TRAJECTORIES OF PEDIATRIC SLEEPINESS AND ASSOCIATIONS WITH HEALTH-RELATED QUALITY OF LIFE: A LONGITUDINAL STUDY USING A PERSON-CENTERED APPROACH

By

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Abstract

Adequate sleep is paramount for children's healthy development of emotion regulation, academic achievement, and cognitive performance. The critical need for sleep in children has sparked extensive research in which four independent domains have emerged, some providing inconclusive support for detrimental outcomes in health-related quality of life (HRQOL) when impaired. Yet, daytime sleepiness, which uniquely captures a child's subjective sleep experience, has seldom been explored. To determine the chronicity of sleepiness, the current study employed latent class growth analysis to identify longitudinal trajectories, or classes, of children's daytime sleepiness. Trajectories were subsequently utilized to assess their association with HRQOL. The present sample included 158 elementary-age children. Children's self-report of daytime sleepiness and HRQOL was collected at three time points across an academic year. Results provided support for three trajectories (i.e., classes) of sleepiness and a significant association between class membership and later HRQOL, $F(2, 124) = 17.38$, $p < .001$. Post hoc tests revealed significant differences in HRQOL between the *Low* and *Moderate* trajectories ($p < .01$), *Low* and *High* trajectories ($p < .001$), and between the *Moderate* and *High* trajectories ($p < .01$). Analyses indicated that children with high and stable sleepiness experienced impairments in HRQOL comparable to children with chronic health conditions. Results suggest that sleepiness is more pervasive and widespread than other facets of sleep behavior. Implications include the establishment of daytime sleepiness as a pervasive state with both statistical and clinical significance. Future research should focus on generating empirically derived normative data to provide researchers and clinicians reference values to assess sleepiness reports relative to clinical impairment.

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Anfangen is leicht, beharren eine Kunst.

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Introduction

Sleep is a universal phenomenon necessary for sustaining life and achieving optimal daily functioning. Despite the seemingly passive nature of the sleep state, sleep is a time in which complex, neurophysiological functions occur (España & Scammell, 2004). The consolidation of memories, regulation of neuroendocrine functioning, and the growth and development of the central nervous system are heavily dependent upon the sleep process (Mindell & Owens, 2009). Adequate sleep is critical for growth, development, and cognitive performance, including learning and executive functioning (Sadeh, 2007).

Children and adolescents spend as much as 40% of their day sleeping (Mindell & Owens, 2015), which has prompted more than a century of research needed to understand how sleep impacts behavior. Initial studies of sleep were largely limited to documentation of "quantitative aspects of sleep" (i.e., sleep duration) of children in orphanages and nursery schools (Reynolds & Mallay, 1933, p. 349). Subsequently, researchers have studied sleep from many perspectives, and have therefore developed more precise terminology to characterize aspects of sleep behavior. Four main constructs have emerged as domains used to understand children's sleep: quality, disturbances, duration, and sleepiness. Although these domains share some commonalities and may influence one another, research suggests that they have unique characteristics, and at times, different outcomes (Dewald, Meijer, Oort, Kerkhof, & Bögels, 2010; Meijer, Habekothé, & van den Wittenboer, 2000; Pilcher, Ginter, & Sadowsky, 1997).

Sleep quality, one domain of sleep behavior, measures the feeling of restfulness and satisfaction with the sleep experience (Pilcher et al., 1997). Sleep quality, when measured objectively through actigraphy, is commonly reported as *efficiency* (Paavonen et al., 2010), and includes factors such as early onset of sleep and fewer sleep disturbances and early awakenings

(Meijer et al., 2000). Correlations between number of hours slept and sleep quality are low or nonsignificant, indicating that sleep quality is a unique and independent construct from duration (Dewald et al., 2010; Meijer et al., 2000; Pilcher et al., 1997).

Research suggests that sleep quality is more strongly associated with subsequent daytime sleepiness, emotional state, behavior, and cognitive function than other sleep domains (Dewald et al., 2010). For example, Segura-Jiménez, Carbonell-Baeza, Keating, Ruiz, and Castro-Piñero (2015) examined the relationship between perceived sleep quality and positive psychological health in a sample of children ages 6-11 years. Sleep quality was associated with improved reported health status, life satisfaction, positive family relationships, and better academic performance. Consistent with these findings, sleep quality has also been related to academic and cognitive performance (Dewald et al., 2010; Paavonen et al., 2010; Sadeh, Gruber, & Raviv, 2002). Sadeh et al. (2002) reported that children's performance on complex neurobehavioral tasks is impaired in the presence of poor sleep quality. Paavonen et al. reported similar findings in that sleep quality negatively impacts verbal reasoning. In a meta-analysis by Dewald et al. (2010), the negative effects of poor sleep quality are especially pronounced when using subjective sleep quality reports and in samples of younger children. The sequela of negative outcomes associated with poor sleep quality is indicative of its impact on a child's functioning in a wide array of domains.

Sleep disturbances collectively describe difficulties with the initiation or maintenance of sleep, and include phenomena such as restless legs symptoms, nightwakings, night terrors, sleep walking/talking, and insomnia. Despite their occasional use as a proxy for sleep quality (Paavonen et al., 2010), sleep disturbances may also impact sleep duration. This domain may be described as "sleep disruptions" or "problems," and is commonly measured through self-report assessments (e.g., Children's Report of Sleep Problems, Meltzer et al., 2013; Sleep Disturbance Scale for Children, Bruni et al., 1996). Sleep disturbances may also be assessed using objective measures including polysomnography and actigraphy (Meltzer et al., 2013). Approximately 25-40% of healthy, typically developing children experience some type of sleep problem (Mindell & Owens, 2009), including difficulty with sleep onset latency, bedtime resistance, and increased nighttime fears (Mindell, Carskadon, Chervin, & Meltzer, 2004; Smaldone, Honig, & Byrne, 2007).

A growing body of research has examined the relationship between sleep problems and child outcomes. For example, in a prospective longitudinal study of child sleep, Price, Wake, Ukoumunne, and Hiscock (2012) found that parent-reported infant sleep problems (at 12 months) were related to poorer self-reported psychosocial and physical health-related quality of life (HRQOL) at 6 years. Evidence for a concurrent association between these variables was also found. Quach, Hiscock, Canterford, and Wake (2009) studied patterns of sleep problems at two time points over a two-year period. At wave 1, 33.6% of parents reported a sleep problem; whereas, at wave 2, a reduction was found with only 22.6% of parents reporting their child had a sleep problem. Children with parent-reported sleep problems at both time points (2.9%) and those with sleep problems during the second time point (2.8%) presented with the poorest HRQOL. Finally, in a cross-sectional study of children ages 4-8 years, 38.6% of parents reported their child had a sleep problem, which yielded a strong, adverse association with all HRQOL domains (Quach, Hiscock, & Wake, 2012). These findings suggest that past and present sleep problems in childhood have strong implications for child outcomes, specifically, HRQOL.

Sleep Duration may be viewed as the most objective domain of children's sleep (Dewald et al., 2010). It is defined as the actual time a child is asleep, and is assessed via parent- and/or child-report and actigraphy and polysomnography. In the literature, it may be referred to as "insufficient," "diminished," "disrupted," or "inadequate" sleep duration, sleep "quantity," or (less precisely) as "time in bed" (Dewald et al., 2010; Graef, Janicke, McCrae, & Silverstein, 2014; Matricciani, Olds, & Petkov, 2012b; Pilcher et al., 1997).

Although age-based recommendations for sleep duration have been provided (e.g., American Academy of Sleep Medicine, 2012; Blair et al., 2012), recent challenges to these recommendations have been published (Matricciani, Olds, Blunden, Rigney, & Williams, 2012). Indeed, research has consistently demonstrated that sleep duration is highly variable among children and considerable inter-individual variability exists. Blair et al. (2012) noted that sleep duration ranged from 10 to 17 hours in infancy, although this window narrowed to 8.5 to 11 hours at age 11 years. Similar findings were reported by other investigatory teams (Iglowstein, Jenni, Molinari, & Largo, 2003; Jenni, Molinari, Caflisch, & Largo, 2007).

