedness helps students stay connected to their future goals, contributing to their subjective control over academic-related tasks; and 3) Social Support is helpful in contributing to students’ subjective control over stressful academic tasks by increasing students’ sense of social resourcefulness. These findings have important theoretical implications in that it calls for incorporation of future-oriented motivational constructs and social-regulatory constructs as appraisal antecedents into the Control Value Theory.

Notably, the studies in this dissertation have been proposed to examine students’ chronic well-being, thus the hypothesis with regard to Learning-related Hopelessness, which was arguably associated with a more chronic academic experience. Findings, however, showed that momentary well-being could be assessed
by diurnal cortisol parameter CAR. Given the importance of temporal specificity and the non-significance with Learning-related Hopelessness, it would be worthy to bring the attention of researchers to other discrete academic-related emotions that are anticipatory in nature as well (which could also be associated with future-oriented motivation and diurnal cortisol parameters, such as Learning-related Hope); also, it would be important to explore different academic domains, such as test-related academic emotions and classroom-related academic emotions, in addition to learning-related academic emotions, for future research.

Practical Implications

The dissertation informs educators and policy makers in two main ways. First of all, the importance of students’ future-oriented motivation cannot be overlooked. Specifically, it may be helpful to develop interventions or built-in classroom curricula that enhance post-secondary students’ FTP, for example, curriculum that emphasizes students’ future goal and plans to achieve that future goal, which could have an influence on students’ well-being and academic experience.

Secondly, it may be useful to give attention to students’ social support. Specifically, non-academic and academic social support may both be important for university students’ well-being (especially for Engineering students, who are the participants of the dissertation studies). To enhance students’ well-being and academic experience in the university, it may be beneficial for academic programs (in particular Engineering programs) to build infrastructures for social support within the academic environment. It may be equally important for university counselors or
academic advisors to attend to students’ non-academic social network as well. Special attention should be given to non-traditional students, for example, female students or students of minority status in the engineering departments, as they may experience less scaffolding in the academic environment or have less practical support from their home environments (Martin, Simmons, & Yu, 2013), which could have negative implications on their well-being.

**Strengths, Limitations, and Directions for Future Research**

The main strengths of this dissertation include the combination of self-reported survey data with objective salivary biomarker data, the assessment of educational data in ecological academic settings (e.g., in real life academic stress periods), and the examination of longitudinal assessments of diurnal cortisol. These strengths are particularly significant in the field of educational research. For example, the survey and salivary data students provide prior to or during a stressful academic period could be more authentic compared to data collected via experimentally manipulated laboratory stress, such as implementing the Trier Social Stress Task (Kirschbaum, Pirke, & Hellhammer, 1993), or via experimental simulations of academic stress.

Both studies presented here, however, have significant limitations. The primary limitation is sample size. Salivary studies in the educational context typically have smaller samples (N = 20-60) (e.g., Hewig et al., 2008; McGregor et al., 2016; Spangler et al., 2002) compared to the typical large sample size of educational research studies which focus on survey methods (e.g., Pekrun et al., 2011). This set of
studies sought to combine survey and salivary methods. The trends found within both studies provide are interesting, however, to interpret these findings larger samples are required.

Limitation in sample size posed restrictions in adjusting for critical covariates that are associated with diurnal cortisol fluctuation due to lack of model identification. In addition, larger samples could provide greater statistical power, and allow for advanced statistical analyses to be conducted (such as multivariate modeling or growth mixture modeling), which could account for more variance in the diurnal cortisol pattern change over time, to make reliable and valid statistical inferences. Further, to bridge the implications of the two studies, future research that include key variables from both studies tested under the specific time spans of each study may be helpful to integrate the research questions.

Consequently, future collaboration between salivary bioscience researchers and educational researchers are required to 1) consider the most effective methods for retaining participants in interdisciplinary ecological longitudinal studies and 2) reduce the fiscal limitations of the studies.

Future research that examines diurnal cortisol patterns (diurnal cortisol slope, cortisol awakening response, as well as area under the curve [AUC]; Granger et al., 2012) in relation with discrete academic-related emotions, such as enjoyment, anger, anxiety, and shame (Pekrun et al., 2011; Pekrun et al., 2014) would provide additive meaning to this line of research. Lastly, it would also be beneficial to assess situational motivational, emotional, and regulatory constructs associated with the
different diurnal cortisol parameters, as well as address the potential bidirectional influences in diurnal cortisol patterns and students’ well-being.

**Conclusion**

In sum, this dissertation provides an integral outlook of post-secondary students’ well-being represented by diurnal cortisol patterns with regard to their future-oriented motivation, academic-related emotion, and socio-emotional regulation. Study interpretations are limited by the sample sizes of both studies. However, findings provide innovative implications for educational theories, specifically, for Future Time Perspective Theory (Lens et al., 2012) and Control Value Theory (Pekrun, 2006; Pekrun et al., 2009). Future research that resolves current limitations are required. Findings also have practical implications, such as informing educators and policy makers to attend to interventions and curriculum-building that address the importance of students’ future time perspective and social support, which could enhance students’ well-being and academic experience. Notably, the current studies add to diurnal cortisol research with its ecological assessments within the educational context. The explorations of current studies are important in weaving past and future interdisciplinary research that aim to address and enhance university students’ well-being.
Table 1

