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BED AND BREAKFAST: THE ROLE OF SLEEP AND AFFECT IN BREAKFAST INTAKE

Ashley R. MacPherson
Virginia Commonwealth University

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A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science
at Virginia Commonwealth University.

By: ASHLEY MACPHERSON, M.A.
Bachelor of Arts, University of New Hampshire, May 2015
Master of Arts, Boston College, May 2017

Director: Natalie Dautovich, Ph.D.
Assistant Professor of Psychology
Department of Psychology

Virginia Commonwealth University
Richmond, Virginia
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Abstract

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Breakfast intake is associated with numerous positive physical and mental health outcomes, yet breakfast skipping remains common in adults. Chronotype and sleep show potential as predictors of breakfast intake; however the existing literature has methodological limitations and fails to examine how psychological mechanisms might explain the relation between sleep and breakfast. The current investigation explored the association of means and variability of sleep behaviors (bedtime, midsleep, sleep duration) as predictors of breakfast intake frequency and high-protein breakfast intake frequency. Additionally, the role of positive and negative affect as mediators in the sleep—breakfast association was examined. Hierarchical regressions and PROCESS parallel mediation models were conducted to assess direct and indirect associations. Variability in bedtime was a significant predictor of breakfast intake frequency, with greater variability associated with less frequent intake. Future work is necessary to examine further the association of sleep and breakfast behaviors, and psychological mechanisms in this relation.

Bed and Breakfast: The Role of Sleep and Affect in Breakfast Intake

Breakfast is considered the most important meal of the day; yet breakfast skipping remains common among American adults (Kant & Graubard, 2006). In fact, 18% of American adults skip breakfast according to the National Health and Nutrition Examination Survey (NHANES; Kant & Graubard, 2006). Consequently, there is a need to identify factors that serve to facilitate or act as a barrier to eating breakfast on a regular basis. Given that consuming breakfast is a circadian behavior that occurs once per 24-hour period, other circadian events occurring during the same 24-hour period show potential as predictors of breakfast intake. In particular, a small body of research has shown that the timing of the sleep period and the time of day preference for sleep (e.g., chronotype) are associated with breakfast consumption (Meule, Roeser, Randler, & Kübler; 2012; Ogilvie et al., 2017; Reutrakul et al, 2014; Teixeira, Mota, & Crispim, 2017; Walker & Christopher, 2015). However, the existing small body of research examining sleep as a predictor of breakfast outcomes has significant limitations. In particular, existing research has relied on retrospective, single-time assessments of sleep, and failed to examine macronutrient composition of breakfast intake. Additionally, these studies have overlooked important components of sleep, relied on averages of sleep behaviors as indicators of sleep, and neglected to examine potential mediators tying sleep to breakfast intake. Consequently, the ultimate aim of the current study is to add to the existing knowledge base regarding the role of sleep in breakfast intake by addressing these methodological limitations.

Furthermore, the role of affect as a potential mediator of the sleep—breakfast association is explored to advance the current knowledge on processes that predict breakfast intake.

The Importance of Breakfast Intake

Breakfast, the first meal of the day that breaks the nightly fasting period, is often regarded as the most important meal of the day (Spence, 2017). Breakfast is a marker for the beginning of a new day and provides energy for all activities that lay ahead (Spence, 2017). Nutrition is well recognized as a critical factor affecting our physical and mental health, and breakfast consumption is known to be one of the key components of a healthy diet (Rampersaud, Pereira, Girard, Adams, & Metzl, 2005). Breakfast serves as a catalyst for a series of physiological effects, which, in turn, set off a chain of events throughout the day (Jakubowicz, Barnea, Wainstein, & Froy, 2013; Smith, 2002). For example, breakfast intake has strong entraining effects on other circadian rhythms including hormonal activity (Froy, 2010; Green, Takahashi, & Bass, 2008; Panda et al., 2002). Given the crucial impact breakfast has on physical and mental well-being, there is a need to identify factors that promote its intake. Currently, the majority of research examining the benefits of eating breakfast has focused on children and adolescents. Breakfast intake has been associated with better memory, grades, and school attendance (Rampersaud et al., 2005; Sampasa-Kanyinga & Hamilton, 2016), and decreased stress, anxiety, and depression (Richards & Smith, 2016). However, there also are notable benefits associated with eating breakfast in adults.

Specifically, for adults, breakfast intake is associated with better cognitive, mental health, cardiometabolic, and weight outcomes. Eating breakfast daily is associated with better memory, motor, and executive functioning in adults (Galioto & Spitznagel, 2016), and higher reading scores in older adults (Smith, 1998). In addition to the cognitive benefits of breakfast consumption, eating breakfast has also been associated with more positive mental health outcomes. College students who consumed breakfast were found to have higher happiness and lower depressive symptoms in comparison to peers who skipped breakfast (Lee et al., 2017; Lesani, Mohammadpoorasl, Javadi, Esfeh, & Fakhari, 2016). Greater health-related quality of life, social functioning, and mental health were also associated with breakfast intake in Taiwanese adults (Huang, Hu, Fan, Liao, & Tsai, 2010). These studies collectively suggest that breakfast intake is associated with better cognitive and mental health outcomes.

Breakfast intake is also consistently associated with better cardiometabolic and health outcomes. Men who consume breakfast have been shown to have significantly lower risk for coronary heart disease and stroke (Cahill et al., 2013; Kubota, Iso, Sawada, & Tsugane, 2016). Furthermore, Type 2 diabetes risk was found to be lower for both males and females who consumed breakfast in comparison to their peers who skipped breakfast (Mekary, Giovannucci, Willett, van Dam, & Hu, 2012; Mekary et al., 2013). In addition to cardiometabolic outcomes such as coronary heart disease and diabetes, much of the literature has examined the role of breakfast in achieving healthy weight outcomes. In a study investigating the effects of breakfast intake in participants enrolled in obesity treatment, baseline breakfast intake did not predict weight loss during treatment; however increases in breakfast eating during treatment were associated with better weight loss outcomes (Megson, Wing, & Leahy, 2016). Additionally, when examining the weight loss strategies in a sample of overweight participants with Type 2 diabetes, those with fewer breakfast meals in a week had higher BMIs (Raynor, Jeffery, Ruggiero, Clark, & Delahanty, 2008). Experimental studies have also demonstrated an association between breakfast intake and weight. In a study with participants identified as overweight with metabolic syndrome or obese with metabolic syndrome, researchers assigned participants to a group that consumed a higher calorie breakfast and lower calorie dinner, or a group that consumed a lower calorie breakfast and higher calorie dinner (Jakubowicz et al., 2013). Participants who had the higher calorie breakfast had significantly greater weight loss and decreases in waist circumference. These results indicate that when calories are distributed towards breakfast meals, as opposed to other meals, there are better weight outcomes. Overall, the existing research suggests that breakfast intake is associated with better weight outcomes.

When examining obesity outcomes, it is necessary to investigate other markers of obesity in addition to weight loss or gain, such as waist circumference and intra-abdominal adipose tissue. In particular, individuals who skipped breakfast in both childhood and adulthood had larger waist circumferences in comparison to individuals who consumed breakfast in childhood and adulthood (Smith et al., 2010). Breakfast skipping was also associated with higher intra-abdominal adipose tissue in a sample of overweight Latino youth (Alexander et al., 2009). This literature consistently suggests that breakfast intake is associated with many indices of obesity (e.g., weight, BMI, waist circumference, intra-abdominal adipose tissue), and breakfast intake is associated with better weight outcomes.

In addition to the positive outcomes associated with breakfast intake, a small body of literature has begun to examine the positive outcomes associated with higher-protein breakfasts. Similar to literature examining general breakfast intake, higher-protein breakfasts have been linked to better cognitive functioning, particularly attention and executive functioning (Galioto & Spitznagel, 2016). Additionally, an experimental study found that high-protein breakfast intake, in comparison to normal-protein breakfast intake or skipped breakfast intake, was associated with prevented fat mass gains over 12 weeks (Leidy, Hoertel, Douglas, Higgins, & Shafer, 2015). Therefore, those who skipped breakfast or had normal-protein breakfasts experienced fat mass gains over 12 weeks, and those who had high-protein breakfast did not have an increase in fat mass. The authors found that the prevented fat mass gains were likely due to observed decreases in caloric intake and hunger. This finding is consistent with other literature which found high-protein breakfast intake to decrease grehlin concentrations more than a high-carbohydrate breakfast (Blom et al., 2006). As the hormone grehlin increases feelings of hunger, it is plausible that decreased grehlin concentrations are associated with reductions in caloric intake and hunger. Decreases in hunger and caloric intake might be of special importance in times of energy restriction, such as when someone is reducing calories to lose weight. When in a period of energy restriction, increased dietary protein at breakfast was associated with both initial and continued feelings of fullness, more than when increased dietary protein was distributed at other meal times (Leidy, Bossingham, Mattes, & Campbell, 2009). Overall, these findings suggest that higher-protein breakfast intake is associated with better cognitive and cardiometabolic outcomes.

Predictors of Breakfast Intake

Although the positive outcomes associated with breakfast intake are well established, breakfast is commonly skipped among American adults (Kant & Graubard, 2006). Consequently, it is necessary to examine factors that can promote or prevent breakfast intake. As breakfast is a behavior that occurs roughly on a 24-hour rhythm, it is likely affected by other daily rhythms such as the sleep-wake cycle. Humans have endogenous “body clocks” which govern numerous physiological rhythms including circadian cycles of approximately 24 hours (Reddy & O’Neill, 2009). These clocks guide the timing of multiple physical, mental, and behavioral processes (Delezie & Challet, 2011). One of the most obvious circadian rhythms in humans is the sleep-wake cycle (Markov, Goldman, & Doghramji, 2012), which is regulated by the internal master biological clock located in the suprachiasmatic nucleus. However, feeding behaviors are also regulated by the master biological clock (Escobar et al., 2011). Given the shared chronobiology of sleep and eating behaviors, it follows that disruption in one of these rhythms could negatively impact the other. Consequently, research on breakfast intake and diet has begun to examine the impact of sleep on dietary behaviors such as breakfast.