Despite a high degree of variability across children, sleep duration tends to be a trait-like quality in that sleep patterns remain relatively stable (i.e., within person) through childhood. For instance, children who sleep shorter periods than their peers tended to do so throughout their childhood (Blair et al., 2012; Jenni et al., 2007; Magee, Gordon, & Caputi, 2014). Jenni et al. (2007) further noted that smaller intra-individual yearly fluctuations, relative to inter-individual differences, in sleep duration also occur. Findings from these recent longitudinal sleep studies necessitate that recommendations for appropriate sleep duration in children must consider the significant individual variability related to child characteristics (Blair et al., 2012; Jenni et al., 2007). In light of the literature on insufficient sleep and various outcomes, Matricciani, Blunden, Rigney, Williams, and Olds (2013) commented on sleep as a complex phenomenon, which may not be accurately summarized into a set of age-dependent recommendations. Rather, the amount of sleep a child needs is largely influenced by a number of factors including intra-individual variability (Jenni et al., 2007), gender (Blair et al., 2012), socioeconomic status (Blair et al., 2012), and cultural background (Liu, Liu, Owens, & Kaplan, 2005). This suggests that there is something more to the relationship between obtaining, or failing to obtain, the recommended sleep duration and various dependent variables.

Despite the controversy regarding age-based recommendations, inadequate sleep duration has been linked to a range of maladaptive physical and psychosocial outcomes including increased sensitivity to emotional and stressful events (for review see Vandekerckhove & Cluydts, 2010), more internalizing and externalizing behavior problems (Paavonen, Porkka-Heiskanen, & Lahikainen, 2009), and higher family stress (Sadeh et al., 2000). Research has further associated insufficient sleep with key health behaviors such as higher rates of obesity (Chaput, Brunet, & Tremblay, 2006) and greater perceptions of health problems (Graef et al., 2014). Generally speaking, insufficient sleep is thought to increase risk for these outcomes by increasing emotional instability and impairment in executive functioning (Graef et al., 2014; Hiscock, Canterford, Ukoumunne, & Wake, 2007; Paavonen et al., 2009).

Daytime sleepiness is the most common byproduct of inadequate sleep duration and poor sleep quality (e.g., Blunden et al., 2006; Dahl & Lewin, 2002; Dewald et al., 2010; Liu et al., 2005; Quach et al., 2012; Shochat, Cohen-Zion, & Tzischinsky, 2014). Sleepiness can be assessed from physiological, subjective, and/or behavioral perspectives (Fallone et al., 2002).

Physiologically, sleepiness is characterized by homeostatic and circadian influences, including length of time since the last sleep period and the amount of sleep debt (Fallone, Owens, & Deane, 2002). Several laboratory-based measures of sleepiness and wakefulness have been developed to objectively measure the physiological experience of daytime sleepiness.

During these assessments, the tendency to fall asleep or the ability to stay awake are measured. Despite advances in these objective measures of sleepiness, weak correlations have been found between the subjective self-report measures of sleepiness and values obtained from the objective tests (Arand et al., 2005; Chervin, Aldrich, Pickett, & Christian, 1997), suggesting that subjective and objective measures assess different aspects of sleepiness (Arand et al., 2005).

Subjective and behavioral manifestations of sleepiness commonly rely on self- and proxy-report measures. Subjective sleepiness, or children's psychological experience, is typically measured using questionnaires and scales (e.g., Children's Report of Sleep Patterns – Sleepiness Scale [Meltzer et al., 2012], Pediatric Daytime Sleepiness Scale [Drake et al., 2003]). As a behavioral dimension, sleepiness can be assessed through manifestations of "sleepy" behavior, such as yawning, rubbing eyes, and even inattentiveness and hyperactivity. For instance, the Teacher's Daytime Sleepiness Questionnaire (Owens, Spirito, McGuinn, & Nobile, 2000) was developed to assess the frequency of yawning, complaining about sleep, and difficulty staying awake in the classroom. Similarly, parents may be asked to report daytime hyperactivity and propensity for a child to fall asleep during daytime situations (Melendres, Lutz, Rubin, & Marcus, 2004; Moore et al., 2009).

Previous research has demonstrated a strong relationship between psychosocial health and sleepiness (Blunden et al., 2006; Carskadon & Acebo, 2002; Dahl & Harvey, 2007; Dahl & Lewin, 2002; Shochat et al., 2014). Associations between sleepiness and mood (Shochat et al., 2014) and poor coping skills (Matthews, Hall, Cousins, & Lee, 2015) have been found in both child and adolescent samples. Additionally, researchers have noted associations between sleepiness and impairments in attention, learning, executive functioning, and mood (Beebe, 2011; Chorney, Detweiler, Morris, & Kuhn, 2008; Curcio, Ferrara, & De Gennaro, 2006;

Gregory & Sadeh, 2012). Within academic domains, sleepiness is a stronger predictor of school performance than sleep duration or quality (Dewald et al., 2010). Specifically, sleepiness has been negatively correlated with reading, math, and language achievement (Keller, El-Sheikh, & Buckhalt, 2008). Parents and teachers tend to report more behavioral difficulties, poorer emotion regulation, and difficulties with higher-order cognitive processes when children are sleepy (Dewald et al., 2010; Smedje, Broman, & Hetta, 2001).

Findings from the aforementioned studies provide general insight into the relationship between psychosocial outcomes of interest (e.g., anxiety, attention, mood) and sleep duration; however, they are limited in their ability to characterize a child's overall adjustment across a range of contexts. These previous studies have relied on very specific, sometimes narrow, outcome assessments that do not address the "overall functioning" of the child (e.g., Chorney et al., 2008; Curcio et al., 2006). Further, the use of assorted psychosocial measurements is problematic as it introduces variability in outcome variables because measures diverge in conceptual frameworks, length of administration, and change over time (Drotar, 2014; Spieth & Harris, 1996). Therefore, it may be more beneficial to assess a child's health and functioning by capturing their physical, mental, and social adjustment in one measure (Drotar, 2014; Eiser & Varni, 2013).

As first conceptualized by the World Health Organization (WHO) in 1947, the construct of HRQOL emerges as a possible avenue for exploring a child's overall well-being. Defined by the WHO (1947), HRQOL refers to a multidimensional approach to understanding health by way of three identified dimensions: physical, mental, and social. HRQOL has emerged as a construct used to understand individuals' perceptions of their physical, emotional, and social well-being, focusing on individuals' disease- or treatment-specific experiences (National Institutes of Health, 2014). Subsequently, HRQOL is important as a patient-reported outcome and individuals with a chronic condition evidence poorer HRQOL relative to their healthy peers. This effect is further compounded for individuals with comorbid diseases (Rothrock et al., 2010). Since its inception in 1947, the core components of HRQOL have expanded and additional domains have been suggested as important constructs to consider when measuring HRQOL (Spieth & Harris, 1996).

Currently, evidence for the relationship between sleep duration and HRQOL is relatively mixed. Although a number of measures of HRQOL have been developed and validated (see Palermo et al., 2008, for review), a dearth of research has explored the relationship between sleepiness and HRQOL. Findings from one study of 4- to 5-year-old children determined that morning tiredness (i.e., daytime sleepiness) most negatively impacted HRQOL, more so than sleep problems such as snoring and nightwakings (Hiscock et al., 2007). Therefore, this study documents a concurrent relationship between sleepiness and HRQOL and, thereby indicates that sleepiness has a global impact on a child's well-being.

A number of recent studies has provided mixed evidence for a relationship between HRQOL and sleep duration. In a longitudinal sleep duration study spanning from infancy to age 7 years, Magee, Gordon, and Caputi (2014) identified four sleep trajectories (typical sleepers, initially short sleepers, poor sleepers, and persistent short sleepers), each with unique implications for HRQOL. Children classified as "initially short" and "poor sleepers" had poorer physical HRQOL. "Persistent short sleepers" evidenced greater impairment across HRQOL domains and had significantly lower physical, emotional, and social HRQOL compared with "typical sleepers." In a second study, Vella, Magee, and Cliff (2015) modeled longitudinal trajectories of HRQOL in children beginning at age 4 through 13 years with sleep duration data collected every 24 months. Sleep duration at ages 4 and 5 years was not found to be a significant predictor of HRQOL trajectories in their sample. The null finding may be attributed to intra-individual variability, as well as changes in sleep need from preschool to adolescence. Finally, in a cross-sectional study, children with poorer HRQOL at age 6-7 years had increased sleep duration (Price, Quach, Wake, Bittman, & Hiscock, 2015), but this relationship was not found in children ages 4-5 and 8-9 years. Taken together, these findings demonstrate that the link between sleep duration and HRQOL is not well understood and there are many factors, such as developmental age range, study design, and frequency and format of assessment that likely contribute to the mixed findings.