*Timeline for Study 1*

<table>
<thead>
<tr>
<th>Timeline</th>
<th>Week before mid-term (Wave 1)</th>
<th>Week of Midterm (Wave 2)</th>
</tr>
</thead>
</table>
| **Research Activity**  | Recruitment, Informed Consent  
Survey & Diurnal samples (two consecutive days)                                                 | Survey & Diurnal samples (two consecutive days prior to mid-term)                          |
Table 2

**Timeline for Study 2**

<table>
<thead>
<tr>
<th>Timeline</th>
<th>2\textsuperscript{nd} week of semester</th>
<th>3\textsuperscript{rd} week – Wave 1</th>
<th>Week of Midterm – Wave 2</th>
<th>Two weeks before finals – Wave 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Research Activity</td>
<td>Recruitment, Informed Consent</td>
<td><strong>Survey &amp; Diurnal sample</strong></td>
<td><strong>Survey &amp; Diurnal sample</strong></td>
<td><strong>Survey &amp; Diurnal sample</strong></td>
</tr>
</tbody>
</table>
Table 3

*Study 1 Number of Participants with Regards to Demographic Information*

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Survey N (%)</th>
<th>W1 Cortisol n (%)</th>
<th>W2 Cortisol n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Gender</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>41 (68.3)</td>
<td>32 (69.6)</td>
<td>27 (67.5)</td>
</tr>
<tr>
<td>Female</td>
<td>16 (26.7)</td>
<td>12 (26.1)</td>
<td>11 (27.5)</td>
</tr>
<tr>
<td>Missing</td>
<td>3 (5.0)</td>
<td>2 (4.3)</td>
<td>2 (5.0)</td>
</tr>
<tr>
<td><strong>Race/Ethnicity</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>American Indian</td>
<td>1 (1.7)</td>
<td>0 (0.0)</td>
<td>0 (0.0)</td>
</tr>
<tr>
<td>Asian</td>
<td>9 (15.0)</td>
<td>7 (15.2)</td>
<td>6 (15.0)</td>
</tr>
<tr>
<td>Hispanic</td>
<td>9 (15.0)</td>
<td>6 (13.0)</td>
<td>3 (7.5)</td>
</tr>
<tr>
<td>Black</td>
<td>2 (3.3)</td>
<td>2 (4.3)</td>
<td>1 (2.5)</td>
</tr>
<tr>
<td>White</td>
<td>32 (53.3)</td>
<td>26 (56.5)</td>
<td>25 (62.5)</td>
</tr>
<tr>
<td>Mixed Race</td>
<td>5 (8.3)</td>
<td>3 (6.5)</td>
<td>3 (7.5)</td>
</tr>
<tr>
<td>Missing</td>
<td>2 (3.3)</td>
<td>2 (4.3)</td>
<td>2 (5.0)</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>60</strong></td>
<td><strong>46</strong></td>
<td><strong>40</strong></td>
</tr>
</tbody>
</table>

*Note.* Gender and race/ethnicity information of those who completed surveys (N = 60), those who participated in Wave 1 (W1) cortisol collection (n = 46), and those who participated in Wave 2 (W2) cortisol collection (n = 40).
Table 4

*Retention of Study 1 Diurnal Cortisol Data Sample Size at Each Time Point*

<table>
<thead>
<tr>
<th>Wave 1</th>
<th>Day 1</th>
<th>Day 2</th>
<th>Valid Pairwise</th>
<th>Valid Listwise</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wake</td>
<td>45</td>
<td>44</td>
<td>45</td>
<td>44 (97.78%)</td>
</tr>
<tr>
<td>Peak</td>
<td>45</td>
<td>44</td>
<td>45</td>
<td>44 (97.78%)</td>
</tr>
<tr>
<td>Bed</td>
<td>45</td>
<td>44</td>
<td>45</td>
<td>44 (97.78%)</td>
</tr>
<tr>
<td>Wave 2</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wake</td>
<td>37</td>
<td>37</td>
<td>39</td>
<td>35 (89.74%)</td>
</tr>
<tr>
<td>Peak</td>
<td>37</td>
<td>38</td>
<td>39</td>
<td>36 (92.31%)</td>
</tr>
<tr>
<td>Bed</td>
<td>37</td>
<td>39</td>
<td>39</td>
<td>37 (94.87%)</td>
</tr>
<tr>
<td>Total</td>
<td>–</td>
<td>–</td>
<td>39</td>
<td>35 (–)</td>
</tr>
</tbody>
</table>

*Notes.* Wake = Upon awakening; Peak = 30-minutes upon awakening; Bed = Bedtime. Number of participants who completed raw cortisol samples during each of the two consecutive days for each wave out of all 60 participants; listwise % were out of 45 for Wave 1 and out of 39 for Wave 2. These numbers do not include the case excluded from cortisol analysis.
Table 5

Descriptive Statistics: Mean Cortisol Levels (µg/dL) between Two Consecutive Days at Upon-awakening (Wake), 30-minutes Upon-awakening (Peak), and Bedtime (Bed) for Wave 1 (W1) and Wave 2 (W2)