Chronotypes. We all share a time of day preference for certain behaviors such as sleeping. These "time of day preferences" are known as chronotypes and can be classified as morning types (preferences for wakening early and going to bed early), evening types (preferences for wakening late and going to bed late), and intermediate types (preferring neither early wakenings nor late bedtimes; Horne & Östberg, 1976). Chronotypes have been examined as predictors of diet behaviors including breakfast intake. Although specific breakfast composition has not yet been examined, evening chronotypes are associated with greater likelihood of skipping breakfast in general (Meule et al., 2012; Reutrakul et al., 2014; Teixeira et al., 2017). Additionally, chronotype was found to mediate the association between personality and breakfast intake, such that personality traits of conscientiousness, extraversion, and agreeableness predicted breakfast intake through earlier time-of-day preferences (Walker & Christopher, 2015). Similar results have been found when investigating the association between chronotype and dietary behaviors and attitudes other than breakfast intake. Those with earlier chronotypes had more servings of fruits and vegetables (Patterson et al., 2016), and those with evening chronotypes had higher total caloric intake, carbohydrate intake, and lipid intake (Teixeira et al., 2017). These results support the contention that earlier chronotypes tend to have healthier dietary behaviors, including breakfast consumption, in comparison to evening chronotypes. It is possible that the association between evening chronotypes and less healthy dietary behaviors could be explained by changes in dietary attitudes. Eveningness preference is associated with higher anticipation of positive reinforcement from eating and less guilt for giving into cravings, which suggests that chronotypes might influence dietary attitudes, which in turn influence dietary behaviors (Meule et al., 2012). Furthermore, in terms of breakfast intake, evening types may be more vulnerable to skipping breakfast due to a lack of sufficient time resulting from "sleeping in" later in the morning.

Sleep. Much of the current research on the association between sleep and breakfast intake has focused on chronotype, or time of day preference. However, there are many other markers of the sleep-wake cycle that warrant consideration as predictors of breakfast intake. Currently, only one study has specifically examined sleep as a predictor of breakfast intake (Ogilvie et al., 2017). Breakfast skipping was more likely in those who had bedtimes after 00:30 hours, suggesting that sleep timing might predict breakfast behaviors. The authors suggest that circadian disruption could be a mechanism underlying the association between sleep timing and breakfast intake, such that later sleep timing disrupts other circadian rhythms which then impact breakfast intake. Although the Ogilvie et al. (2017) study is novel in that it examined the association between sleep and breakfast intake, only one characteristic of sleep was examined, and the macronutrient composition of breakfast was unexplored. Additionally, sleep timing and breakfast intake were measured using a single time self-report questionnaire that inquired about participants' usual bedtimes and waketimes. The use of retrospective questionnaires is problematic in that this method is vulnerable to recall bias (Shadish, Cook, & Campbell, 2002). Lastly, this study is limited in that it relied solely on information about mean sleep timing, which does not account for the typical variations in sleep behaviors (Bei et al., 2016; Dillon et al., 2015). Given that highly variable sleep is associated with less healthy dietary behaviors (Duncan et al., 2016; He et al., 2015), there is a need to examine sleep in association with breakfast intake while preserving sleep's inherent night-to-night variability. Although the mechanism by which highly variable sleep is associated with less healthy dietary behaviors was not explored, these authors propose that highly variable sleep might lead to daytime fatigue, disruptions in hormonal rhythms, or increased stress, which in turn influences dietary behaviors (He et al., 2015).

Sleep and diet. Although there is little research examining sleep patterns as a predictor of breakfast behaviors specifically, there is good justification for examining sleep as a predictor of breakfast intake given sleep's known association with diet in general. A large body of research has found an association between inadequate sleep duration and weight gain (Chan, Levsen, & McCrae, 2017; Fatima, Doi, & Mamun, 2016; Itani, Jike, Watanabe, & Kaneita, 2017), suggesting that sleep duration contributes to the energy balance equation (diet and exercise). Sleep duration is defined as the total amount of sleep obtained in a 24-hour period (Buysse, 2014). According to the National Sleep Foundation's most recent recommendations for sleep duration, young adults (18-25) and adults (26-64) should obtain seven to nine hours of sleep each night (Hirshkowitz et al., 2015).

Interestingly, the association between sleep duration and diet tends to follow a U-shaped distribution, where both short and long sleep duration have been associated with less healthy eating behaviors (Haghighatdoost et al., 2012; Kant & Graubard, 2014; Kim, DeRoo, & Sandler, 2011; National Sleep Foundation, 2004). Specifically, short and long sleep durations are associated with consuming more snacks instead of meals, eating during less conventional hours, increased fat intake, increased sweet product intake, and higher intake of empty calories (Kim et al., 2010; Xiao et al., 2016). Additionally, short and long sleep durations are associated with decreased fruit, vegetable, and protein consumption (Kim et al., 2010; Shechter, Grandner, & St-

Onge, 2014; Xiao et al., 2016). In a study that experimentally manipulated short sleep duration, participants had increased hunger, appetite for sweet and salty foods, calorie consumption, fat intake, and carbohydrate intake (Shechter et al., 2012). Using a measure of overall diet quality, Mossavar-Rahmani et al. (2017) found that longer sleep duration was associated with greater diet quality.

Although most of the research on sleep and diet focuses on sleep duration, sleep timing is another important factor to consider in this association. A small body of research suggests that the later bedtimes are linked to poorer dietary choices. For example, experimentally manipulated earlier bedtimes were associated with decreases in appetite and desires for sweet and salty foods (Tasali et al., 2014). Additionally, later bedtimes were associated with increased intake of sugar-sweetened beverages, energy drinks, and fast food (Ogilvie et al., 2017). Timing of bedtimes appears to be distinct from chronotypes in that chronotypes refer to the timing of the entire sleep period, whereas the timing of bedtimes focuses on the start of the sleep period. Although less research has examined the role of sleep timing in dietary behaviors, overall, existing literature supports the hypotheses that short sleep duration, long sleep duration, and later bedtimes would be associated with less frequent breakfast intake. Of note, although this review has focused on sleep as a predictor of dietary behaviors, it is important to mention that research has also found diet to predict sleep, which implies that the association between sleep and diet is likely bidirectional (Knowlden, Hackman, & Sharma, 2016).

Mechanisms Linking Sleep and Diet

In addition to a lack of research investigating sleep as a predictor of breakfast intake, little is known about the mechanisms that could tie sleep to breakfast intake. Through examining the mechanisms by which sleep is associated with breakfast intake, factors in the process leading to increased breakfast intake could be identified and modified in order to achieve more desirable dietary outcomes. Research in this area is needed as existing studies have focused on mechanisms linking sleep to more general diet outcomes. In particular, in a review of the literature, the association between sleep and diet was found to have biological, behavioral, and psychological mechanisms (Chaput, 2013). From a biological perspective, experimental studies show sleep restriction (e.g., decreased duration) to increase levels of grehlin, a hormone which stimulates appetite, and decrease levels of leptin, a hormone which inhibits hunger (Benedict et al., 2011; Spiegel et al., 2014; Spiegel, Tasali, Penev, & Van Cauter, 2004). These findings suggest that hormones tied to appetite such as leptin and grehlin, might be altered in a way which enhances hunger sensations, and therefore influences dietary behaviors.

Another biological mechanism by which sleep influences diet is via reward activation. Sleep restriction increases rewards activation in response to food, and particularly unhealthy foods, so that unhealthy foods become even more rewarding to individuals with insufficient sleep (Benedict et al., 2012; St-Onge et al., 2012; St-Onge et al., 2013). Additionally, from a behavioral perspective, for those who have decreased sleep duration, there is subsequent increased awake time and therefore more time and opportunities for eating, often during inopportune times for eating such as late at night. Chaput (2013) also posits that it is possible that those who have increased awake time to need to consume more food to have enough energy for their extended wakefulness.

Mechanisms regarding the association between long sleep duration and diet outcomes are less understood. One potential explanation for this relation is that individuals with long sleep duration may subsequently have less time in the day to prepare foods or make plans in relation to their diet, which then results in lower diet quality (Xiao et al., 2016).

In addition to potential biological mechanisms that explain the association between sleep and diet, research has begun to examine the role of psychological variables as a factor linking sleep and diet. As sleep influences mental health (Asplund et al., 2004; Robotham, 2011), and mental health influences eating behaviors (Dalrymple et al., 2018; Litwin et al., 2017; Meng & D'Arcy, 2015), it is plausible that these variables are interconnected. For example, daytime sleepiness was associated with the consumption of sweetened products, mediated by anxiety and depressive symptoms (Moubarac, Cargo, & Receveur, 2013). As sweetened food products have been found to temporarily alleviate fatigue, stress, and anxiety, it follows that the consumption of sweets could be initiated by anxiety and depressive symptoms brought on by inadequate sleep (Adam & Epel, 2007; Gibson, 2006; Macht, 2008). Accordingly, depression and stress have been associated with less healthy dietary patterns (Gonzales & Miranda-Massari, 2014; Jacka et al., 2015). Additionally, depression has been associated with the specific dietary behavior of breakfast skipping (Lee et al., 2016; Sampasa et al., 2016). These results suggest that worse mental health is associated with less healthy dietary patterns, including breakfast skipping. Given existing research tying mental health to both sleep and diet outcomes, this study assesses the role of affect as a precursor to poor mental health as a mechanism linking sleep and breakfast intake.

Summary and Purpose of Current Study

Breakfast consumption is an important predictor of numerous positive health and psychological outcomes. Breakfast intake is associated with improved nutritional profiles (Rampersaud et al., 2005), better cognition and memory (Galioto & Spitznagel, 2016), and more positive mental health outcomes (Huang et al., 2010; Lee et al., 2016; Lesani et al., 2016; Richards & Smith, 2016). There is also a strong association between breakfast intake and cardiometabolic and weight outcomes (Alexander et al., 2009; Cahill et al., 2013; Jakubowicz et al., 2013; Kubota et al., 2016: Megson et al., 2016; Mekary et al., 2012; Mekary et al., 2013; Raynor et al., 2008; Smith et al., 2010). Furthermore, higher-protein breakfast has been associated with similar positive outcomes for cognition and cardiometabolic outcomes (Blom et al., 2006; Galioto & Spitznagel, 2016; Leidy et al., 2009; Leidy et al., 2015). Despite the abundant literature supporting the importance of breakfast intake, breakfast skipping remains common among American adults. Results from the 2002 National Health and Nutrition Examination Survey (NHANES) showed that 18% of American adults skip breakfast (Kant & Graubard, 2006).

Given that breakfast skipping is common among American adults, there is a need to identify factors that can predict breakfast behaviors. Much of the research investigating predictors of breakfast intake has focused on children and adolescents (Bartfeld & Ryu, 2011; Olsta, 2013; Pearson et al., 2009; Reddan et al., 2002; Sampasa-Kanyinga et al., 2014). However, a small body of research has begun to identify predictors of breakfast intake in adults. Specifically, earlier chronotypes have been shown to have more frequent breakfast intake (Meule et al., 2012; Reutrakul et al, 2014; Teixeira et al., 2017; Walker & Christopher, 2015). However, these studies are limited in that they have only used single time retrospective self-report measures of chronotype and breakfast intake. Additionally, less research has investigated how other sleep variables may predict breakfast intake. Only one study has examined sleep timing and breakfast behaviors, indicating that later bedtimes were associated with breakfast skipping (Ogilvie et al., 2017). However, this study did not include other markers of the sleep-wake cycle that are known predictors of diet choices such as sleep duration. Additionally, information about the macronutrient composition was unexplored, despite evidence suggesting the benefits of a higher-protein breakfast (Blom et al., 2006; Galioto & Spitznagel, 2016; Leidy et al., 2009;

Leidy et al., 2015). Furthermore, this study relied on a single-item retrospective question about mean sleep timing. Not only are daily variations in sleep-wake patterns common and considered less healthy (Bei et al., 2016), higher sleep variability is associated with less healthy dietary behaviors (Duncan et al., 2016; He et al., 2015). Therefore, it is necessary to also examine daily variations in sleep around the mean in relation to breakfast intake (Bei et al., 2016).