Limitations of Existing Research

Despite an abundance of research exploring the outcomes of poor sleep quality and insufficient sleep duration, the current literature remains limited in several areas. First, longitudinal research in children’s sleep in relation to HRQOL is scarce, particularly with regard to longitudinal evaluations of sleepiness. The data provided by currently available longitudinal studies of sleep *duration* and *problems* (Magee et al., 2014; Price et al., 2012; Price et al., 2015; Quach et al., 2009) provide insight into children’s sleep behavior and its association with HRQOL. However, no studies to date have examined longitudinal associations between *sleepiness* and HRQOL. Given that, concurrently, sleepiness is a better predictor of HRQOL than sleep problems, longitudinal studies of the association between sleepiness and HRQOL are needed to inform future research and clinical practice. Based on the literature reviewed above, it is anticipated that trajectories of daytime *sleepiness* will evidence significant associations with HRQOL.

The current longitudinal research is also limited to samples of children up to age 7 years (e.g., Magee et al., 2014; Price et al., 2012; Price et al., 2015), using sleep duration and problems, and often focusing on preschool children preparing to transition into school. This is problematic as sleep recommendations change from 11 to 13 hours per night in preschoolers to 10 to 11 hours in elementary-aged children. Without biological basis to substantiate these recommendations, and given the significant inter-individual variability, it is unclear how these transitional periods may affect outcomes. Therefore, studies assessing the longitudinal associations between sleepiness and outcome measures are needed across the range of developmental periods of children, including middle childhood (Iglowstein et al., 2003; Jenni et al., 2007).

Third, existing longitudinal studies of both sleep duration or sleep problems and associations with HRQOL frequently rely on parent-reported assessments of sleep. For example, parents have been asked if their child has sleep problems (“no”, “mild”, “moderate”, or “severe”; Price et al., 2012; Quach et al., 2009). When assessing sleep duration, parents were provided a sleep diary and were asked to report on sleep patterns during an interview (Magee et al., 2014). Sleep duration and problems assessed in this manner may lack accuracy and sensitivity to factors that could affect quality and quantity (e.g., Magee et al., 2014; Price et al., 2012; Price et al., 2015). Additionally, in the majority of longitudinal studies, parents provided proxy ratings of HRQOL. Unfortunately, there is substantial evidence to suggest that HRQOL measured by parent-report may not accurately capture children’s well-being as it is a subjective experience (e.g., Buttitta, Iliescu, Rousseau, & Guerrien, 2014; Vella et al., 2015). Studies that examine child-reported sleep problems (including daytime sleepiness) and HRQOL will add to the growing literature on the impact of sleep on HRQOL.

Fourth, extant longitudinal studies of sleep and HRQOL typically rely on annual or biennial assessments of sleep behavior (e.g., Magee et al., 2014; Price et al., 2015). Although it is believed that sleep duration is trait-like (Jenni et al., 2007), research indicates that there may be significant intra-individual variability (e.g., Quach et al., 2009). However, children with persistent sleep problems have been shown to evidence compromised HRQOL (Price et al., 2012; Quach et al., 2009; Quach et al., 2012). Therefore, multiple assessments may be needed to capture true patterns and fluctuations of sleep behavior. Also, for children with persistent sleep problems, it is imperative to know how pervasive the effects of long-term sleepiness are and how sleepiness continues to impact their HRQOL. Although previous research has included HRQOL as an outcome measure (e.g., Hiscock et al., 2007; Magee et al., 2014; Price et al., 2012; Price et al., 2015), it is unclear whether continued sleep problems affect HRQOL over time. Several researchers have noted this as a limitation and have called for research to better delineate how sleep patterns and behavior affect overall functioning (e.g., Dahl & Lewin, 2002; Fallone et al., 2002; Shochat et al., 2014).

Finally, although evidence in preschool children provides preliminary support for a concurrent relationship between sleepiness and HRQOL (Price et al., 2012; Price et al., 2015; Quach et al., 2009), the dynamic, longitudinal association between the two constructs remains unexplored (Dahl & Harvey, 2007; Dahl & Lewin, 2002; Shochat et al., 2014). Several publications have recognized these limitations and call for investigations of longitudinal data following sleep patterns and daytime functional outcomes (Dewald et al., 2010; Shochat et al., 2014). As of yet, these questions remain unanswered, but if studied, may shed insight into the pervasive effects of sleepiness in childhood.

Present Study

The present study was designed to evaluate two previously unexamined questions regarding the longitudinal pattern of sleepiness and its association with HRQOL. In Aim 1, this study explored the longitudinal trajectories (patterns) of sleepiness over an academic year (nine-month span). Previous work has highlighted the relative intra-individual stability of sleep duration (Jenni et al., 2009), with some fluctuations noted (Quach et al., 2009). What remains to be examined is the trajectory of sleepiness across time. Assessing sleepiness longitudinally will likely capture any changes or fluctuations that may occur, and may better represent children's experiences. Additionally, by using a person-centered analytical approach, it can be determined whether a child's sleepiness is persistent, or even chronic. Previous research has suggested several patterns of sleep problems and duration across childhood (e.g., Magee et al., 2014; Quach et al., 2009); however, the literature lacks a conceptualization of sleepiness patterns, which limits the ability to estimate or hypothesize the number of trajectories that will emerge. *Therefore, an exploratory approach was employed, which allowed the data to guide the model selection process.* Identifying and determining these trajectories will lead to an improved understanding of how sleepiness influences health and well-being.

Aim 2 of the present study was designed to use the trajectories gathered in Aim 1 to make determinations about the associations between trajectories of sleepiness and HRQOL. Literature has previously demonstrated that different patterns of sleep behavior (i.e., problems, duration) have important implications for children's psychosocial well-being (Magee et al., 2015; Price et al., 2012; Price et al., 2015; Quach et al., 2009; Quach et al., 2012), but only one study has documented the negative impact of morning tiredness (i.e., sleepiness) on HRQOL (Hiscock et al., 2007). Using trajectories, rather than a single assessment, will provide more specific information about patterns of sleepiness that ultimately contribute to a global outcome, HRQOL. Although the exact number of classes (i.e., trajectories) that will emerge cannot be estimated *a priori*, *it was hypothesized that children with chronic and/or worsening sleepiness across time* *will evidence the poorest HRQOL; whereas, children with low and/or decreasing sleepiness will experience stable or improved HRQOL at Time 3 (T3HRQOL).*

This study is unique in that it relies solely on children's perceptions of these constructs. In the present literature, parent-reports of HRQOL and sleep duration and problems are generally used (e.g., Magee et al., 2014; Price et al., 2012; Quach et al., 2009). However, as children enter school, they are more able to provide meaningful reports of their behavior and experiences (Meltzer et al., 2008; Riley, 2004). Further, evidence suggests that parents tend to under- or overestimate HRQOL (Buttitta et al., 2014; Eiser & Morse, 2001; Tsiros et al., 2009) and under-report sleep behavior (Owens et al., 2000; Paavonen et al., 2000). Taken together, evidence indicates that proxy reporters may not adequately capture the relationship between sleepiness and HRQOL. Therefore, children's perceptions (through self-report) will guide the extent and severity of sleepiness and will indicate how impairing their sleepiness trajectory is at the end of the school year.

Method

Participants

After receiving approval from the University of Kansas Institutional Review Board, Unified School District 497, and respective building principals and teachers, 3rd, 4th, and 5th grade students were recruited from two elementary schools in Lawrence, Kansas. Eligibility criteria were (a) the child was enrolled in 3rd–5th grade, (b) the student spoke and read English, and (c) the child's parent or custodial caregiver provided consent for participation. All eligible students were given a consent form that was completed by the child's parents before the child could participate in the proposed study. In addition, children were assented prior to data collection and were given the opportunity to withdraw from the study.