<table>
<thead>
<tr>
<th></th>
<th>Mean cortisol levels</th>
<th>Log-transformed mean cortisol levels</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Skewness</td>
</tr>
<tr>
<td>N</td>
<td>M</td>
<td>SD</td>
</tr>
<tr>
<td>W1 Wake</td>
<td>4</td>
<td>0.3</td>
</tr>
<tr>
<td>W1 Peak</td>
<td>5</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4</td>
</tr>
<tr>
<td>W1 Bed</td>
<td>5</td>
<td>1</td>
</tr>
<tr>
<td>W2 Wake</td>
<td>3</td>
<td>0.3</td>
</tr>
<tr>
<td>W2 Peak</td>
<td>9</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3</td>
</tr>
<tr>
<td>W2 Bed</td>
<td>9</td>
<td>3</td>
</tr>
</tbody>
</table>

Notes. The average values allowed for one day of missing data to retain the maximum amount of participant data. Valid listwise N = 39.
Table 6

Descriptive Statistics for Diurnal Cortisol Parameters: Diurnal Cortisol Slope (DS) and Cortisol Awakening Response (CAR) for Wave 1 (W1) and Wave 2 (W2)

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>M</th>
<th>SD</th>
<th>Median</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>W1 DS</td>
<td>39</td>
<td>0.10</td>
<td>0.06</td>
<td>.10</td>
<td>0.34</td>
<td>0.31</td>
</tr>
<tr>
<td>W2 DS</td>
<td>34</td>
<td>0.09</td>
<td>0.07</td>
<td>.09</td>
<td>-0.06</td>
<td>0.34</td>
</tr>
<tr>
<td>W1 CAR</td>
<td>45</td>
<td>0.38</td>
<td>0.54</td>
<td>.34</td>
<td>0.51</td>
<td>0.41</td>
</tr>
<tr>
<td>W2 CAR</td>
<td>39</td>
<td>0.42</td>
<td>0.63</td>
<td>.37</td>
<td>0.83</td>
<td>0.50</td>
</tr>
</tbody>
</table>

*Note. Valid listwise N = 32.*
Table 7

*Bivariate Correlations between the Diurnal Cortisol Parameters*

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 W1 DS</td>
<td>–</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 W2 DS</td>
<td>.593***</td>
<td>–</td>
<td></td>
</tr>
<tr>
<td>3 W1 CAR</td>
<td>-.452**</td>
<td>-.263</td>
<td>–</td>
</tr>
<tr>
<td>4 W2 CAR</td>
<td>-.276</td>
<td>-.231</td>
<td>.742***</td>
</tr>
</tbody>
</table>

*Note. **p < .01; ***p < .001 (2-tailed).*
Table 8

Results of t-tests and Descriptive Statistics: Examining Gender Differences in Mean-level Cortisol (log-transformed µg/dL) and Diurnal Cortisol Parameters

<table>
<thead>
<tr>
<th></th>
<th>Male</th>
<th>Female</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>M</td>
<td>SD</td>
<td>n</td>
<td>M</td>
<td>SD</td>
<td>n</td>
</tr>
<tr>
<td>W1</td>
<td>Wake</td>
<td>-1.06</td>
<td>0.47</td>
<td>31</td>
<td>-1.15</td>
<td>0.43</td>
</tr>
<tr>
<td>W1</td>
<td>Peak</td>
<td>-0.75</td>
<td>0.43</td>
<td>31</td>
<td>-0.56</td>
<td>0.70</td>
</tr>
<tr>
<td>W1</td>
<td>Bed</td>
<td>-2.67</td>
<td>0.75</td>
<td>31</td>
<td>-2.33</td>
<td>0.79</td>
</tr>
<tr>
<td>W2</td>
<td>Wake</td>
<td>-1.10</td>
<td>0.60</td>
<td>26</td>
<td>-1.13</td>
<td>0.57</td>
</tr>
<tr>
<td>W2</td>
<td>Peak</td>
<td>-0.76</td>
<td>0.59</td>
<td>26</td>
<td>-0.50</td>
<td>0.61</td>
</tr>
<tr>
<td>W2</td>
<td>Bed</td>
<td>-2.60</td>
<td>0.92</td>
<td>26</td>
<td>-2.26</td>
<td>0.65</td>
</tr>
<tr>
<td>W1</td>
<td>DS</td>
<td>0.11</td>
<td>0.07</td>
<td>27</td>
<td>0.07</td>
<td>0.04</td>
</tr>
<tr>
<td>W2</td>
<td>DS</td>
<td>0.10</td>
<td>0.07</td>
<td>25</td>
<td>0.06</td>
<td>0.06</td>
</tr>
<tr>
<td>W1</td>
<td>CAR</td>
<td>0.31</td>
<td>0.58</td>
<td>31</td>
<td>0.59</td>
<td>0.41</td>
</tr>
<tr>
<td>W2</td>
<td>CAR</td>
<td>0.34</td>
<td>0.68</td>
<td>26</td>
<td>0.63</td>
<td>0.50</td>
</tr>
</tbody>
</table>

Notes. <sup>a</sup> Equal variances not assumed for the two groups (Levine’s test p < .05). <sup>b</sup> All effect sizes reported as Cohen’s d except for those with equal variances not assumed, whose effect size was reported as Glass’s delta.