Another largely unexplored area in the literature is the role of psychological mechanisms as a potential pathway by which sleep influences dietary variables, and specifically breakfast intake. Over the past few decades, our understanding of the many potential biological mechanisms by which sleep predicts dietary behaviors has increased (Chaput, 2013). For example, inadequate sleep might increase appetite hormones and food-related reward activation. In addition to biological explanations, there is a need to investigate psychological mechanisms underlying the sleep—breakfast intake association given the potential to target psychological variables to improve breakfast intake. Existing research has identified anxious and depressive symptoms as a mediator between daytime sleepiness and increased sweetened product consumption (Moubarac et al., 2013). These findings suggest that sleep, mood, and diet might be interconnected; inadequate sleep decreases mental health which then leads to less healthy dietary behaviors. This pathway is plausible as sleep has been associated with mental health (Asplund et al., 2004; Robotham, 2011) and mental health has been associated with eating behaviors (Dalrymple et al., 2018; Litwin et al., 2017; Ment & D'Arcy, 2015). Specifically, depression and stress have been associated with less healthy dietary patterns, including breakfast skipping (Gonzales & Miranda-Massari, 2014; Jacka et al., 2015; Lee et al., 2016; Sampasa et al., 2016).

The current study investigated the association between sleep, affect, and breakfast in adults. Although a small body of research has examined the associations among chronotypes, sleep timing, and breakfast intake, macronutrient composition of breakfast intake and other markers of sleep have not yet been explored (i.e., sleep duration). Furthermore, previous research has been methodologically homogenous in that it has relied on single-time retrospective self-report measures of sleep and chronotypes. The current study expanded upon existing literature by examining sleep duration, sleep timing, chronotype, and breakfast intake using an archival analysis of data collected with an ecological momentary assessment approach. This methodology involves the collection of data in real-time and in a variety of settings and conditions, which reduces recall bias and more accurately reflects the day-to-day lives of participants. Variability in sleep timing, sleep duration, and mid-sleep were also examined, as daily variations in sleep patterns are common. Prior studies have overlooked intraindividual variability (IIV) of sleep behaviors, despite the importance of variability in sleep behaviors (Bei et al., 2016; Duncan et al., 2016; He et al., 2015). Lastly, other than biological mechanisms, the means by which sleep might predict breakfast behaviors is largely unexplored. Psychological variables could explain the association between sleep and diet, therefore this study investigated affect as a mechanism by which sleep predicts breakfast intake.

In summary, the current study is novel in that it is the first to: a) use ecological momentary assessment measures of sleep duration, sleep timing, chronotype, and breakfast intake; b) explore predictors of high-protein breakfast intake; c) examine intraindividual variability of these sleep variables; d) use concurrent measures of breakfast intake and sleep; and e) investigate affect as a mediator of the sleep—breakfast intake association.

Therefore, this study had three aims:

Aim 1. The first aim of this study was to examine how sleep behaviors predict breakfast intake. Specifically, this study investigated whether mean sleep duration, bed time, and midsleep predicted breakfast intake and high-protein breakfast intake. Based on a review of the literature, I hypothesized that:

1. Higher mean sleep duration would be associated with more frequent breakfast intake and high-protein breakfast intake.
2. Later mean bed time would be associated with less frequent breakfast intake and high-protein breakfast intake.
3. Later mean mid-sleep would be associated with less frequent breakfast intake and high-protein breakfast intake.

Aim 2. The second aim of the study was to examine how variability in sleep behaviors predict breakfast intake. Specifically, this study investigated whether variability in sleep duration, bed time, and mid-sleep predict breakfast intake and high-protein breakfast intake. Informed by existing research, I hypothesized that:

1. Greater variability in sleep duration would be associated with less frequent breakfast intake and high-protein breakfast intake.
2. Greater variability in bed time would be associated with less frequent breakfast intake and high-protein breakfast intake.
3. Greater variability in mid-sleep would be associated with less frequent breakfast intake and high-protein breakfast intake.

Aim 3. The third aim of the study was to investigate the mechanism by which sleep predicts breakfast intake. Specifically, this study explored the role of affect as a potential link between sleep and breakfast intake and high-protein breakfast intake. Following a review of the literature, I hypothesized that:

1. Negative affect would mediate any significant relationships found between identified sleep variables and breakfast intake. As such, less adequate sleep (e.g., shorter sleep duration, higher sleep duration variability, etc.) would predict greater negative affect which, in turn, would predict less frequent breakfast intake and high-protein breakfast intake.
2. Positive affect would mediate any significant relationships found between identified sleep variables and breakfast intake. For example, more healthful sleep (e.g., earlier bed time, lower bed time variability, etc.) would predict greater positive affect which, in turn, would predict more frequent breakfast intake and high-protein breakfast intake.

Method

Design

A secondary data analysis was performed using data from baseline assessments and ecological momentary assessments (EMA) included in the Pittsburgh Cold Study 3 (PCS3). The Pittsburgh Cold Study 3 was a prospective viral challenge study that collected data from 2007-2011. The study aimed to investigate the role of childhood experiences, social variables, psychological variables, and behavioral measures in common cold susceptibility. These data were collected by the Laboratory for the Study of Stress, Immunity, and Disease at Carnegie Mellon University under the directorship of Sheldon Cohen, PhD; and were accessed via the Common Cold Project (CCP) website (www.commoncoldproject.com). CCP data are made publicly available through a grant from the National Center for Complementary and Integrative Health (AT006694). The conduct of the studies was supported by grants from the National Institute of Allergy and Infectious Diseases (AI066367), with secondary support provided by a

grant from the National Institutes of Health to the University of Pittsburgh Clinical and Translational Science Institute (UL1 RR024153 and UL1 TR000005).

Participants

Participants completed the Pittsburgh Cold Study 3 (PCS3), which included daily evening telephone interviews. All eligible participants were English-speaking adults in good general health, between 18 and 55 years of age. Participants also had to meet criteria necessary for testing the effects of inoculation of a cold virus such as having no allergies to egg products, no psychiatric hospitalizations within last five years, no regular medication regimens, etc. Data collection for PCS3 took place from 2007 - 2011 and the sample consisted of 213 participants (57.75% men).

Procedure

During the baseline phase of PCS3, participants completed a pencil-and-paper self-report questionnaire measuring demographic (age, sex, race/ethnicity, education, employment status, and income) and psychological variables (personality traits). Additionally, participants completed daily telephone interviews five to seven weeks after completing baseline questionnaires. Measures of the daily sleep variables, breakfast intake variables, and affect variables were collected during the daily evening telephone interviews. The daily interviews took place over 14 days, and lasted about 30 minutes. The interviews were scheduled to be at the same time each evening, between the hours of 5:00 p.m. and 9:30 p.m. Participants who missed interviews were scheduled to have make-up interviews, and if a participant missed more than four of the interviews they were dropped from the study. Finally, 5 weeks after completing daily interviews, subjects participated in a viral challenge. Participants were administered a common cold virus, and observed throughout five days of a quarantine protocol.

Measures

Sleep. Daily sleep variables (sleep duration, bed time, and chronotype) were computed using items from the Daily Social Rhythm Metric included in the daily interviews (Monk, Flaherty, Frank, & Kupfer, 1994). This measure was originally designed to assess the extent to which an individual is regular or irregular in terms of the timing of daily events, and was adapted for the Pittsburgh Cold Study 3 (PCS3) to be a 16-item measure by excluding one item. The original measure included two optional items which asked participants if they engaged in an activity other than the activities listed in prior items. The adapted measure used in this study only included one of the two optional items. Participants were asked whether/when and with whom they engaged in 16 daily activities (first contact with another person, had morning beverage, etc.). The original measure demonstrated fair test-retest reliability in adults ($r = 0.48$, $p < .002$), good construct validity, and good criterion validity (Monk, Flaherty, Frank, Hoskinson, & Kupfer, 1990, Monk et al., 1994).

Both mean sleep variables and variability in sleep behaviors were analyzed using items from the Daily Social Rhythm Metric. Sleep variability was computed by calculating intraindividual variability in sleep behaviors for each participant across 14 days. To calculate intraindividual variability, intraindividual standard deviations were calculated and then detrended for time to control for any variations due to the effects of observing behaviors over time. Specifically, detrending for time produces a variable that precisely reflects variability over time that is not due to the effects of time (e.g., practice effects, participation fatigue, etc.), but rather due to inherent variations in the behavior of interest. Detrending was conducted via linear regression analyses for all participants, where time (linear, quadratic, and cubic functions) was inputted as the independent variables and sleep variables was inputted as the dependent outcomes. Intraindividual standard deviations values were then calculated for the sleep behavior variables using the time-independent residuals from the aforementioned linear regression analyses. This detrending process resulted in measures of sleep variability that were independent of any influences of time.

Sleep duration. Sleep duration was analyzed using mean sleep duration values and sleep duration variability. Mean sleep duration was calculated by subtracting the time participants went to sleep from the time participants woke up, and taking the average across 14 days of daily interviews. Variability in sleep duration was quantified by calculating intraindividual variability in sleep duration over 14 days of daily interviews.

Bed Time. Bed time was assessed by calculating mean bed time values and bed time variability. Bed time was assessed using the item which asks participants what time they went to sleep. Mean bed time was calculated by taking the average of the bed time values over 14 days. Variability in bed time was quantified by calculating intraindividual variability in bed time over 14 days of daily interviews.

Chronotype. Mid-sleep was used as an indicator of chronotype. Mid-sleep, defined as the midpoint between sleep onset and wake time, is a unique indicator of chronotype that takes into account both sleep duration and sleep timing (Reutrakul et al., 2014). Mid-sleep was assessed by calculating mean mid-sleep values and mid-sleep variability. Mean mid-sleep values were calculated by subtracting the time participants went to sleep from the they woke up, dividing this by two, and adding this value to the time participants went to sleep. Mean mid-sleep was calculated as the average of mid-sleep values across 14 days. Variability in mid-sleep was quantified by calculating intraindividual variability in mid-sleep over 14 days of daily interviews.