Procedures

Questionnaire packets included measures about physical activity, eating attitudes, HRQOL, and affect as part of a three-year longitudinal study. Time 1 (October 2015) and Time 3 (April 2016) data collection occurred in the schools. Research assistants read questionnaires to participating children. Time 2 (December 2015) packets were distributed at school and sent home for completion. Research assistants provided reminder calls and sent emails to ensure successful return rate of packets. Research assistants returned to the schools to collect the questionnaire packets. Students who completed packets at Time 1 and Time 3 were mailed a $5 gift card as an incentive for participation.

Measures

The *Children's Report of Sleep Patterns – Sleepiness Scale* (CRSP-S; Meltzer et al., 2012) is a 5-item self-report measure of sleepiness that has been shown to differentiate between children presenting to a primary care provider, sleep laboratory, and sleep clinic. The CRSP-S has been validated in children ages 8-12 years (Meltzer et al., 2012) and has demonstrated good internal consistency ($\alpha = .86$; Poppert Cordts & Steele, 2016; George & Mallery, 2003). Test-retest reliability was .82, $p < .001$ and the intraclass correlation between parent- and child-report was .20, suggesting that children are able to uniquely contribute information that parent reports may not be capturing (Meltzer et al., 2012). Internal consistencies for the present sample are provided in Table 2 (p. 21).

The *PedsQL 4.0 Generic Core Scales* (PedsQL; Varni, Seid, & Kurtin, 2001) is a 23-item self-report measure of HRQOL, which has been widely used in sleep research (Magee et al., 2014; Price et al., 2012; Price et al., 2015; Quach et al., 2009; Quach et al., 2012). The measure provides four subscale scores: Physical (8 items), Emotional (5 items), Social (5 items), and

School Functioning (5 items), as well as a Psychosocial Health Summary Score (15 items) and Total Score. Consisting of a 5-point Likert scale, response options range from “Never a problem” to “Almost always a problem.” Responses are reverse scored to a “0” to “100” scale and the subscale scores are derived by summing items and dividing by the number of items answered with higher scores signifying better HRQOL. Internal consistency statistics are consistently in or above the acceptable range for research use ($\alpha > .80$; Streiner, 2003). Internal consistencies for the present study are provided in Table 2.

Data Analytic Plan

Data were examined for skewness and non-normality. Robust (full information) maximum likelihood estimation were used to model the data. Full information maximum likelihood allows use of all available data points by modeling missing data (Little, Jorgensen, Lang, & Moore, 2014). The use of auxiliary variables to predict missingness and multiple imputation were considered to handle missing data; however, these approaches are either not possible in a mixture modeling framework or prevented the later use of model comparison likelihood ratio tests (Berlin, Parra, & Williams, 2014). In robust maximum likelihood, non-normally distributed data are accounted for by adjusting the standard errors and scales chi-square statistics (Berlin et al., 2014).

Latent class growth analysis (LCGA), a subtype of growth mixture modeling, is a person-centered approach used to identify significant predictors of outcomes (Jung & Wickrama, 2008). LCGA allows researchers to identify response patterns and group individuals into classes based on similarities. LCGA differs from growth mixture modeling in that variances and covariances within each class are fixed to zero. By doing this, homogeneity of individual growth trajectories is assumed. LCGA was performed using structural equation modeling in Mplus 7 (Muthén & Muthén, 2014).

To evaluate Aim 1, an exploratory approach was taken to identify trajectories of classes. Factor loadings were set to 0, 1, and 3 to represent equidistant time intervals. A single-class latent growth curve model was specified first. This model served as the baseline and comparison model for subsequent analyses. After establishing the baseline model, additional models were specified while increasing the number of classes. Classes were continually estimated as long as they produced proper solutions, including model nonconvergence, nonplausible values, or unidentified local maxima (Berlin et al., 2014; Ram & Grimm, 2009). Comparisons between the models were used to determine the most likely number of unobserved groups.

Various fit statistics were considered when assessing model fit and determining the final model. First, although specific criteria cannot be determined, lower values on the Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) indicated better fitting models (Muthén, 2003; Nylund, Asparouhov, & Muthén, 2007; Ram & Grimm, 2009). Next, entropy, ranging from 0.00 to 1.00, was used as a summary indicator of the probability of group membership (Jedidi, Ramaswamy, & DeSarbo, 1993). Entropy values approaching 1.00 suggest clear class delineation (Celeux & Soromenho, 1996); values greater than 0.80 are generally interpreted to indicate that individuals are correctly classified. Higher entropy values also suggest significance of class separation and greater certainty of class membership and classification accuracy (Berlin et al., 2014; Ram & Grimm, 2009). As recommended by Ram and Grimm (2009), models with higher entropy were selected when multiple models had similar fit indices (e.g., BIC). Finally, a series of likelihood ratio tests was used to compare models. Specifically, the Vuong-Lo-Mendell-Rubin likelihood ratio test (VLMR-LRT) and adjusted Lo-

Mendell-Rubin likelihood ratio test (Adjusted LRT) were used to compare the models (Lo, Mendell, & Rubin, 2001; Muthén, 2004; Nylund et al., 2007; Vuong, 1989). A significant likelihood ratio test ($p < .05$) indicated that the model with fewer classes ($C - 1$) should be rejected in favor of the model with more classes (C). Finally, class trajectories were plotted to further examine their distinctiveness as recommended by Jung and Wickrama (2008) and Ram and Grimm (2009).

As an added step of trajectory confirmation, a *k*-fold cross-validation procedure was used to empirically examine the number of extracted classes (Grimm, Mazza, & Davoudzadeh, 2016). This procedure was designed to determine whether the number of classes derived in finite mixture modeling is meaningful and substantively useful. In finite mixture modeling, fit indices tend to improve as additional classes are specified because the model is more accurately representing the data with each increasing class. Additionally, model selection becomes more subjective when fit indices are not unanimous (e.g., the AIC provides support for one model, but the Adjusted LRT indicates another) and provide conflicting information about the optimal number of classes (Grimm et al., 2016).

To evaluate Aim 2, and using trajectory class membership obtained in Aim 1, an analysis of covariance (ANCOVA) was used to test the hypothesis that sleepiness trajectories are associated with T3HRQOL while controlling for T1HRQOL. Only T3HRQOL was included as the outcome measure as the present study intended to assess the cumulative effect of sleepiness on children’s psychosocial well-being, and focused less on the changes in HRQOL over time.

Statistical Power

Currently, no rule exists specifying how large a sample size should be when conducting growth mixture modeling (Ram & Grimm, 2009). Further, determining the necessary sample size in LCGA is difficult due to a number of factors, including the size of the between-group differences, group sizes, and measurement reliability (Ram & Grimm, 2009). However, other longitudinal methods often require greater statistical power than LCGA and are more limited in their ability to handle non-normally distributed data and partially missing data (Curran, Obeidat, & Losardo, 2010). Despite limitations in using sophisticated power analytic techniques (e.g., Monte Carlo simulation studies), rudimentary programs can be used to provide a baseline, generalized estimate of sample size. Therefore, a power analysis using the G*Power computer program version 3.1.6 (Faul, Erdfelder, Lang, & Buchner, 2007) was conducted to estimate the approximate sample size needed to detect significant results. Using ANOVA repeated measures between factors design with 95% power and alpha at .05, the power analysis indicated that a total sample size of 168 was needed to detect medium effects (f = .25; defined by Cohen, 1992).

Results

Descriptive Statistics

Data presented in this study were collected as part of a larger investigation of psychosocial variables associated with health behaviors and academic performance. Research assistants attended school events, provided information about the study, and distributed consent forms to parents of eligible children. Additionally, study information was sent home in weekly folders by classroom teachers and parents were prompted to return the completed consent form regardless of whether they gave consent. At the time of the first data collection, 314 students were eligible for the study, according to the State Department of Education. Recruitment efforts resulted in 246 (78.3%) returned parental consent forms. Of these, 174 (70.7%) consent forms granting participation were returned and 72 (29.3%) denied parental permission. Of the 174 potential participants for whom parental permission was granted, 15 (8.6%) participants moved away from the school and one participant was unable to complete the measures due to data collection time constraints. The final sample included 158 3rd, 4th, and 5th grade students (M_{age} = 9.42 years, *SD* = .95). Demographic characteristics and descriptive statistics for the CRSP and PedsQL are presented in Table 1 and Table 2, respectively. Children predominantly identified as Caucasian (60.8%), although nearly 10% of participating children identified as "bi-racial" or "multiracial," while 12% indicated that they belonged to a racial or ethnic category that was not presented (i.e., "Other"). Slightly more than half (52.5%) were female.