<sup>†</sup>p < .10 (two-tailed).
Table 9

Results of $t$-tests and Descriptive Statistics: Examining Minority Status Differences in Mean-level Cortisol (Log-transformed $\mu$g/dL) and Diurnal Cortisol Parameters

<table>
<thead>
<tr>
<th></th>
<th>Minority</th>
<th></th>
<th>White</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$M$</td>
<td>$SD$</td>
<td>$n$</td>
<td>$M$</td>
<td>$SD$</td>
<td>$n$</td>
<td>$t$</td>
<td>$df$</td>
</tr>
<tr>
<td>W1 Wake</td>
<td>-1.29</td>
<td>0.44</td>
<td>18</td>
<td>-0.94</td>
<td>0.42</td>
<td>25</td>
<td>2.61*</td>
<td>41</td>
</tr>
<tr>
<td>W1 Peak</td>
<td>-0.67</td>
<td>0.63</td>
<td>18</td>
<td>-0.72</td>
<td>0.43</td>
<td>25</td>
<td>-0.33</td>
<td>41</td>
</tr>
<tr>
<td>W1 Bed</td>
<td>-2.76</td>
<td>0.60</td>
<td>18</td>
<td>-2.44</td>
<td>0.86</td>
<td>25</td>
<td>1.37</td>
<td>41</td>
</tr>
<tr>
<td>W2 Wake</td>
<td>-1.21</td>
<td>0.64</td>
<td>13</td>
<td>-1.05</td>
<td>0.55</td>
<td>24</td>
<td>0.8</td>
<td>35</td>
</tr>
<tr>
<td>W2 Peak</td>
<td>-0.66</td>
<td>0.57</td>
<td>13</td>
<td>-0.70</td>
<td>0.63</td>
<td>24</td>
<td>-0.18</td>
<td>35</td>
</tr>
<tr>
<td>W2 Bed</td>
<td>-2.62</td>
<td>0.85</td>
<td>13</td>
<td>-2.43</td>
<td>0.87</td>
<td>24</td>
<td>0.63</td>
<td>35</td>
</tr>
<tr>
<td>W1 DS</td>
<td>0.09</td>
<td>0.05</td>
<td>16</td>
<td>0.10</td>
<td>0.07</td>
<td>21</td>
<td>0.86</td>
<td>35</td>
</tr>
<tr>
<td>W2 DS</td>
<td>0.09</td>
<td>0.09</td>
<td>11</td>
<td>0.09</td>
<td>0.06</td>
<td>22</td>
<td>-0.19</td>
<td>31</td>
</tr>
<tr>
<td>W1 CAR</td>
<td>0.63</td>
<td>0.62</td>
<td>18</td>
<td>0.22</td>
<td>0.43</td>
<td>25</td>
<td>-2.51*</td>
<td>41</td>
</tr>
<tr>
<td>W2 CAR</td>
<td>0.55</td>
<td>0.76</td>
<td>13</td>
<td>0.36</td>
<td>0.57</td>
<td>24</td>
<td>-0.89</td>
<td>35</td>
</tr>
</tbody>
</table>

Notes. Equal variances were assumed for all $t$-tests. Effect sizes reported as Cohen’s $d$.

*p < .05 (two-tailed).
Table 10

*Estimated Descriptive Statistics of Diurnal Cortisol Parameters after Adjusting for Missingness*

<table>
<thead>
<tr>
<th></th>
<th>M</th>
<th>SD</th>
<th>SE</th>
</tr>
</thead>
<tbody>
<tr>
<td>W1 DS</td>
<td>.104</td>
<td>.010</td>
<td>10.35</td>
</tr>
<tr>
<td>W2 DS</td>
<td>.095</td>
<td>.011</td>
<td>8.99</td>
</tr>
<tr>
<td>W1 CAR</td>
<td>.383</td>
<td>.087</td>
<td>4.39</td>
</tr>
<tr>
<td>W2 CAR</td>
<td>.452</td>
<td>.090</td>
<td>5.02</td>
</tr>
</tbody>
</table>
Table 11

*Cross Tabulation for Association between DS Group Status and CAR Group Status*

<table>
<thead>
<tr>
<th>DS Group</th>
<th>CAR Group</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>High-high</td>
<td>High-low</td>
</tr>
<tr>
<td>High-high</td>
<td>4</td>
<td>0</td>
</tr>
<tr>
<td>High-low</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Low-low</td>
<td>6</td>
<td>0</td>
</tr>
<tr>
<td>Low-high</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>14</strong></td>
<td><strong>2</strong></td>
</tr>
<tr>
<td>Characteristic</td>
<td>W1 Survey</td>
<td>W1 Cortisol</td>
</tr>
<tr>
<td>---------------------</td>
<td>-----------</td>
<td>-------------</td>
</tr>
<tr>
<td></td>
<td>N (%)</td>
<td>n (%)</td>
</tr>
<tr>
<td>Gender</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>37 (55.2)</td>
<td>37 (58.7)</td>
</tr>
<tr>
<td>Female</td>
<td>29 (43.3)</td>
<td>25 (39.7)</td>
</tr>
<tr>
<td>Missing</td>
<td>1 (1.5)</td>
<td>1 (1.6)</td>
</tr>
<tr>
<td>Race/Ethnicity</td>
<td></td>
<td></td>
</tr>
<tr>
<td>American Indian</td>
<td>1 (1.5)</td>
<td>1 (1.6)</td>
</tr>
<tr>
<td>Asian</td>
<td>23 (34.8)</td>
<td>23 (36.5)</td>
</tr>
<tr>
<td>Hispanic</td>
<td>4 (6.1)</td>
<td>3 (4.8)</td>
</tr>
<tr>
<td>Black</td>
<td>1 (1.5)</td>
<td>1 (1.6)</td>
</tr>
<tr>
<td>White</td>
<td>33 (50.0)</td>
<td>30 (47.6)</td>
</tr>
<tr>
<td>Mixed Race</td>
<td>4 (6.1)</td>
<td>4 (6.3)</td>
</tr>
<tr>
<td>Missing</td>
<td>1 (1.5)</td>
<td>1 (1.6)</td>
</tr>
<tr>
<td>Total</td>
<td>67</td>
<td>63</td>
</tr>
</tbody>
</table>