Frequency of breakfast intake. Breakfast intake was assessed by calculating the frequency of breakfast intake over 14 days of daily interviews. Breakfast intake was measured using an item from the Daily Interview Health Behavior scale, which was created for the Pittsburgh Cold Study 3 and informed by prior research (Brissette & Cohen, 2002; Cohen, Doyle, Alper, Janicki-Deverts, & Turner, 2009; Cohen & Lemay, 2007). Participants were asked "What did you have for breakfast this morning?" Responses were coded as either consuming breakfast or not consuming breakfast based on the open-ended responses.

Frequency of high-protein breakfast intake. High-protein breakfast intake was assessed by calculating the frequency of high-protein breakfast intake over 14 days of daily interviews. High-protein breakfast intake was measured using an item from the Daily Interview Health Behavior scale, which was created for the Pittsburgh Cold Study 3 and informed by prior research (Brissette & Cohen, 2002; Cohen, Doyle, Alper, Janicki-Deverts, & Turner, 2009; Cohen & Lemay, 2007). Participants were asked "What did you have for breakfast this morning?" Responses were coded as either consuming a high-protein breakfast or not consuming a high-protein breakfast based on the open-ended responses.

Affect. Affect was assessed by calculating mean negative affect and positive affect values. Measures of affect were collected using the Daily Interview Affect Scale, created for the study and informed by prior research (Brissette & Cohen, 2002; Cohen, Alper, Doyle, Treanor, & Turner, 2006; Cohen, Doyle, Turner, Alpter, & Skoner, 2003; Cohen & Lemay, 2007; Doyle, Gentile, & Cohen, 2006). A previous study which used this measure reported good internal reliability for the positive affect scale (0.82 to 0.90) and negative affect scale (0.83 to 0.90) (Cohen et al., 2006). Participants completed the scale over 14 days of daily interviews. The scale includes 14 items of mood adjectives (e.g., sad, full of pep, tired), and requires participants to rate the extent to which the adjectives described how they had been feeling that day on a 4-point scale (0 - "haven't felt that way at all today"; 4 – "felt that way a lot today"). Positive affect was calculated by taking the mean of three relevant individual subscales (e.g., calm, well-being, vigor), and negative affect was calculated similarly (e.g., anxiety, depression, anger, fatigue).

Potential covariates. Although the current study focused on the associations between sleep, affect, and breakfast intake; there are potential covariates which are important to consider. Age, personality traits, income, and education have been associated with breakfast intake (Lee et al., 2016; Morgan, Zabik, & Stampley, 1986; Walker & Christopher, 2015). Additionally, race/ethnicity, gender, income, and employment status have been associated with sleep (Crain, Brossoit, & Fisher, 2017; El-Sheikh, Kelly, Sadeh, & Buckhalt, 2014; Mallampalli & Carter, 2014). Therefore, potential covariates examined in the current study included age, personality traits, income, education, gender, race/ethnicity, and employment status. These variables were obtained from the baseline questionnaires. The measure of race/ethnicity consists of six categories (e.g., White/Caucasian, Black/African-American, Native American/Eskimo/Aleut, Asian/Pacific Islander, Hispanic/Latino, Other) and educational level includes nine categories (did not finish high school to doctoral degree). Employment status was assessed by asking participants if they were employed, and coded as "yes" or "no". Annual income is a continuous variable which is based on a question assessing participants' total household income. Lastly, personality was measured using the International Personality Item Pool (IPIP) Big-Five Factor Markers (Goldberg, 1999; Goldberg et al., 2006), which assesses the five major dimensions of personality (extraversion, agreeableness, conscientiousness, emotional stability, openness). The measure requires participants to rate the extent 50 self-referent descriptive phrases accurately reflect how they are generally, in order to derive relative levels of each of the five personality dimensions.

Statistical Analyses

To assess aims 1 and 2, hierarchical regressions were conducted while controlling for selected covariates. To assess aim 3, Hayes' SPSS PROCESS macro (Hayes, 2013) was used to run parallel mediation models to test the mediating roles of positive and negative affect in the association between sleep and breakfast intake. All parallel mediation models controlled for identified covariates. Using the PROCESS macro, the indirect effect of positive and negative affect was tested using a non-parametric, bias-corrected bootstrapping procedure that provided an empirical approximation of the sampling distribution of the product of the estimated coefficients in the indirect paths using 5,000 resamples from the dataset.

Power calculations using G*Power (Faul, Erdfelder, Buchner, & Albert-Georg, 2009) suggested that a hierarchical regression analysis with three predictors, and a maximum of seven potential covariates, would require a sample size of at least 55 participants to predict an effect size of at least .15 at an alpha level of .05, with a power of .80. In the current study, assuming a medium effect size, 213 participants was sufficient to detect an effect. Additionally, power calculations using G*Power (Faul, Erdfelder, Buchner, & Albert-Georg, 2009) suggested that for a simple mediation analysis using a maximum of seven potential covariates, would require a sample size of at least 114 participants to predict an effect size of at least .15 at an alpha level of .05, with a power of .80. In the current study, assuming a medium effect size, 213 participants was again sufficient enough to detect an effect.

Results

Data Preparation and Data Cleaning

SPSS 24.0 was used for all data analyses. To assure that data met assumptions of planned analyses, data were cleaned and descriptive statistics were first calculated (means, standard deviations, and frequencies). Skewness, kurtosis, and outliers for all main variables and covariates of interest were calculated to check assumptions of normality and outliers. Skewness and kurtosis values for mean midsleep, breakfast intake frequency, high protein breakfast intake frequency, and positive affect were close to or below an absolute value of 1, indicating, that they were approximately normally distributed. Additionally intraindividual variability of waketime, bedtime, duration, and midsleep presented with normal distributions. Mean sleep timing, mean negative affect, and income were positively skewed and had positive kurtosis (i.e., values greater than 1). After windsorizing identified outliers for each variable, newly calculated skewness and kurtosis values indicated the variables were normally distributed. Mean sleep duration and mean wake time were negatively skewed and had negative kurtosis (i.e., values less than -1). After windsorizing identified outliers for each variable, newly calculated skewness and kurtosis values indicated the variables were normally distributed. In addition to a review of skewness, kurtosis, and outliers, assumptions of independence, normality, multicollinearity, and homoscedasticity were assessed. All remaining assumptions were sufficiently met. Less than 4% of the data from daily diaries used to calculate sleep, affect, and breakfast variables were missing.

Descriptive and Correlational Results

First, bivariate correlations were conducted between potential covariates (weight, age, personality traits, income, education, race, gender, employment status) and dependent variables (breakfast intake frequency and high protein breakfast intake frequency) to assess which potential covariates to include in subsequent analyses. Income was significantly negatively correlated with breakfast intake frequency, and education and employment were significantly positively correlated with high protein breakfast intake frequency. Therefore, income, education, and employment were included as covariates in all statistical models. Mean wake time was also included as a covariate in models assessing mean sleep characteristics as independent variables, and intraindividual variability of wake time was included as a covariate in models assessing intraindividual variability of sleep characteristics as independent variables.

Next, descriptive statistics for sociodemographic characteristics were examined (Table 1). On average, participants were 30.32 years old (*SD* = 10.91), primarily male (57.70%), and mostly White (65.40%). The majority were employed (59.40%) and had a High School diploma (28.50%). The median annual household income was $12,500 (*M* = $20,740.31, *SD* = 19,879.99). Descriptive statistics were also examined for variables of interest (Table 2). Participants had an average of 8.44 (*SD* = 4.53) days of breakfast intake out of a possible 14 days, and an average of 3.40 (*SD* = 3.39) days of high-protein breakfast intake out of a possible 14 days. Participants had a mean negative affect score of 2.86 (*SD* = 2.65) out of a possible range of scores of 0-32. Participants had a mean positive affect score of 14.50 (*SD* = 4.29) out of a possible range of scores of 0-24. Regarding sleep characteristics, the sample had a mean bedtime of approximately 12:30 A.M (*SD* = 86.38 minutes), a mean midsleep of approximately 4:30 A.M. (*SD* = 87.65 minutes), a mean wake time of approximately 8:45 A.M. (*SD* = 93.37 minutes), and a mean duration of approximately 7.61 hours (*SD* = 67.83 minutes). Next, Pearson correlations were conducted to examine bivariate associations between all main variables of interest (i.e., mean sleep characteristics, intraindividual variability of sleep characteristics, breakfast intake frequency, high-protein breakfast intake frequency, mean negative affect, and mean positive affect; Table 3).

Table 1

Sociodemographic Characteristics of Participants

	N	Percentage (%)
Age		
18-29	133	64.25
30-39	25	12.08
40-49	27	13.04
50-55	22	10.63
Gender		
Male	120	57.97
Female	87	42.03
Race/Ethnicity		
White/Caucasian	136	65.70
Black/African American	58	28.02
Native American/Eskimo/Aleut	1	.37
Asian/Pacific Islander	4	1.93
Hispanic/Latino	3	1.45
Other	5	2.42
Education		
Did not finish high school	6	2.90
High school graduate	59	28.50
Less than 2 years of college	41	19.81
Associate's degree or equivalent	49	23.67
Bachelor's degree	43	20.77
Master's degree	8	3.86
Doctoral degree	2	0.97

Table 2

Descriptive Statistics for Breakfast, Sleep, and Affect Variables

	M	*SD*	Range
Breakfast			
Frequency of breakfast intake over 14 days	8.44	4.53	0 - 14
Frequency of high-protein breakfast intake over 14 days	3.40	3.38	0 - 14
Sleep			
Wake time (Military Time)	08:44	93.37 minutes	04:22 - 12:58
Bedtime (Military Time)	00:39	86.38 minutes	21:02 - 05:41
Sleep duration (minutes)	456.74	67.83	235.77 - 673.93
Midsleep (Military Time)	04:28	87.65 minutes	00:34 - 06:26
Affect			
Negative affect	2.85	2.65	0 - 11.86

Positive affect	14.50	4.29	2.71 - 24.00

Table 3

Pearson Correlation Coefficients Among Breakfast, Sleep, Affect, and Covariates

	Breakfast intake frequency	High-protein breakfast intake frequency	Positive affect	Negative affect
High-protein breakfast intake frequency	-.07			
Positive affect	.01	-.02		
Negative affect	<.01	-.07	-.39**	
Mean bedtime	-.28**	-.03	.02	-.03
Mean sleep duration	-.06	-.10	-.08	.06
Mean midsleep	-.30**	-.07	-.01	-.01
Mean wake time	-.34**	-.08	-.01	-.01
IIV bedtime	-.17*	-.02	.04	-.11
IIV sleep duration	-.25**	-.04	.07	-.02
IIV midsleep	-.15*	-.02	-.01	-.11
IIV wake time	-.19**	-.02	-.03	-.05

Note. * $p < .05$. ** $p < .001$.