Table 1
Demographic Characteristics of the Present Sample

Demographics	Quail Run Elementary (*n* = 104)	New York Elementary (*n* = 54)	Total Sample (*N* = 158)
Age (years)	9.42 (*SD* = .99)	9.41 (*SD* = .88)	9.42 (*SD* = .95)
Gender			
Male	48 (46.2%)	27 (50%)	75 (47.5%)
Female	56 (53.8%)	27 (50%)	83 (52.5%)
Race/Ethnicity			
White (non-Hispanic)	73 (70.2%)	23 (42.6%)	96 (60.8%)
Black (non-Hispanic)	6 (5.8%)	0 (0%)	6 (3.8%)
Hispanic	6 (5.8%)	3 (5.6%)	9 (5.7%)
Asian	5 (4.8%)	0 (0%)	5 (3.2%)
American Indian	2 (1.9%)	6 (11.1%)	8 (5.1%)
Biracial/Multiracial	6 (5.8%)	9 (16.7%)	15 (9.5%)
Other	6 (5.8%)	13 (24.1%)	19 (12.0%)

Table 2

Summary of Bivariate Correlations, Means, and Standard Deviations for Study and Demographic Variables

	1	2	3	4	5	6	7	8	9
1. T1 CRSP	-								
2. T1 HRQOL	**-.43****	-							
3. T2 CRSP	**.35****	**-.41****	-						
4. T3 CRSP	**.49****	**.40****	**.45****	-					
5. T3 HRQOL	**-.26****	**.67****	**-.37****	**-.53****	-				
6. Age	-.11	.12	.01	-.12	.04	-			
7. Gender	-.07	.01	-.10	-.14	-.04	**.24****	-		
8. Race/Ethnicity	.04	-.06	**.22***	.10	.06	-.07	-.11	-	
9. School	**-.27****	**.25****	.02	-.16	**.22****	.01	-.04	**-.29****	-
M	8.12	77.94	7.03	7.11	79.89	9.42	-	-	-
SD	3.60	14.97	3.05	2.40	12.67	.95	-	-	-
α	.80	.90	.83	.61	.90	-	-	-	-

Note. ***p* < .001; **p* < .05. T1 CRSP = Time 1 CRSP Sleepiness Scale; T1 HRQOL = T1 PedsQL HRQOL Total Score; T2 CRSP = Time 2 CRSP Sleepiness Scale; T3 CRSP = Time 3 CRSP Sleepiness Scale; T3 HRQOL = Time 3 PedsQL HRQOL Total Score.

Data Screening

Prior to performing analyses, data were screened for non-normality and the majority of items were found to be positively skewed (i.e., < 1.0). Patterns of missingness were assessed using Little's Missing Completely at Random test in SPSS version 23 (IBM Corp., 2015). Data were determined to be missing completely at random after the test failed to reject the null hypothesis ($X^2(8) = 7.30$, $p > .50$). Therefore, to accommodate skewness and missingness, robust (full information) maximum likelihood was used to estimate all models.

Aim 1

Structural equation modeling (SEM) in Mplus Version 7 (Muthén & Muthén, 2014) was used for model generation. Latent class growth analyses were estimated using robust maximum likelihood and slope and intercept variances were fixed to zero. Maximum likelihood values, entropy, adjusted LRT, and VLMR-LRT are presented in Table 3. Initially, a univariate growth model was specified in which the data were forced to converge into one class. In line with recommendations by Ram and Grimm (2009), additional classes were added to the model until convergence issues were encountered. Two-, three-, and four-class models were estimated. Relative to the 2-class model, the 3-class model yielded better model fit as evidenced by a decrease in the AIC and BIC; however, likelihood ratio tests were not significant, indicating the 2-class model should not be rejected in favor of the 3-class model. When comparing the 3-class and 4-class models, fit indices marginally decreased as the number of classes increased. Likelihood ratio tests of the 4-class model were significant, suggesting that the more parsimonious, 3-class model should be retained. A 5-class model was specified, but failed to converge; therefore, no additional models were specified. Entropy was adequate for the 2- to 4-class solutions (.92, .86, & .86 for 2-class to 4-class models, respectively).

Table 3
Parameters of fit of latent class growth analysis

Class	AIC	BIC	ABIC	Entropy	Adjusted LRT		VLMR-LRT
					2LL	*p*	*p*
1	1899.161	1914.474	1898.646	-	-	-	-
2	1813.696	1838.197	1812.873	.916	85.814	.0007	.0004
3	1779.488	1813.177	1778.357	.857	37.724	.0801	.0675
4	1769.305	1812.181	1767.864	.863	15.184	.5052	.4909

Notes. AIC, Akaike information criterion; BIC, Bayesian information criterion; ABIC, Sample-size adjusted BIC; Adjusted LRT, Lo-Mendell-Rubin likelihood ratio test; VLMR-LRT, Vuong-Lo-Mendell-Rubin likelihood test.

As outlined in the Data Analysis Plan and following recommendations from Jung and Wickrama (2008) and Ram and Grimm (2009), visual inspection of plotted means was also used as an ancillary step in model evaluation. Specifically, graphs generated by Mplus for class trajectories were evaluated after each model was specified (Figure 1). The visual display of class means provided another opportunity to assess if there were logical group differences among the classes, or if the specified model resulted in considerable overlap. While the cursory review of the graphs was not “diagnostic” in model selection, it generated dialogue about the substantive meaningfulness of the classes. When used in conjunction with the aforementioned fit statistics, it provided a more comprehensible understanding of the data and guided model interpretation and selection.

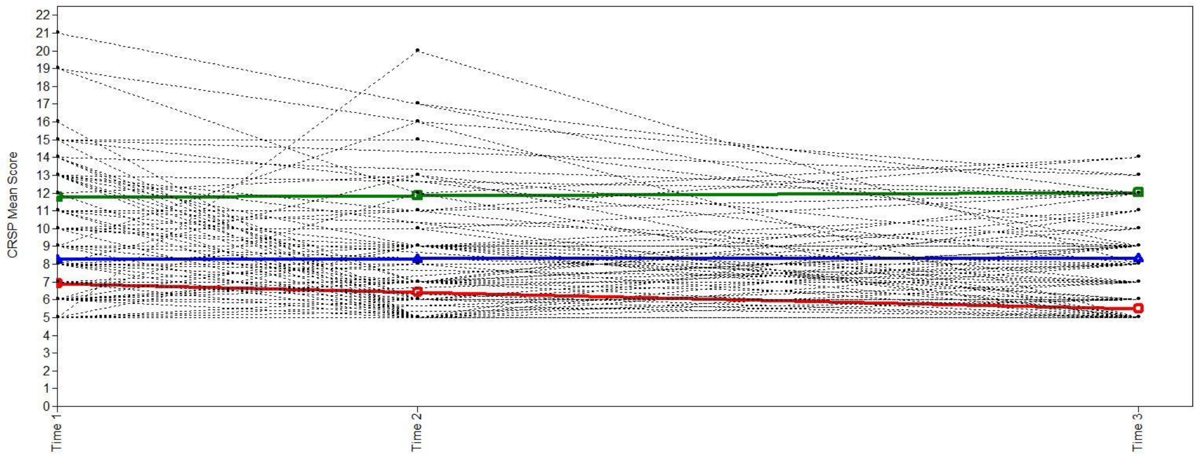

Figure 1. Estimated Means and Observed Individual Growth Trajectories for the 3-Class Model

Although the aforementioned fit statistics provide information for model evaluation and guidance in model selection, ambiguity often remains in interpretation as assorted information criteria may not present a clear or consistent "answer" about model fit. Of further concern is the increased likelihood of Type 1 error inflation when researcher inferences are made following model selection (Hurvich & Tsai, 1990; Lubke & Campbell, 2016). Despite these noted limitations, previous research has predominantly relied on information criteria when conducting growth mixture modeling (e.g., Berlin et al., 2014; Magee et al., 2014; Ram & Grimm, 2009). In light of these concerns, Grimm and colleagues (2016) suggested a supplemental method for model selection, *k*-fold cross-validation, which attempts to standardize the model selection process by relying less on researcher subjectivity. To empirically examine the number of extracted classes, the *k*-fold cross-validation technique was performed using the R statistical program (R Core Team, 2014), the MplusAutomation package (Hallquist & Wiley, 2014), and Mplus (Muthén & Muthén, 2014). Following steps outlined by Grimm, Mazza, and

Davoudzadeh (2016), the dataset was divided into 10 folds in R. Next, the MplusAutomation package was used to specify the model and fit the model to the *k*-1 partitions, creating a "training sample." The MplusAutomation package was then used to specify a "test sample" in which the parameter estimates obtained from the training sample were equated to the parameter values. The -*2LL* and entropy mean and standard deviation were retained from the test sample as indices of model fit (Table 4).