*Note.* Gender and race/ethnicity information of those who completed Wave 1 (W1) surveys (N = 67), those who participated in Wave 1 (W1) cortisol collection (n = 63), those who participated in Wave 2 (W2) cortisol collection (n = 47), and those who participated in Wave 3 (W3) cortisol collection (n = 43).
Table 13

*Retention of Study 2 Diurnal Cortisol Data Sample Size at Each Time Point*

<table>
<thead>
<tr>
<th></th>
<th>Day 1</th>
<th>Day 2</th>
<th>Valid Pairwise</th>
<th>Valid Listwise</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Wave 1</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wake</td>
<td>62</td>
<td>62</td>
<td>63</td>
<td>62 (98.41%)</td>
</tr>
<tr>
<td>Peak</td>
<td>62</td>
<td>62</td>
<td>63</td>
<td>62 (98.41%)</td>
</tr>
<tr>
<td>Bed</td>
<td>60</td>
<td>63</td>
<td>63</td>
<td>60 (95.24%)</td>
</tr>
<tr>
<td><strong>Wave 2</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wake</td>
<td>44</td>
<td>45</td>
<td>47</td>
<td>42 (89.36%)</td>
</tr>
<tr>
<td>Peak</td>
<td>44</td>
<td>46</td>
<td>47</td>
<td>43 (91.49%)</td>
</tr>
<tr>
<td>Bed</td>
<td>44</td>
<td>45</td>
<td>46</td>
<td>43 (91.49%)</td>
</tr>
<tr>
<td><strong>Wave 3</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wake</td>
<td>43</td>
<td>41</td>
<td>43</td>
<td>42 (97.67%)</td>
</tr>
<tr>
<td>Peak</td>
<td>43</td>
<td>41</td>
<td>43</td>
<td>41 (95.35%)</td>
</tr>
<tr>
<td>Bed</td>
<td>43</td>
<td>42</td>
<td>43</td>
<td>41 (95.35%)</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>–</td>
<td>–</td>
<td>43</td>
<td>41 (–)</td>
</tr>
</tbody>
</table>

*Notes.* Wake = Upon awakening; Peak = 30-minutes upon awakening; Bed = Bedtime. Number of participants who completed raw cortisol samples during each of the two consecutive days for each wave out of all 67 participants; listwise % were out of 63 for Wave 1, out of 47 for Wave 2, and out of 43 for Wave 3.
Table 14

Study 2 Descriptive Statistics: Mean Cortisol Levels (µg/dL) and Log-transformed Mean Cortisol Levels between Two Consecutive Days at Upon-awakening (Wake), 30-minutes Upon-awakening (Peak), and Bedtime (Bed) for Wave 1 (W1), Wave 2 (W2), and Wave 3 (W3).

<table>
<thead>
<tr>
<th></th>
<th>Mean cortisol levels</th>
<th>Mean cortisol levels (log)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>M</td>
</tr>
<tr>
<td>W1 Wake</td>
<td>63</td>
<td>10.91</td>
</tr>
<tr>
<td>W1 Peak</td>
<td>63</td>
<td>14.30</td>
</tr>
<tr>
<td>W1 Bed</td>
<td>63</td>
<td>3.88</td>
</tr>
<tr>
<td>W2 Wake</td>
<td>46</td>
<td>11.22</td>
</tr>
<tr>
<td>W2 Peak</td>
<td>47</td>
<td>13.53</td>
</tr>
<tr>
<td>W2 Bed</td>
<td>47</td>
<td>3.55</td>
</tr>
<tr>
<td>W3 Wake</td>
<td>43</td>
<td>10.71</td>
</tr>
<tr>
<td>W3 Peak</td>
<td>43</td>
<td>12.74</td>
</tr>
<tr>
<td>W3 Bed</td>
<td>43</td>
<td>2.65</td>
</tr>
</tbody>
</table>

Notes. The average values allowed for one day of missing data to retain the maximum amount of participant data. Valid listwise N = 39.
Table 15

*Study 2 Descriptive Statistics for Diurnal Cortisol Parameters: Diurnal Cortisol Slope (DS) and Cortisol Awakening Response (CAR) for Wave 1 (W1), Wave 2 (W2), and Wave 3 (W3).*