Association between Mean Sleep Variables and Breakfast Intake

To investigate how well mean sleep duration, bedtime, and midsleep predicted breakfast intake frequency when controlling for mean wake time, income, education, and employment, a hierarchical linear regression was computed. Mean wake time, income, education, and employment were entered as covariates into the first model, and were significantly associated with breakfast intake frequency, $F(4, 193) = 326.31$, $p < .001$, $R^2 = .83$. Lower income (β = -.87, $t(193) = -28.415$, $p < .001$) and lower education (β =-.06, $t(193) = -2.03$, $p = .044$) were associated with greater breakfast intake frequency. Furthermore, earlier waketime (β -.13, $t(193) = -4.11$, $p < .001$) was associated with greater breakfast intake frequency. This initial model shows that 83.00% of the variance in breakfast intake frequency can be predicted by mean wake time, income, education, and employment of participants. When mean sleep duration, bedtime, and midsleep were added to the model, they did not significantly improve the prediction ΔR^2 = .01, $\Delta F(3, 190) = 2.47$, $p = .063$. All variables together significantly predicted breakfast intake frequency $F(7, 190) = 139.18$, $p < .001$, $R^2 = .83$ (Table 4), however income was the only predictor that remained significant (β < .01, $t(190) = -28.28$, $p < .001$) with lower income predicting greater breakfast intake frequency.

Table 4

Mean Sleep Variables as Predictors of Breakfast Intake

	β	*T*	*F*	R^2
Model 1			236.31	.83**
Income	-.87	-28.42**		
Education	-.06	-2.03*		
Employment	.01	.16		
Mean Wake Time	-.13	-4.11**		
Model 2			139.18	.84**
Income	-.87	-28.28**		
Education	-.06	-1.95		
Employment	.01	.22		
Mean Wake Time	-.04	-.36		
Mean Midsleep	1.34	1.05		
Mean Bedtime	-1.43	-1.13		
Mean Sleep Duration	-.52	-1.03		

Note. $*p < .05$, $**p < .001$

Association Between Mean Sleep Variables and Breakfast Protein Intake

To investigate how well mean sleep duration, bedtime, and midsleep predicted high-protein breakfast intake frequency when controlling for mean wake time, income, education, and employment, a hierarchical linear regression was computed. Mean wake time, income, education, and employment were entered as covariates into the first model, and significantly predicted high-protein breakfast intake frequency, $F(4, 201) = 4.97$, $p = .001$, $R^2 = .09$. Higher education (β =.18, $t(198) = 2.56$, $p = .011$) and being employed (β .19, $t(198) = 2.81$, $p = .005$) was associated with greater high-protein breakfast intake frequency. This initial model shows that 9.00% of the variance in high-protein breakfast intake frequency is predicted by the mean wake time, income, education, and employment of participants. When mean sleep duration, bedtime, and midsleep were added to the model, they did not significantly improve the prediction $\Delta R^2 = .01$, $\Delta F(3, 198) = .54$, $p = .654$. All variables together significantly predicted breakfast intake frequency $F(7, 198) = 3.05$, $p = .005$, $R^2 = .10$ (Table 5). Although, only education (β = .17, $t(198) = 2.5$`, $p = .013$) and employment (β = .19, $t(198) = -2.73$, $p = .007$) remained significant, indicating that higher education and being employed were associated with greater high-protein breakfast intake frequency.

Table 5

Mean Sleep Variables as Predictors of High-Protein Breakfast Intake

	β	*t*	*F*	R^2
Model 1			4.97	.09*
Income	.08	1.21		
Education	.18	2.56*		
Employment	.19	2.82*		
Mean Wake Time	-.12	-1.67		
Model 2			3.05	.10*
Income	.07	1.05		
Education	.17	2.51*		
Employment	.19	2.73*		
Mean Wake Time	-.03	-.14		
Mean Midsleep	-2.09	-.70		
Mean Bedtime	2.02	.69		
Mean Sleep Duration	.71	.61		

Note. $*p < .05$. $**p < .001$.

Association between Intraindividual Variability of Sleep Variables and Breakfast Intake

To investigate how well intraindividual variability of sleep duration, bedtime, and midsleep predicted breakfast intake frequency when controlling for intraindividual variability of wake time, income, education, and employment, a hierarchical linear regression was computed. Intraindividual variability of wake time, income, education, and employment were entered as covariates into the first model, and significantly predicted breakfast intake frequency, $F(4, 191)$

= 211.22, p < .001, R^2 = .82. Both lower income (β = -.90, t(188) = -28.34, p < .001) and lower education (β = -.06, t(188) = -2.04, p = .043) were associated with greater breakfast intake frequency. This initial model shows that 81.60% of the variance in breakfast intake frequency is predicted by the intraindividual variability of wake time, income, education, and employment of participants. When intraindividual variability of sleep duration, bedtime, and midsleep were added to the model, they significantly improved the prediction Δ R^2 = .01, ΔF(3, 188) = 4.63, p = .004. Additionally, all variables together significantly predicted breakfast intake frequency F(7, 188) = 129.55, p < .001, R^2 = .83 (Table 6). Although intraindividual variability of sleep duration (p = .159) and midsleep (p = .144) were not significant individual predictors of breakfast intake frequency, intraindividual variability of bedtime was a significant individual predictor (β = -.14, t(188) = -2.06, p = .041). Higher variability in bedtimes was associated with decreased breakfast intake frequency. Income (β = -.89, t(188) = -28.71, p < .001) and education (β = -.07, t(188) = -2.37, p = .052) were also significant individual predictors of breakfast intake frequency. Lower income and education were associated with greater breakfast intake frequency.

Table 6

Intraindividual Variability of Sleep Variables as Predictors of Breakfast Intake

	β	*t*	*F*	R^2
Model 1			211.22	.82**
Income	-.99	-28.34**		
Education	-.06	2.04*		
Employment	<-.01	-.05		
IIV Wake Time	-.03	-.96		
Model 2			129.55	.83**
Income	-.89	-28.71**		
Education	-.07	-2.37*		
Employment	-.01	-.20		
IIV Wake Time	-.04	-.57		
IIV Midsleep	.13	-1.47		
IIV Bedtime	-.14	-2.06*		
IIV Sleep Duration	-.06	-1.41		

Note. Intraindividual variability (IIV). *p < .05. **p < .001.

Association between Intraindividual Variability of Sleep Variables and Breakfast Protein Intake

To investigate how well intraindividual variability of sleep duration, bedtime, and midsleep predicted high-protein breakfast intake frequency when controlling for intraindividual variability of wake time, income, education, and employment, a hierarchical linear regression was computed. Intraindividual variability of wake time, income, education, and employment were entered as covariates into the first model, and significantly predicted high-protein breakfast intake frequency, $F(4, 199) = 4.10$, $p = .003$, $R^2 = .06$. Higher education ($\beta = .18$, $t(196) = 2.54$, $p = .012$) and being employed ($\beta = .18$, $t(196) = 2.63$, $p = .009$) was associated with greater high-protein breakfast intake frequency. This initial model shows that 5.80% of the variance in high-protein breakfast intake frequency is predicted by the mean wake time, income, education, and employment of participants. When intraindividual variability of sleep duration, bedtime, and midsleep were added to the model, they did not significantly improve the prediction $\Delta R^2 < .01$, $\Delta F(3, 196) = .07$, $p = .975$. All variables together significantly predicted high-protein breakfast intake frequency $F(7, 196) = 2.34$, $p = .026$, $R^2 = .08$ (Table 7), although only education ($\beta = .18$, $t(196) = 2.50$, $p = .013$) and employment ($\beta = .18$, $t(196) = 2.61$, $p = .010$) remained significant individual predictors. Higher education and being employed were associated with greater high-protein breakfast intake frequency.

Table 7

Intraindividual Variability of Sleep Variables as Predictors of High-Protein Breakfast Intake

	β	*t*	*F*	R^2
Model 1			4.10	.06*
Income	.06	.82		
Education	.18	2.54*		
Employment	.18	2.63*		
IIV Wake Time	<.01	<.01		
Model 2			2.34	.08*
Income	.06	.84		
Education	.18	2.50*		
Employment	.18	2.61*		
IIV Wake Time	-.03	-.24		
IIV Midsleep	.07	.39		
IIV Bedtime	-.04	-.97		
IIV Sleep Duration	-.01	-.07		

Note. Intraindividual variability (IIV). *p < .05. **p < .001.

Affect as a Mediator of the Association between Sleep and Breakfast Intake

To examine the indirect effect of sleep variables on breakfast intake variables via negative and positive affect, parallel mediation models using PROCESS were conducted using 5,000 bootstraps (Hayes, 2012).

Indirect association of mean sleep variables with breakfast intake frequency. To examine the indirect effect of mean sleep variables (bedtime, midsleep, and sleep duration) on breakfast intake frequency via negative and positive affect, parallel mediation models were conducted. Overall models were not significant, and no significant indirect effects of positive or negative affect were detected (See Appendix for Figures 1-3).

Indirect association of mean sleep variables with high-protein breakfast intake frequency. To examine the indirect effect of mean sleep variables (bedtime, midsleep, and sleep duration) on high-protein breakfast intake frequency via negative and positive affect, parallel mediation models were conducted. Overall models were not significant, and there were no significant indirect effects of positive or negative affect (See Appendix for Figures 4-6).

Indirect association of IIV sleep variables with breakfast intake frequency. To examine the indirect effect of IIV sleep variables (bedtime, midsleep, and sleep duration) on breakfast intake frequency via negative and positive affect, parallel mediation models were conducted. Overall models were not significant, and no significant indirect effects of positive or negative affect (See Appendix for Figures 7-9).

Indirect association of IIV sleep variables with high-protein breakfast intake frequency. To examine the indirect effect of IIV sleep variables (bedtime, midsleep, and sleep duration) on high-protein breakfast intake frequency via negative and positive affect, parallel mediation models were conducted. Overall models were not significant, and there were no significant indirect effects of positive or negative affect on breakfast intake frequency (See Appendix for Figures 10-12).

Discussion

The aim of the current study was to uncover what aspects of sleep are connected to healthier breakfast habits, including consuming breakfast more often and consuming higher-protein breakfasts. This study also examined how sleep is connected to breakfast behaviors; for example, do aspects of sleep predict affect, which then predicts breakfast behaviors? Although no associations were observed between average sleep characteristics and breakfast behaviors, and affect did not explain how sleep characteristics are linked to breakfast behaviors, variability in bedtimes was associated with breakfast behaviors. Specifically, having more regular bedtimes was associated with consuming breakfast more often.