Given the novelty of the *k*-fold cross-validation approach, four different approaches were used to interpret the -*2LL* findings and discern the appropriate number of classes. *First*, the model with the smallest mean -*2LL* was examined, indicating that the <u>3-class model</u> would be selected (See Table 4). The *second* approach recommended by Grimm et al. (2016) is to choose the model with the fewest parameters whose mean -*2LL* is within one standard error of the best-fitting model. Using this criterion, the <u>2-class model</u> is preferred. The *third* approach shares similarities with commonly used likelihood ratio tests. Beginning with the univariate model, models that differ by one class are compared. Using this approach, the <u>2-class</u> model was indicated. The 1-class model mean was within one standard error of the 2-class model mean. *Finally*, in the same vein as the third approach, the model with the smallest -*2LL* (i.e., 3-class model) is compared to the 4-class model. Because they were within one standard error of one another, this suggests that they fit similarly.

Table 4

k-fold Cross-Validation Parameters of Fit

Class	*-2LL* Mean (SD)	95% Confidence Interval		Entropy (SD)	95% Confidence Interval	
		Lower Bound	Upper Bound		Lower Bound	Upper Bound
1	190.02 (19.47)	177.95	202.09	-	-	-
2	182.27 (17.27)	171.57	192.97	.91 (.06)	.87	.94
3	170.16 (16.66)	159.83	180.49	.86 (.06)	.82	.90
4	177.82 (27.41)	163.92	191.72	.86 (.05)	.83	.95

Of note, the confidence intervals for the *-2LL* and entropy values overlap in each of the models specified by the *k*-fold cross-validation. Traditionally, overlapping confidence intervals signals a lack of statistical significance, despite instances in which statistically significant differences exist (e.g., Austin & Hux, 2002; Knezevic, 2008; Payton, Greenstone, & Schenker, 2003; Schenker & Gentleman, 2001). Nevertheless, the first criterion proposed by Grimm et al. (2016) does not rely on confidence intervals for interpretation, but rather posits that the model with the smallest mean *-2LL* (3-class model) could be used for model selection. In sum, findings were evaluated following recommendations by Grimm et al. (2016), but should be interpreted with caution as this is a novel approach with budding empirical support and guidance around this issue is not yet available.

In light of the overlapping confidence intervals produced by the *k*-fold cross-validation and novelty of the technique, supplemental multiple comparisons of CRSP scores across time and class were conducted (Table 7). A one-way analysis of variance (ANOVA) was used to further elucidate differences among classes of sleepiness. There was a significant effect of class on T1CRSP [$F(2, 129) = 22.05$, $p < .001$], T2CRSP [$F(2, 99) = 14.90$, $p < .001$], and T3CRSP [$F(2, 141) =$, $p < .001$]. Tukey post hoc tests demonstrated a statistically significant difference between the *Low* and *High* ($p < .001$) and *Moderate* and *High* ($p < .001$), but not between *Low* and *Moderate* ($p = .50$) classes at Time 1. For Time 2, differences were observed between the

Low and *Moderate* (p < .01) and *Low* and *High* (p < .001), but not between *Moderate* and *High* (p = .07) classes. Finally, at Time 3, there was a statistically significant difference among and between all classes, *Low* and *Moderate* (p < .001), *Low* and *High* (p < .001), and *Moderate* and *High* (p < .001).

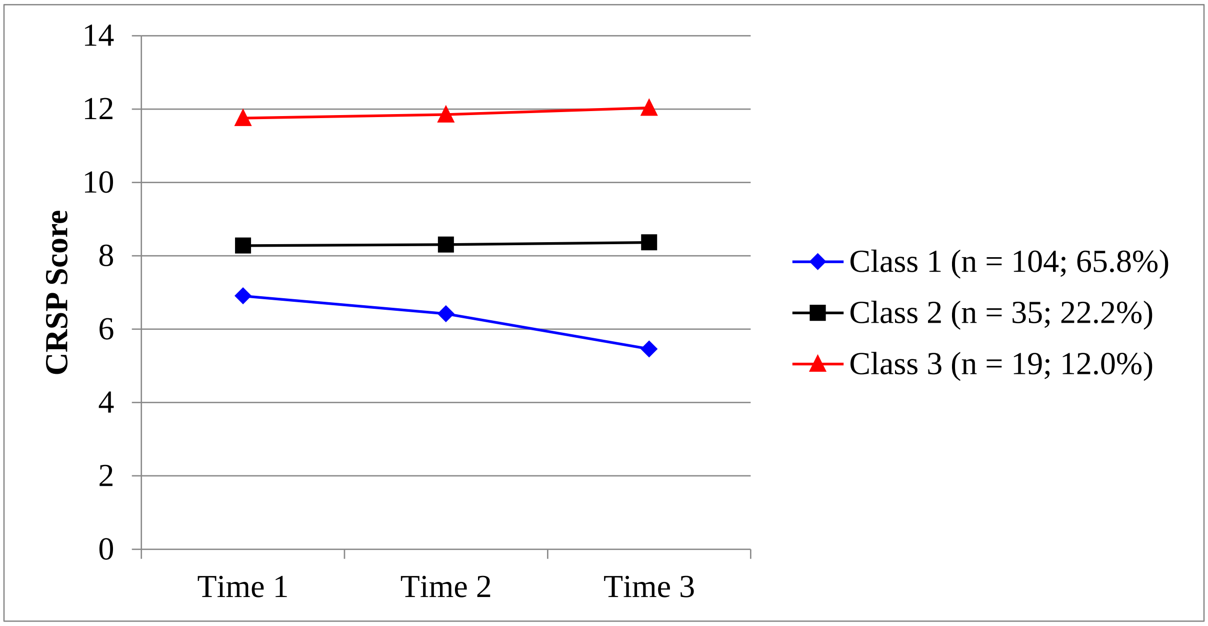

Figure 2. Mean trajectories obtained from the 3-Class Model of the latent class growth analysis.

Using information obtained from the fit indices in the LCGA, the *k*-fold cross-validation, and researcher interpretation of substantive usefulness, it was concluded that the 3-class model provides the best fit to the data and contributes the most meaningful number of classes. These classes were seen as representing three distinct trajectories of sleepiness over the course of an academic year: *Low*, *Moderate*, and *High* sleepiness classes.

Aim 2

To evaluate Aim 2, class membership assignments were extracted from Mplus and analyses were conducted in SPSS Version 23 (IBM, 2015). The deviation from the data analytic plan arose from an unforeseen challenge associated with conducting the Aim 2 analyses in latent space. Research indicates that adding a covariate and a distal outcome variable increases the likelihood that class membership will change (Asparouhov & Muthén, 2014; Vermunt, 2010). Class membership is based on posterior probabilities, meaning an individual's likelihood of belonging to a class, rather a definitive class membership assignment. Therefore, when adding covariates and outcome variables, it creates opportunities for individuals to shift classes. Such shifts can cause substantial changes and yield invalid results (e.g., Asparouhov & Muthén, 2014; Vermunt, 2010).