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>M</th>
<th>SD</th>
<th>Median</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>W1 DS</td>
<td>58</td>
<td>.062</td>
<td>.037</td>
<td>.068</td>
<td>-.39</td>
<td>-.025</td>
</tr>
<tr>
<td>W2 DS</td>
<td>39</td>
<td>.058</td>
<td>.039</td>
<td>.059</td>
<td>-.23</td>
<td>-.90</td>
</tr>
<tr>
<td>W3 DS</td>
<td>40</td>
<td>.061</td>
<td>.032</td>
<td>.059</td>
<td>.10</td>
<td>-.31</td>
</tr>
<tr>
<td>W1 CAR</td>
<td>63</td>
<td>.29</td>
<td>.56</td>
<td>.33</td>
<td>-.54</td>
<td>1.74</td>
</tr>
<tr>
<td>W2 CAR</td>
<td>47</td>
<td>.16</td>
<td>.54</td>
<td>.057</td>
<td>-.39</td>
<td>1.89</td>
</tr>
<tr>
<td>W3 CAR</td>
<td>43</td>
<td>.15</td>
<td>.55</td>
<td>.12</td>
<td>.18</td>
<td>-.75</td>
</tr>
</tbody>
</table>

*Note.* Valid listwise N = 30.
Table 16

*Study 2 Bivariate Correlations between the Diurnal Cortisol Parameters*

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<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 W1 DS</td>
<td>–</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 W2 DS</td>
<td>.54***</td>
<td>–</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 W3 DS</td>
<td>.28†</td>
<td>.19</td>
<td>–</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4 W1 CAR</td>
<td>.024</td>
<td>-.17</td>
<td>-.084</td>
<td>–</td>
<td></td>
</tr>
<tr>
<td>5 W2 CAR</td>
<td>-.003</td>
<td>-.28†</td>
<td>.24</td>
<td>.19</td>
<td>–</td>
</tr>
<tr>
<td>6 W3 CAR</td>
<td>.31*</td>
<td>.083</td>
<td>-.038</td>
<td>.28†</td>
<td>.16</td>
</tr>
</tbody>
</table>

*Note.* †p < .10, *p < .05, ***p < .001 (2-tailed).
Table 17

Study 2 Results of t-tests and Descriptive Statistics: Examining Gender Differences in Mean-level Cortisol (log-transformed µg/dL) and Diurnal Cortisol Parameters

<table>
<thead>
<tr>
<th></th>
<th>Male</th>
<th>Female</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>M</td>
<td>SD</td>
<td>n</td>
<td>M</td>
<td>SD</td>
<td>n</td>
<td>t</td>
</tr>
<tr>
<td>W1 W</td>
<td>2.13</td>
<td>.52</td>
<td>37</td>
<td>2.34</td>
<td>.70</td>
<td>25</td>
<td>-1.40</td>
</tr>
<tr>
<td>W1 P</td>
<td>2.26</td>
<td>.61</td>
<td>37</td>
<td>2.75</td>
<td>.66</td>
<td>25</td>
<td>-3.01**</td>
</tr>
<tr>
<td>W1 B</td>
<td>.54</td>
<td>1.02</td>
<td>37</td>
<td>.70</td>
<td>1.25</td>
<td>25</td>
<td>-5.4</td>
</tr>
<tr>
<td>W2 W</td>
<td>2.26</td>
<td>.44</td>
<td>25</td>
<td>2.37</td>
<td>.57</td>
<td>21</td>
<td>-.73</td>
</tr>
<tr>
<td>W2 P</td>
<td>2.40</td>
<td>.66</td>
<td>25</td>
<td>2.51</td>
<td>.55</td>
<td>21</td>
<td>-.61</td>
</tr>
<tr>
<td>W2 B</td>
<td>.86</td>
<td>1.07</td>
<td>25</td>
<td>.91</td>
<td>.71</td>
<td>20</td>
<td>-.21a</td>
</tr>
<tr>
<td>W3W</td>
<td>2.28</td>
<td>.56</td>
<td>22</td>
<td>2.24</td>
<td>.51</td>
<td>20</td>
<td>.27</td>
</tr>
<tr>
<td>W3 P</td>
<td>2.20</td>
<td>.44</td>
<td>22</td>
<td>2.58</td>
<td>.64</td>
<td>20</td>
<td>-2.26*</td>
</tr>
<tr>
<td>W3 B</td>
<td>.62</td>
<td>1.05</td>
<td>22</td>
<td>.64</td>
<td>.67</td>
<td>20</td>
<td>-0.07</td>
</tr>
<tr>
<td>W1 DS</td>
<td>.062</td>
<td>.038</td>
<td>34</td>
<td>.064</td>
<td>.035</td>
<td>24</td>
<td>0.22</td>
</tr>
<tr>
<td>W2 DS</td>
<td>.052</td>
<td>.043</td>
<td>23</td>
<td>.067</td>
<td>.033</td>
<td>16</td>
<td>-1.17</td>
</tr>
<tr>
<td>W3 DS</td>
<td>.059</td>
<td>.038</td>
<td>20</td>
<td>.062</td>
<td>.024</td>
<td>20</td>
<td>-0.28a</td>
</tr>
<tr>
<td>W1CAR</td>
<td>.17</td>
<td>.58</td>
<td>37</td>
<td>.41</td>
<td>.44</td>
<td>25</td>
<td>-1.74†</td>
</tr>
<tr>
<td>W2CAR</td>
<td>.15</td>
<td>.62</td>
<td>25</td>
<td>.14</td>
<td>.43</td>
<td>21</td>
<td>.07</td>
</tr>
<tr>
<td>W3CAR</td>
<td>-.081</td>
<td>.49</td>
<td>22</td>
<td>.34</td>
<td>.49</td>
<td>20</td>
<td>-2.80**</td>
</tr>
</tbody>
</table>

Notes. W = Wake, P = Peak, B = Bedtime.