The current study's finding that more variable bedtimes are predictive of less frequent breakfast intake is similar to a broader body of research which found variability in sleep behaviors was associated with negative health outcomes including multiple physical health conditions, higher body mass index, weight gain, and unipolar and bipolar depression symptoms (Bei et al., 2016). Additionally, the current findings support research more specifically related to diet outcomes that has shown highly variable sleep is associated with less healthy dietary behaviors (Duncan et al., 2016; He et al., 2015). Specifically, more variable sleep, but not mean sleep duration, was associated with less healthy dietary behaviors such as increased frequency of snack consumption, increased overall daily caloric intake (He et al., 2015), and decreased habitual dietary quality (Duncan et al., 2016). The current study builds upon these findings by examining the specific healthy dietary behavior of consuming breakfast on a daily basis. Although the process by which variable sleep negatively predicts health behaviors is not fully known, it is possible that more variable sleep disrupts the sleep-wake cycle, which then contributes to the misalignment of other daily rhythms. Circadian rhythms are not only responsible for guiding the sleep-wake cycle, they also guide numerous mental and physical processes such as affective rhythms (Miller et al., 2015), hormonal secretions controlling hunger and fullness, and feeding behaviors (Delezie & Challet, 2011). Since the sleep-wake cycle and dietary behaviors follow daily rhythms, disruption of the timing of one cycle likely contributes to disruption in other cycles. Therefore, variability in sleep may disrupt other daily rhythms, such as feeding behaviors like breakfast intake (Escobar et al., 2011). For example, an individual may exhibit variable bedtimes by going to sleep at 1 A.M. one night and 8 P.M. the next night. This variability in bedtime could contribute to misalignment of the sleep-cycle and subsequent effects on other circadian rhythms. Daily rhythms of hormonal secretions which guide feeding behaviors could misalign, influencing hunger levels. When the sleep-cycle and other daily rhythms are aligned, hunger should occur in the morning to encourage the consumption of breakfast. In this example, after having highly irregular bedtimes, the individual may not experience hunger in the morning and therefore be less likely to consume breakfast.

Although this study found variability in bedtime was associated with less frequent breakfast intake, mean sleep variables did not emerge as predictors of breakfast behaviors. Variations in sleep behaviors are common, in fact within-person variability in sleep behaviors is more prevalent than between-person variability (Dillon, Lichstein, Dautovich, Taylor, Riedel, & Bush, 2014). Therefore, variability in sleep behaviors may give a more accurate picture of true sleep behaviors in comparison to relying on mean information of sleep (Bei et al., 2016).

There are also unique characteristics of the sample that may suggest variability is particularly important to examine for this sample. A large portion of the sample, 40.6%, reported having no part-time or full-time employment. The unemployment rate for the U.S. population was 3.8% as of May 2018, which is substantially lower than the unemployment rate found in the current study’s sample (Bureau of Labor Statistics, 2018). The sample’s employment characteristics suggest that the participants had the opportunity to follow different and more flexible schedules than typical adults, which could have increased the sleep variability in the sample. Therefore, variability may be an especially relevant marker of sleep in this sample, as opposed to mean sleep characteristics, because it captures the more variable and flexible schedules of participants.

To encourage more regularity in bedtimes, and potentially increase the likelihood of consuming breakfast more frequently, increased awareness of healthy sleep behaviors, such as regular bed timing, is necessary. As such, clinical implications of the current study include increasing awareness of core sleep hygiene practices, such as maintaining regular bed and wake times across weekdays and weekends. Additionally, other sleep hygiene recommendations that could improve regularity in bedtimes include spending less time in bed, not using electronics before bedtime, and setting up a consistent bedtime routine (Stepanski & Wyatt, 2003). Engaging in these sleep hygiene behaviors better entrains the circadian system to encourage healthful sleep and can become a cue for feeling sleepy at a similar time each night. By not using electronics before bed, and not spending excess time in bed (e.g., using the bed for activities other than sleep or sex), individuals may be better able to fall asleep easier, which then encourages more regular bed timing. Education programming to increase knowledge and awareness of healthy sleep behaviors is a plausible avenue to convey this information to the general public. Sleep education programming has been effective in improving sleep hygiene knowledge and behaviors in a college student sample (Hershner & O'Brien, 2018). Participants spent about 20 minutes on a website which aimed to provide general sleep hygiene education insight into participant's individual sleep patterns. After spending time on this sleep education website, there were improvements in knowledge of sleep hygiene, as well as improvements in specific sleep hygiene behaviors (stopping electronic use earlier, keeping a more regular sleep schedule, napping less, and waking earlier in the week). As this sleep education intervention was short and based online, it would likely be accessible and feasible for a broader population than just college students.

Lastly, this study found that both positive and negative affect did not underlie the association between sleep characteristics and breakfast behaviors. One possible explanation for the lack of a significant mediation by negative affect is that reported negative affect in the sample was relatively low (M = 2.86, range of 0 - 11.86), especially when considering the range of possible scores (0-32). As such the ability to assess negative affect's role as a mediator is limited by the low reported value and consequent restricted range. The positive affect scores, however, were more typical, suggesting that the lack of significant mediation by positive affect may be more valid. It is possible that positive affect plays less of an important role in predicting breakfast behaviors compared to negative affective states. For example, variables related to negative affect such as higher depressive symptoms have been associated with more breakfast skipping (Lee et al., 2016; Sampasa et al., 2016), which suggests negative affect should still be explored as a potential pathway between sleep behaviors and breakfast behaviors.

Importantly, the study results need to be interpreted within the context of the unique study design. As participants were required to take part in a five-day quarantine for the study's protocol, the employment and income characteristics of the sample may be a reflection of the type of participant who is able to meet this eligibility criteria. It is likely that those who are unemployed, or have very flexible work schedules, are the type of participants who are able to participate in a quarantine protocol. Accordingly, the median annual household income of the current sample is lower than recent population estimates. The current sample's median annual household income between 2007-2011 was $12,500, however reports from the U. S. Census Bureau indicate that the median household income in 2016 was $59,039 (Semega, Fontenot, & Kollar, 2018). Additionally, as mentioned earlier, it is of note that 40.6% of the sample reported having no part-time or full-time employment. Although no occupation-specific data was collected, it is possible that the employment and income demographics describe a sample of college students. The age of the majority of the sample was consistent with college-aged students (64.3% between the ages of 18-29), as the National Center for Education Statistics (2015) found that 75.97% of college students were between the ages of 18-29 in 2015. Consequently, it is possible that the majority of the sample may have been enrolled as students and, hence, had more flexible schedules that allowed them to participate in a quarantine protocol.

The uniqueness of the sample may have influenced sleep and breakfast behaviors, as demographic covariates were significantly associated with breakfast behaviors. Lower income and less education were associated with more frequent breakfast intake. Although research has not yet examined the association between education level and breakfast intake, prior studies have found low income to be associated with breakfast skipping (Lee et al., 2016), which is discordant from this study's findings. As the income and education characteristics of the current sample were particularly unique, these unexpected results may have been influenced by the unique context of the sample. **Strengths and Limitations**

The current study has many strengths and builds upon the previous literature, however there are several limitations to address. In addition to the income and employment characteristics mentioned above, the sample reported breakfast and sleep behaviors that were unexpected in comparison to the general population and may limit the generalizability of the current study. For example, although breakfast intake frequency over time has not been previously examined, rates of breakfast skipping in adults appears to be lower than the average breakfast intake frequency of the current sample (Kant & Graubard, 2006). Based on a one-time 24-hour dietary recall, results of the National Health and Nutrition Examination Survey indicate that 18% of American adults skip breakfast (Kant & Graubard, 2006); whereas individuals in the current study consumed breakfast on average 8.44 out of 14 days. Additionally, although there is no research examining the prevalence of adequate macronutrient consumption in breakfast, the intake of high-protein breakfast in this study's sample seems to be relatively low, with individuals in the current study consuming high-protein breakfast on average 3.4 days out of 14 days.

The sleep behaviors of the sample are also divergent from research using nationally representative samples. The current sample reported a mean bedtime of 12:30 A.M., however 73% of American adults go to bed between 10 P.M. and 12 A.M. on both weekdays and weekends (National Sleep Foundation, 2005). The current sample also reported a mean wake time of 8:45 A.M., which is much later than what 72% of American adults report (between 5 A.M. and 8 A.M.; National Sleep Foundation, 2005). These findings suggest that the current sample may have a different overall timing of the sleep period compared to most American adults which could have differentially affected their breakfast behaviors. Despite the delayed timing of the sleep period, the sample had an average sleep duration of 7.61 hours a night, which is similar to averages reported by American adults (6.8-7.4 hours; National Sleep Foundation, 2005) and meets the National Sleep Foundation recommendations of 7-9 hours of sleep a night (National Sleep Foundation, 2005).

Another limitation of the current study is the restricted range of reported negative affect which may have limited the study's ability to assess negative affect's role as a mediator. It is possible that the sample responded in socially desirable ways to items assessing negative affect (Chen et al., 1997). It is also possible that affect was not collected at appropriate times, as participants were asked to recall their average affective experiences towards the end of the day. Due to recall bias, this may not be the best methodology to assess affect. As affect is a highly variable experience, it may be better to measure affect at multiple time-points throughout the day (Eid & Diener, 1999).

Additionally, although G*Power calculations concluded that the current sample was powered to detect a medium effect size, the sample may not have had enough power to detect small effects which could have contributed to the lack of significant findings. Post-hoc G*Power analyses indicate that to detect a small effect size assessing the study's aims, a sample size of at least 725 participants (versus current sample of 207 participants) would be necessary.

Lastly, the current study did not account for shift work when measuring sleep, affect, and breakfast variables over 14 days. Engaging in shift work could alter both sleep and eating schedules, potentially confounding results (Oexman, Knotts, & Koch, 2002). Consequently, future studies should assess for shift work in participants. The current study also did not compare sleep and breakfast behaviors across weekdays and weekends. Given that sleep behaviors can be altered on weekend days in comparison to weekdays, comparison of weekday versus weekends may have yielded differing results (Knutson, Van Cauter, Rathouz, DeLeire, & Lauderdale, 2010; Roepke & Duffy, 2010).

Although the current study includes several limitations, there are many strengths in this study's design. Prior research has measured sleep and breakfast intake variables using one-time self-report questionnaires (Ogilvie et al., 2017). This methodology does not provide enough information to assess variability in sleep behaviors, which are known to be highly variable (Bei et al., 2016). Additionally, retrospective single-time assessments are more subject to recall bias. Therefore, the current study used ecological momentary assessment over 14 days, to capture the variability in these behaviors and reduce the risk of recall bias. The current study also calculated intraindividual variability in sleep behaviors, as opposed to simply relying on the means of variables.