Table 5
Descriptive statistics of CRSP and T3HRQOL scores by class

	Class	Mean (SD)	95% Confidence Interval	
			Lower Bound	Upper Bound
T1 CRSP	Low	7.24 (2.79)	6.48	8.00
	Moderate	8.14 (2.39)	6.87	9.42
	High	12.40 (4.53)	10.55	14.25
T2 CRSP	Low	6.07 (2.12)	5.37	6.77
	Moderate	8.00 (3.63)	6.83	9.17
	High	10.30 (3.50)	8.60	12.00
T3 CRSP	Low	5.49 (.77)	5.28	5.70
	Moderate	8.62 (.59)	8.27	8.97
	High	12.10 (1.29)	11.59	12.61
T3 HRQOL	Low	82.77 (.99)	80.80	84.74
	Moderate	77.07 (1.58)	73.93	80.20
	High	68.21 (2.27)	63.72	72.70

Levene's test and normality checks were carried out and the assumptions were met. An ANCOVA was performed in which class membership served as the independent variable, T3HRQOL functioned as the outcome (dependent) variable, and T1HRQOL was entered as the covariate. There was a significant effect of class on T3HRQOL after controlling for T1HRQOL, $F(2, 124) = 17.38$, $p < .001$. Post hoc tests demonstrated a statistically significant difference between *Low* and *Moderate* ($p < .01$), *Low* and *High* ($p < .001$), and *Moderate* and *High* ($p < .01$) classes. Comparisons of the estimated marginal means indicated that T3HRQOL decreased across sleepiness classes. Children in the *High* sleepiness class reported the poorest HRQOL at Time 3 ($\bar{x}$ = 68.21, SD = 2.27). Ratings of T3HRQOL subsequently improved in the *Moderate* ($\bar{x}$ = 77.07, SD = 1.58) and *Low* sleepiness ($\bar{x}$ = 82.77, SD = .99) classes.

Table 6
Multiple Comparisons of Sleepiness Scores Across Classes and Time Points

	Class		Mean Difference (SE)	95% Confidence Interval		*p*
				Lower Bound	Upper Bound	
T1 CRSP	Low	Moderate	-.91 (.75)	-2.69	.88	.50
		High	**-5.16 (1.01)***	-7.56	-2.77	<.001
	Moderate	Low	.91 (.75)	-.88	2.69	.45
		High	**-4.26 (1.13)***	-6.95	-1.56	.001
	High	Low	**5.16 (1.01)***	2.77	7.56	<.001
		Moderate	**4.26 (1.13)***	1.56	6.95	.001
T2 CRSP	Low	Moderate	**-1.93 (.69)***	-3.57	-.30	.016
		High	**-4.23 (.92)***	-6.43	-2.03	<.001
	Moderate	Low	**1.93 (.69)***	.30	3.57	.016
		High	-2.30 (1.04)	-4.77	.17	.07
	High	Low	**4.23 (.92)***	2.03	6.43	<.001
		Moderate	2.30 (1.04)	-.17	4.77	.07
T3CRSP	Low	Moderate	**-3.13 (.20)***	-3.62	-2.64	<.001
		High	**-6.61 (.28)***	-7.27	-5.95	<.001
	Moderate	Low	**3.13 (.20)***	2.64	3.62	<.001
		High	**-3.48 (.31)***	-4.22	-2.74	<.001
	High	Low	**6.61 (.28)***	5.95	7.27	<.001
		Moderate	**3.48 (.31)***	2.74	4.22	<.001

To elucidate class characteristics, assorted demographic information is presented in Table 7. Additionally, a series of parametric and non-parametric analyses were conducted. There was not a statistically significant difference in children's age across groups [$F(2, 155) = 1.61$, $p < .05$], nor was there a difference in race/ethnicity [$X^2(12) = 20.39$, $p > .05$] or school of attendance [$X^2(2) = 5.37$, $p > .05$]. However, a significant association between gender and class membership was observed [$X^2(2) = 7.48$, $p < .05$].

Table 7

Demographic Characteristics Presented by Class

Demographics	Low	Moderate	High	*p*-value
Age (years)	9.46 (.97)	9.49 (.89)	9.05 (.91)	> .05
Gender				**.02**
Male	57 (54.8%)	10 (28.6%)	8 (42.1%)	
Female	47 (45.2%)	25 (71.4%)	11 (57.9%)	
Race/Ethnicity				> .05
White (non-Hispanic)	66 (63.5%)	20 (57.1%)	10 (52.6%)	
Black (non-Hispanic)	3 (2.9%)	1 (2.9%)	2 (10.5%)	
Hispanic	7 (6.7%)	1 (2.9%)	1 (5.3%)	
Asian	2 (1.9%)	3 (8.6%)	0 (0%)	
American Indian	5 (4.8%)	3 (8.6%)	0 (0%)	
Biracial/Multiracial	10 (9.6%)	0 (0%)	0 (0%)	
Other	11 (10.6%)	7 (20.0%)	6 (31.6%)	
School				> .05
Quail Run	75 (72.1%)	19 (54.3%)	10 (52.6%)	
New York	29 (27.9%)	16 (45.7%)	9 (47.4%)	

Discussion

Problematic sleep behavior (broadly defined) has been consistently linked to a range of psychosocial, academic, and cognitive concerns (e.g., Dewald et al., 2010; Paavonen et al., 2010; Sadeh et al., 2002). Specific detriments experienced by children with poor sleep include poor coping skills, greater mood dysregulation, and impairments in attention, learning, executive functioning. Further, some cross-sectional and longitudinal research suggests associations with poorer HRQOL in elementary-aged children (i.e., Price et al., 2012; Quach et al., 2012).

Despite evidence indicating specific impairments across many domains, definitions of sleep behavior are muddled. The inconsistent definition of "problematic" sleep behavior and amalgamation of multiple constructs (e.g., sleep quality, sleepiness, sleep problems, sleep disturbances, inadequate, insufficient, disrupted sleep duration) has created ambiguity in the literature as these distinct constructs have demonstrated different implications for outcomes. Further compounding this issue is the interindividual variability in sleep duration requirements

(Blair et al., 2012; Iglowstein et al., 2003; Jenni et al., 2007; Matricciani et al., 2012), which complicates measurement and the ability to draw conclusions about impairment when assessing outcomes.

Despite these inconsistencies, some research indicates that sleepiness emerges as a more consistent predictor of children's psychosocial wellbeing (e.g., Hiscock et al., 2007). Broadly, research has documented a strong relationship between psychosocial health and sleepiness (e.g., Blunden et al., 2006; Carskadon & Acebo, 2002; Dahl & Harvey, 2007; Dahl & Lewin, 2002; Shochat et al., 2014). More specifically, cross-sectional research in preschool children provides preliminary support for the concurrent relationship between sleepiness and HRQOL (Hiscock et al., 2007). The extant literature lends credence to the notion that sleepiness in children may directly influence their overall well-being and provides support for the present study in which two aims were developed to evaluate this relationship. In Aim 1, the stability of sleepiness over an academic year was investigated. Using a person-centered approach, classes, or trajectories, of sleepiness were identified to determine whether interindividual differences exist in a community sample of elementary-aged children. Using the information derived in Aim 1, Aim 2 gives meaning to the classes and generates implications for how sleepiness (or lack thereof) affects HRQOL.

With respect to the first study objective (i.e., determine classes of sleepiness over the course of an academic year), the LCGA yielded three distinct classes of sleepiness: *Low*, *Moderate*, and *High*. A *k*-fold cross-validation model, a novel statistical approach to provide objective support for the determination of classes (Grimm et al., 2016), confirmed these classes. Previous research has provided evidence for a clustering of children's sleep duration and, for "persistent short sleepers," their inadequate sleep duration may be chronic (Magee et al., 2014, p.

e1561). A similar effect has been demonstrated in children's sleep problems. Quach, Hiscock, Canterford, and Wake (2009) longitudinal research of sleep problems indicated that 10.1% of children with parent-reported problems resolved after two years; however, 2.9% of parents reported a "natural history of moderate/severe sleep problems" continuing across time.