*aEqual variances not assumed for the two groups (Levine’s test p < .05). bAll effect sizes reported as Cohen’s d except for those with equal variances not assumed, whose effect size was reported as Glass’s delta.

†p < .10, *p < .05, **p < .01 (two-tailed).
Table 18

Results of t-tests and Descriptive Statistics: Examining Minority Status Differences in Mean-level Cortisol (log-transformed µg/dL) and Diurnal Cortisol Parameters

<table>
<thead>
<tr>
<th></th>
<th>White</th>
<th>Minority</th>
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<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>M</td>
<td>SD</td>
<td>n</td>
<td>M</td>
<td>SD</td>
<td>n</td>
<td>t</td>
<td>df</td>
<td>95% CI</td>
<td>d</td>
<td></td>
<td></td>
</tr>
<tr>
<td>W1 W</td>
<td>2.15</td>
<td>.67</td>
<td>30</td>
<td>2.28</td>
<td>.54</td>
<td>32</td>
<td>-.86</td>
<td>60</td>
<td>-.44, .17</td>
<td>.21</td>
<td></td>
<td></td>
</tr>
<tr>
<td>W1 P</td>
<td>2.38</td>
<td>.74</td>
<td>30</td>
<td>2.53</td>
<td>.61</td>
<td>32</td>
<td>-.91</td>
<td>60</td>
<td>-.50, .19</td>
<td>.22</td>
<td></td>
<td></td>
</tr>
<tr>
<td>W1 B</td>
<td>.59</td>
<td>1.08</td>
<td>30</td>
<td>.62</td>
<td>1.15</td>
<td>32</td>
<td>-.11</td>
<td>60</td>
<td>-.60, .54</td>
<td>.03</td>
<td></td>
<td></td>
</tr>
<tr>
<td>W2 W</td>
<td>2.26</td>
<td>.41</td>
<td>25</td>
<td>2.36</td>
<td>.60</td>
<td>21</td>
<td>-.64</td>
<td>34.62a</td>
<td>-.41, .22</td>
<td>.24b</td>
<td></td>
<td></td>
</tr>
<tr>
<td>W2 P</td>
<td>2.24</td>
<td>.64</td>
<td>25</td>
<td>2.70</td>
<td>.46</td>
<td>21</td>
<td>-2.75**</td>
<td>.80, -.12</td>
<td>.83</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>W2 B</td>
<td>.83</td>
<td>.95</td>
<td>25</td>
<td>.95</td>
<td>.90</td>
<td>20</td>
<td>-.44</td>
<td>43</td>
<td>-.68, .44</td>
<td>.13</td>
<td></td>
<td></td>
</tr>
<tr>
<td>W3 W</td>
<td>2.23</td>
<td>.61</td>
<td>22</td>
<td>2.30</td>
<td>.44</td>
<td>20</td>
<td>-.46</td>
<td>40</td>
<td>-.41, .26</td>
<td>.13</td>
<td></td>
<td></td>
</tr>
<tr>
<td>W3 P</td>
<td>2.40</td>
<td>.56</td>
<td>22</td>
<td>2.36</td>
<td>.59</td>
<td>20</td>
<td>-.22</td>
<td>40</td>
<td>-.32, 40</td>
<td>.00</td>
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</tr>
<tr>
<td>W3 B</td>
<td>.47</td>
<td>.97</td>
<td>22</td>
<td>.80</td>
<td>.76</td>
<td>20</td>
<td>-1.20</td>
<td>40</td>
<td>-.87, .22</td>
<td>.38</td>
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<tr>
<td>W1DS</td>
<td>.063</td>
<td>.038</td>
<td>28</td>
<td>.063</td>
<td>.037</td>
<td>30</td>
<td>.063</td>
<td>56</td>
<td>-.02, .02</td>
<td>.00</td>
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</tr>
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<td>.039</td>
<td>22</td>
<td>.054</td>
<td>.041</td>
<td>17</td>
<td>.061</td>
<td>37</td>
<td>-.02, .03</td>
<td>.17</td>
<td></td>
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<td>.034</td>
<td>20</td>
<td>.058</td>
<td>.030</td>
<td>20</td>
<td>.064</td>
<td>38</td>
<td>-.01, .03</td>
<td>.19</td>
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<td>W1CAR</td>
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<td>30</td>
<td>.26</td>
<td>.49</td>
<td>32</td>
<td>.15</td>
<td>60</td>
<td>-.26, .30</td>
<td>.04</td>
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<td>25</td>
<td>.34</td>
<td>.49</td>
<td>21</td>
<td>-2.30*</td>
<td>-.66, -.04</td>
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<td>.062</td>
<td>.56</td>
<td>20</td>
<td>.69</td>
<td>40</td>
<td>-.22, .45</td>
<td>.22</td>
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<td></td>
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</tbody>
</table>

Notes. W = Wake, P = Peak, B = Bedtime.

aEqual variances not assumed for the two groups (Levine’s test \( p < .05 \)). bAll effect sizes reported as Cohen’s \( d \) except for those with equal variances not assumed, whose effect size was reported as Glass’s \( \delta \).