Future Directions

Although this study expanded upon prior literature by using ecological momentary assessment to measure sleep behaviors concurrently with breakfast behaviors, other methodological approaches should be used in the future. As actigraphy is regarded as an ecologically valid objective measure of sleep behavior, future studies should utilize actigraphy over one to two weeks to more accurately measure sleep behaviors in addition to sleep diaries (Ancoli-Israel, 2015). Additionally, the use of multiple within-day assessments may be beneficial. This approach using multiple within-day assessments could provide more insight into the within-day variations in daily behaviors and affect which may be affected by bedtime variability. Future research should also account for which day of the week measurements are taken, as sleep behaviors are altered on weekend days in comparison to weekdays (Knutson, Van Cauter, Rathouz, DeLeire, & Lauderdale, 2010; Roepke & Duffy, 2010). Additionally, it would be beneficial to measure breakfast intake, particularly the dietary quality and components of breakfast intake, using measures like dietary recalls to provide more information on macronutrient, micronutrient, and caloric composition of breakfasts. Since variability in bedtime may misalign circadian rhythms, future research should also consider examining other variables associated with circadian rhythms. For example, including measures which assess additional sleep characteristics (sleep quality, daytime fatigue), daily schedules, and ratings of hunger and fullness may provide enough information to assess how variability in bedtime is associated with decreased breakfast intake.

Summary

The current study examined the association between sleep behaviors, affect, and breakfast behaviors. Greater variability in bedtime emerged as a predictor of less frequent breakfast intake. As such, the current study informs recommendations regarding bedtimes. Results suggest that the time one goes to bed is of less importance. However, having a more regular and routine bedtime is predictive of higher breakfast intake frequency. Clinical implications of this study include increasing awareness of core sleep hygiene behaviors, including having more regular sleep schedules. Education programming to increase awareness and knowledge of sleep hygiene behaviors would be a plausible step to improve sleep hygiene behaviors.

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Appendix

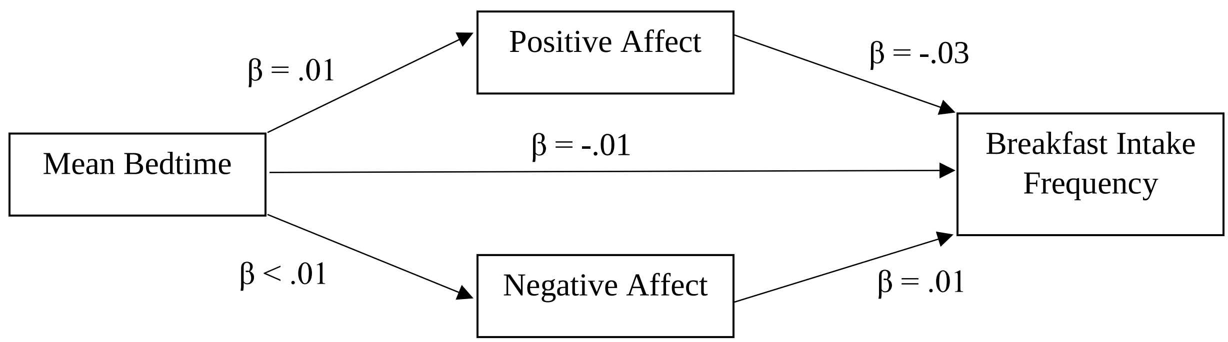

Figure 1. Parallel mediation model for the association between mean bedtime and breakfast intake frequency, mediated by positive and negative affect. *p < .05. **p < .001.

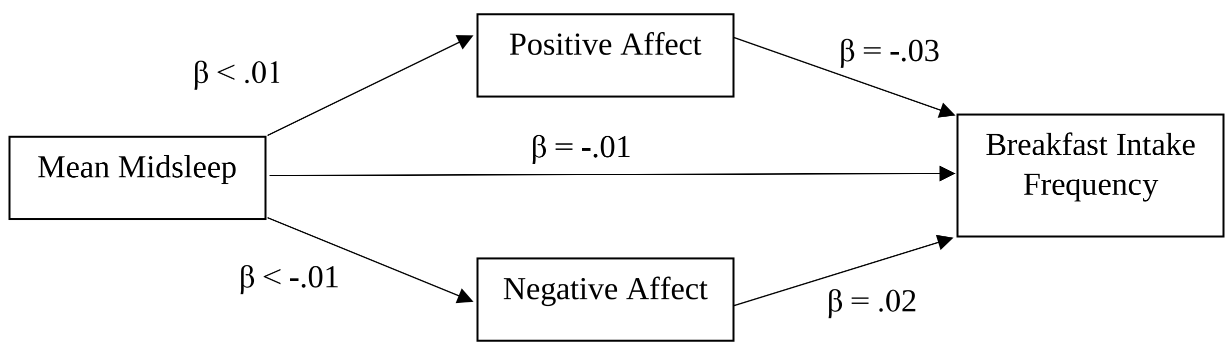

Figure 2. Parallel mediation model for the association between mean midsleep and breakfast intake frequency, mediated by positive and negative affect. *p < .05. **p < .001.

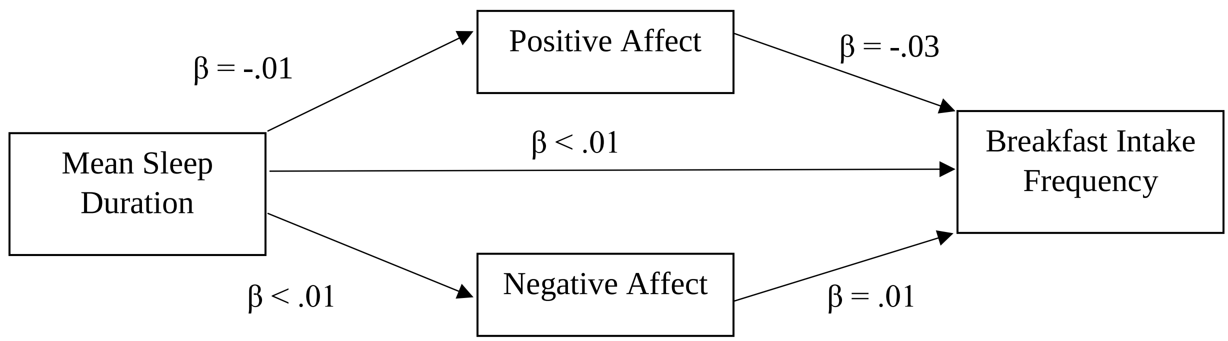

Figure 3. Parallel mediation model for the association between mean sleep duration and breakfast intake frequency, mediated by positive and negative affect. **p* < .05. ***p* < .001.

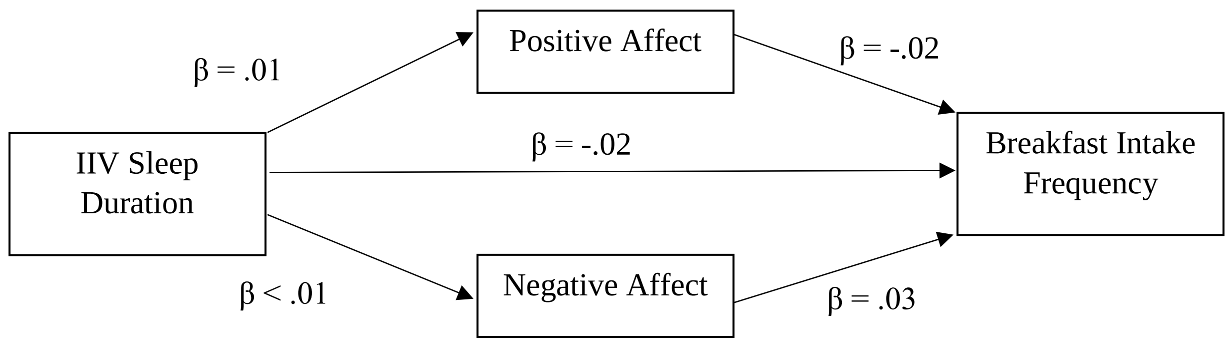

Figure 4. Parallel mediation model for the association between IIV sleep duration and breakfast intake frequency, mediated by positive and negative affect. **p* < .05. ***p* < .001.

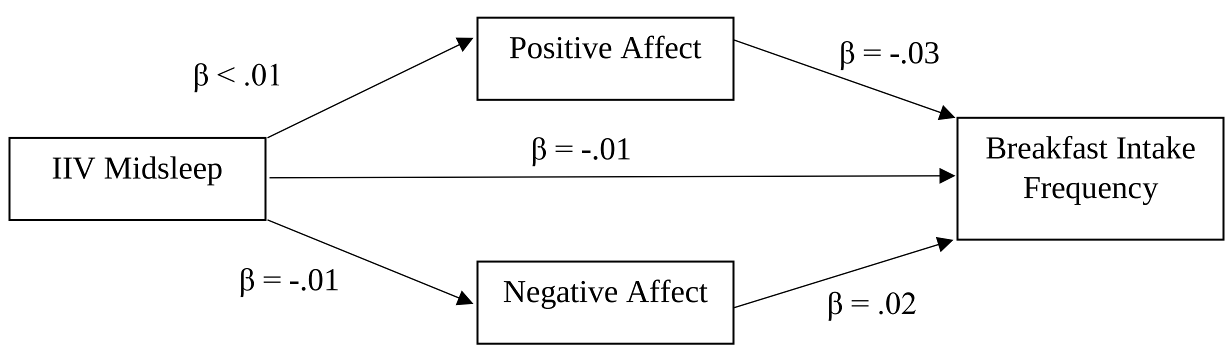

Figure 5. Parallel mediation model for the association between IIV midsleep and breakfast intake frequency, mediated by positive and negative affect. **p* < .05. ***p* < .001.

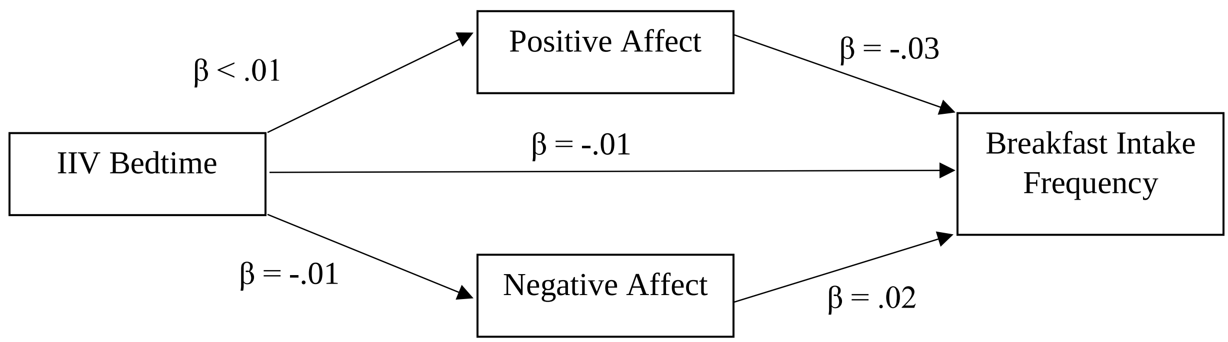

Figure 6. Parallel mediation model for the association between IIV bedtime and breakfast intake frequency, mediated by positive and negative affect. *p < .05. **p < .001.

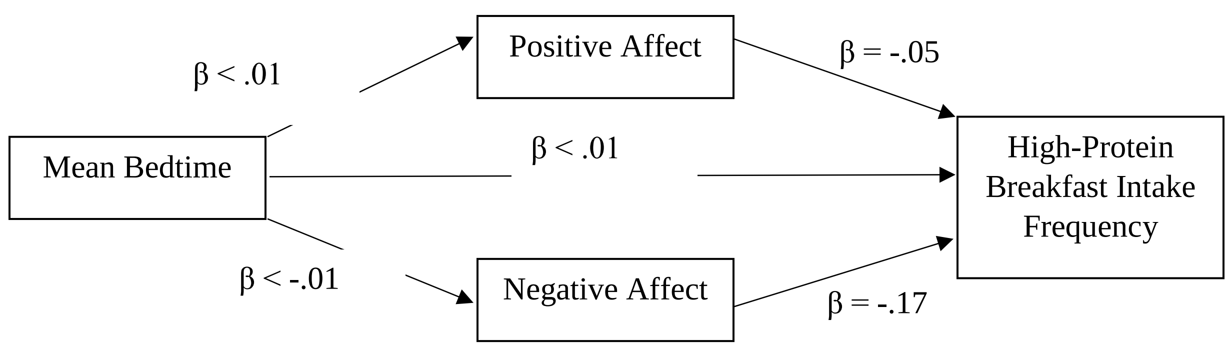

Figure 7. Parallel mediation model for the association between mean bedtime and high-protein breakfast intake frequency, mediated by positive and negative affect. *p < .05. **p < .001.

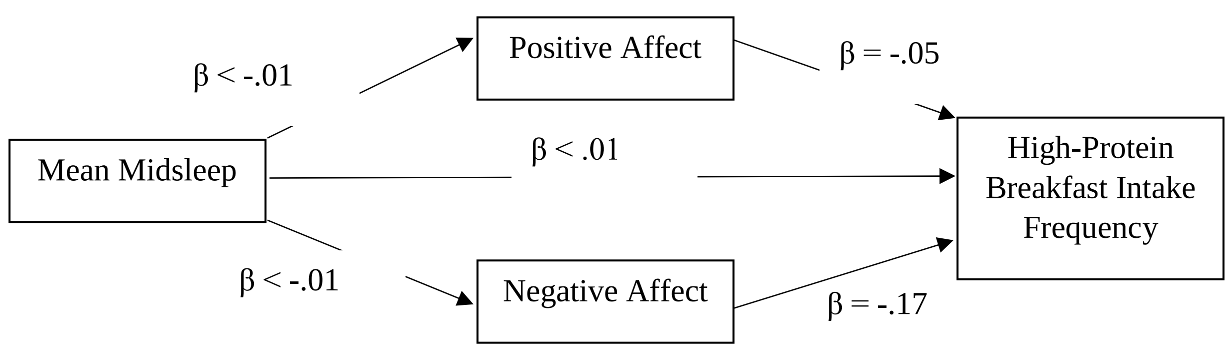

Figure 8. Parallel mediation model for the association between mean midsleep and high-protein breakfast intake frequency, mediated by positive and negative affect. *p < .05. **p < .001.

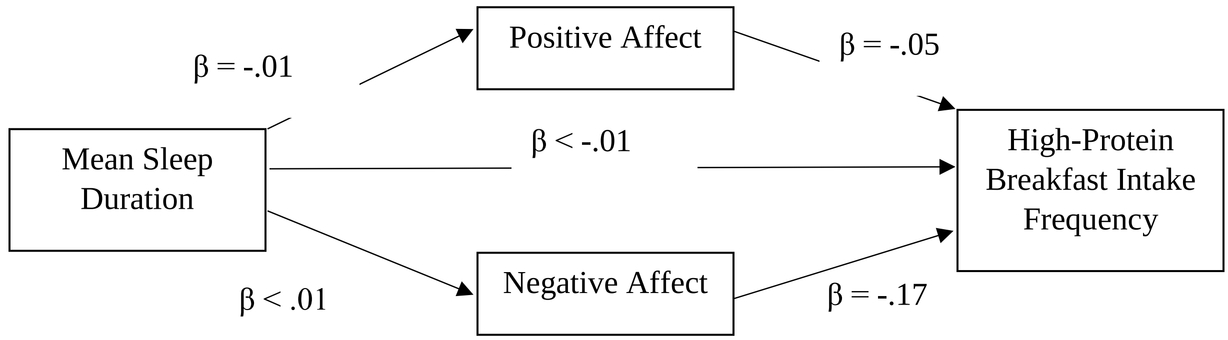

Figure 9. Parallel mediation model for the association between mean sleep duration and high-protein breakfast intake frequency, mediated by positive and negative affect. *$p < .05$. **$p < .001$.

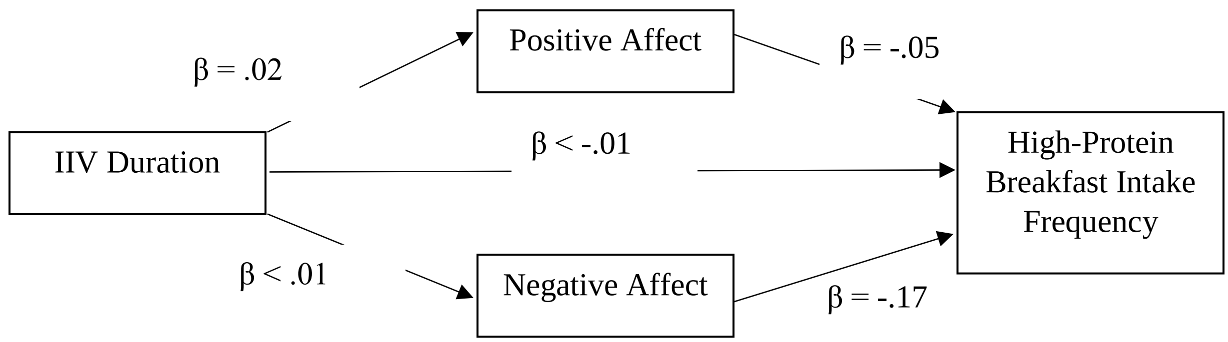

Figure 10. Parallel mediation model for the association between IIV sleep duration and high-protein breakfast intake frequency, mediated by positive and negative affect. *$p < .05$. **$p < .001$.

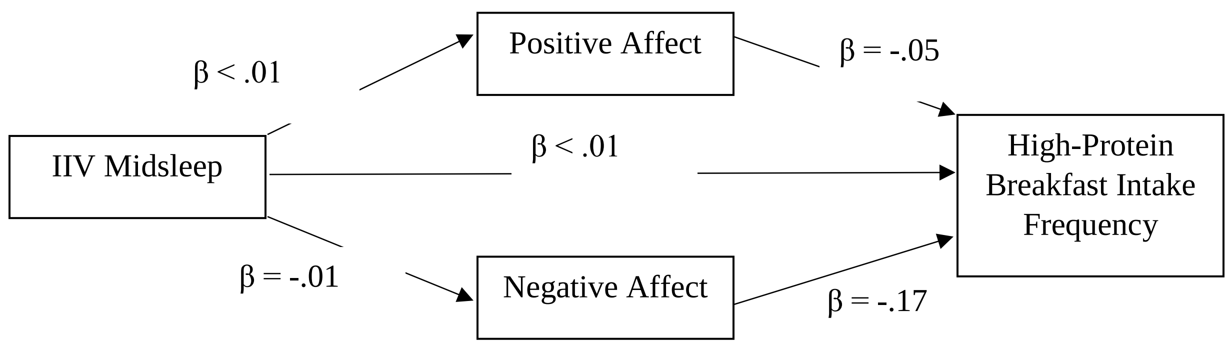

Figure 11. Parallel mediation model for the association between IIV midsleep and high-protein breakfast intake frequency, mediated by positive and negative affect. *$p < .05$. **$p < .001$.

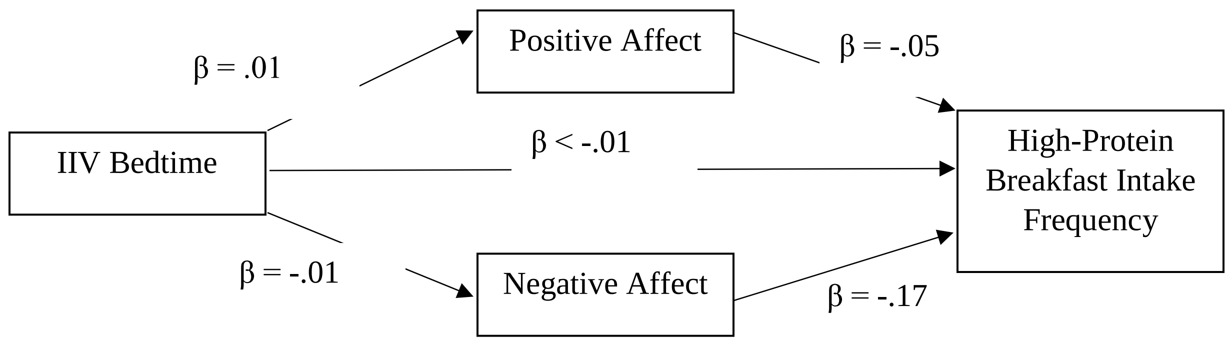

Figure 12. Parallel mediation model for the association between IIV bedtime and high-protein breakfast intake frequency, mediated by positive and negative affect. **p* < .05. ***p* < .001.

Vita

Ashley Rose MacPherson was born on March 31, 1993 in Boston, Massachusetts and is an American citizen. She graduated from Pinkerton Academy in Derry, New Hampshire in 2011. She obtained her Bachelor of Arts degree in Psychology with a minor in Nutrition from the University of New Hampshire in Durham, New Hampshire in 2015. She completed her Masters of Arts in Mental Health Counseling from Boston College in Newton, Massachusetts. She began her graduate work in the Counseling Psychology doctoral program at Virginia Commonwealth University in August 2017 under the mentorship of Natalie D. Dautovich, Ph.D.