*\( p < .05 \), **\( p < .01 \) (two-tailed).
Table 19

Study 2 Results of t-tests and Descriptive Statistics: Examining Under-represented (UR) Minority Status Differences in Mean-level Cortisol (log-transformed µg/dL) and Diurnal Cortisol Parameters

<table>
<thead>
<tr>
<th>Other</th>
<th>UR Minority</th>
<th>M</th>
<th>SD</th>
<th>n</th>
<th>M</th>
<th>SD</th>
<th>n</th>
<th>t</th>
<th>df</th>
<th>95% CI</th>
<th>d</th>
</tr>
</thead>
<tbody>
<tr>
<td>W1 W</td>
<td>2.21</td>
<td>.62</td>
<td>53</td>
<td>2.21</td>
<td>.50</td>
<td>9</td>
<td>.00</td>
<td>60</td>
<td></td>
<td>- .44, .44</td>
<td>.00</td>
</tr>
<tr>
<td>W1 P</td>
<td>2.44</td>
<td>.66</td>
<td>53</td>
<td>2.56</td>
<td>.76</td>
<td>9</td>
<td>-.47</td>
<td>60</td>
<td></td>
<td>- .60, .37</td>
<td>.17</td>
</tr>
<tr>
<td>W1 B</td>
<td>.66</td>
<td>1.12</td>
<td>53</td>
<td>0.28</td>
<td>1.05</td>
<td>9</td>
<td>.95</td>
<td>60</td>
<td></td>
<td>- .42, 1.18</td>
<td>.35</td>
</tr>
<tr>
<td>W2 W</td>
<td>2.28</td>
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<td>.45</td>
<td>6</td>
<td>-.79</td>
<td>44</td>
<td></td>
<td>- .62, .27</td>
<td>.37</td>
</tr>
<tr>
<td>W2 P</td>
<td>2.41</td>
<td>.64</td>
<td>40</td>
<td>2.70</td>
<td>.29</td>
<td>6</td>
<td>-1.08</td>
<td>44</td>
<td></td>
<td>- .82, .25</td>
<td>.58</td>
</tr>
<tr>
<td>W2 B</td>
<td>.84</td>
<td>.91</td>
<td>39</td>
<td>1.14</td>
<td>1.03</td>
<td>6</td>
<td>-.72</td>
<td>43</td>
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<td>-1.11, .52</td>
<td>.31</td>
</tr>
<tr>
<td>W3 W</td>
<td>2.26</td>
<td>.57</td>
<td>37</td>
<td>2.26</td>
<td>.14</td>
<td>5</td>
<td>.01a</td>
<td>27.23a</td>
<td>22.3</td>
<td>- .23, .23</td>
<td>.42</td>
</tr>
<tr>
<td>W3 P</td>
<td>2.42</td>
<td>.59</td>
<td>37</td>
<td>2.15</td>
<td>.37</td>
<td>5</td>
<td>1.00</td>
<td>40</td>
<td></td>
<td>- .28, .82</td>
<td>.55</td>
</tr>
<tr>
<td>W3 B</td>
<td>.68</td>
<td>.90</td>
<td>37</td>
<td>.28</td>
<td>.72</td>
<td>5</td>
<td>.93</td>
<td>40</td>
<td></td>
<td>- .46, 1.24</td>
<td>.49</td>
</tr>
<tr>
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Notes. W = Wake, P = Peak, B = Bedtime.

*aEqual variances not assumed for the two groups (Levine’s test p < .05). bAll effect sizes reported as Cohen’s d, except for those with equal variances not assumed, whose effect size was reported as Glass’s delta.
Table 20

*Study 2 Cross Tabulation for Association between DS patterns and CAR Patterns over Time*

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</table>

Note. *N* = 30. Patterns over Wave 1, Wave 2, and Wave 3: HHH = High-high-high, HHL = High-high-low, HLL = High-low-low, HLH = High-low-high, LHH = Low-high-high, LLH = Low-low-high, LHL = Low-high-low, LLL = Low-low-low. Association between DS and CAR patterns was not significant, $\chi^2_{(49, \ n = 30)} = 43.97, \ p = .68$. 

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Figure 1. The theoretical model: solid lines represent predictions from Study 1, and dashed lines represent predictions from Study 2. LHL = Learning-related Hopelessness, FTPC = Future Time Perspective Connectedness, FTPV = Future Time Perspective Value, Regulatory Resources = Effortful Control and Social Support (as separate constructs but both with regulatory implications); Diurnal Cortisol Patterns Over Time = two waves for Study 1 and three waves for Study 2.
Figure 2. Study 1 bar charts of missing diurnal cortisol data at Wave 2 with regards to minority status; 0 = Data Missing, 1 = Data Present. All four cross tabulation analyses for Pearson Chi-squares were significant at the $p < .05$ level (two-tailed).
REFERENCES


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control, academic relationships, and school avoidance. *Merrill-Palmer Quarterly*, 58(3), 375-408.


APPENDIX A

STUDY I BIVARIATE CORRELATION MATRIX OF RAW DATA
APPENDIX B

STUDY 2 BIVARIATE CORRELATION MATRIX OF RAW DATA