Despite investigations of sleep duration and problems, the longitudinal nature of sleepiness, a stand-alone domain, had not yet been explored. Findings from the present study are particularly important as they suggest that some children display a chronic pattern of sleepiness, which remains stable across an academic year and may be associated with sustained impairment of functioning. This pattern shares commonalities with the trajectories of sleep duration established by Magee et al. (2014), in which 11.6% of the sample was characterized as "persistent short sleepers," but indicates that three classes sufficiently captures trajectories of sleepiness in elementary-aged children. Furthermore, 12% of children in this sample reported chronic sleepiness, suggesting that this distinctive domain is more widespread and pervasive than sleep problems reported by parents (Quach et al., 2009). Not only do these results reflect the functional nature of sleep (sleepiness), a previously unexplored domain, they provide more robust, temporally-sensitive information when considering the collection of three self-reported assessments in nine months.

Further, and consistent with the Aim 2 hypothesis (i.e., children with chronic and/or worsening sleepiness across time will evidence the poorest HRQOL; whereas children with low and/or decreasing sleepiness will experience stable or improved HRQOL at Time 3), the established sleepiness classes have implications for later HRQOL. Results from the present study echo previous cross-sectional and longitudinal research in which children with concurrent and ongoing sleep duration and problems displayed poorer HRQOL (Magee et al., 2014; Price et al., 2012; Quach et al., 2009; Quach et al., 2012). Specifically, children in the *Low* sleepiness class evidenced Time 3 HRQOL in line with community population norms (μ = 80.64; Varni, Burwinkle, & Seid, 2006). Conversely, the *High* sleepiness class reported poorest Time 3 HRQOL, with a mean HRQOL Total Score comparable to samples of children with chronic health conditions (i.e., μ = 71.59; Varni et al., 2006). This suggests that the *High* sleepiness class characterizes their overall well-being as significantly compromised. This finding is particularly concerning as this community sample was recruited to represent a healthy, typically developing population of elementary-aged children. Although chronic illness diagnosis was not collected and is unknown, some children within this sample are exhibiting impairments in HRQOL in line with children in clinic populations. Additionally, the relationship between sleepiness and HRQOL lends support to Hiscock, Canterford, Ukoumunne, and Wake's (2007) cross-sectional study of preschool children in which daytime sleepiness was the greatest predictor of impaired HRQOL, as well as provides evidence for an enduring association between the two constructs in a sample of older, elementary-aged children.

Interestingly, the association between HRQOL and sleepiness in this sample is inconsistent with Price, Quach, Wake, Bittman, and Hiscock's (2015) findings, in which 6-7 year old children with poorer HRQOL slept longer (i.e., an inverse relationship between sleep duration and HRQOL). However, data from 4-5 and 8-9 year olds did not suggest increased sleep duration needs when HRQOL was impaired. Vella et al. (2015) reported similar findings in that longitudinal trajectories or classes of HRQOL could not be predicted by sleep duration. Price et al.'s (2015) null findings could be attributed to the directionality of the study design in which HRQOL was used to predict sleep duration, rather than an attempt to explain children's HRQOL as an outcome of sleepiness. Similarly, Vella et al.'s (2015) use of sleep duration at the first time point likely does not provide sufficient information to be used as a predictor of longitudinal HRQOL trajectories, as extant research indicates that many children do not experience ongoing sleep issues as they age (e.g., Magee et al., 2014; Quach et al., 2012). Therefore, using an initial assessment of sleep duration may be inappropriate and may not be expected to be associated longitudinally with HRQOL unless problems persist.

Beyond statistical significance, and perhaps even more important, are the clinical implications of these findings. As described by Copay, Subach, Blassman, Polly, and Schuler (2007), Minimal Clinically Important Difference (MCID) can be used to evaluate whether a statistical difference between groups translates to observable and "worthwhile" changes in subjective experience (p. 542). Furthermore, in large samples, data considered in aggregate may yield significant findings, but may not reflect changes experienced at the individual level (Copay et al., 2007). One method of assessing MCID is through a distribution-based approach, such as the standard error of measurement (SEM). In SEM, the unreliability of the measure (i.e., measurement error) is considered. Mean group change scores less than the SEM are likely due to measurement error; whereas scores greater than the SEM can be attributed to observed change. Research suggests that one SEM can be used as the "yardstick of true change" (Copay et al., 2007; p. 544).

The MCID is especially important to consider in the case of sleepiness and HRQOL. Presently defined, both constructs are largely subjective and rely on children's perceptions of impairment. Previous research has determined that the MCID for PedsQL is 4.4-point change in Total Scale Score for child self-report (Varni, Burwinkle, Seid, & Skarr, 2003). In the present study, the difference between the *Low* and *High* sleepiness (difference = 14.56) classes is 3.3 times the MCID value suggested by Varni et al. (2003). These findings exceed the recommended standard of one SEM and provide robust support for the effects of chronic sleepiness on children's well-being. Specifically, within a given classroom, children in the *High* sleepiness are experiencing impairments in their HRQOL unmatched by their non-sleepy peers. Without intervention, deficits in HRQOL may result in ongoing, poorer perceptions about their health and promote negative health appraisals as children age (Vingilis, Wade, & Seeley, 2002).

Overall, this study is characterized by several strengths. First, the use of latent class growth analysis, a person-centered approach that is responsive to individual patterns of behavior, provides information about the relationships among *individuals*, rather than describing the relationships among the variables. Conventional growth modeling approaches and variable-centered approaches (e.g., regression, factor analysis) may oversimplify the data and fail to identify complex patterns that explain interindividual change within a larger population (Jung & Wickrama, 2008). For example, the use of traditional approaches (e.g., regression) would have failed to identify different classes of participants and may have yielded null findings or washed out effects. Alternatively, researcher-derived groups in which classes of individuals are categorized based on demographic traits or characteristics (e.g., socioeconomic status, age, race/ethnicity) likely do not account for unobserved heterogeneity within the sample and may not capture intraindividual change among group members (Jung & Wickrama, 2008).

An additional strength of this study is the use of the *k*-fold cross-validation procedure to empirically confirm classes. Previous research has relied on more subjective interpretations of various fit indices, which may lack agreement and are dependent on model characteristics (e.g., number of estimated parameters, sample size). When fit statistics yield different results, determination of classes falls researcher interpretation (Grimm et al., 2016). The cross-validation procedure creates the opportunity to confirm classes quantitatively and increases the likelihood of replication in future studies through improved model selection (Grimm et al., 2016).

Building on previous research, the present study addresses key gaps in the existing literature. First, the longitudinal design and use of multiple assessments over an academic year captures true fluctuations and patterns in children's sleepiness. To date, research has relied on annual or biennial assessments (e.g., Magee et al., 2014; Price et al., 2015). Multiple snapshots of children's sleepiness helps characterize the pervasiveness and provides support for its stability across time. Relatedly, not only is longitudinal research in children's sleep scarce, previous longitudinal studies have predominantly been limited to samples of children up to age 7 years (e.g., Magee et al., 2014; Price et al., 2014; Price et al., 2015). The current study extends this age range by including children ages 8-11 years and captures children in a different developmental period during which sleep recommendations change to 10-11 hours per night. Further, children's self-report of sleepiness and HRQOL offers a unique perspective on their experiences. Extant research has relied on parent-report of HRQOL and sleep behavior (i.e., Magee et al., 2014; Price et al., 2012; Price et al., 2015; Quach et al., 2009). While parents may be able to provide more accurate information about sleep duration, they may be less able to report on the subjective feeling of sleepiness and well-being (Buttitta et al., 2014; Vella et al., 2015).

In light of these findings, some limitations should be considered. First, because both the independent and outcome variables were based on self-report, the results may be subject to common method variance (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Although the use of self-report measures introduces a new source of error, this was a necessary component of this study as sleepiness and HRQOL are defined as subjective constructs. Using a reporter other than the child would likely answer a different research question as caregiver or teacher's perceptions of these constructs may not fully reflect a child's experience (Theunissen et al., 1998). This may be an important area for future research. Concomitant with common rater effects, an additional limitation is the occasional overlap in content between measures of HRQOL and sleepiness. Although only one question on the PedsQL directly asks about sleep behavior (i.e., "*I have trouble sleeping*"), it is a noted limitation that several questions seemingly tap constructs related to outcomes from poor sleep (e.g., "*I have low energy*").

A concern regarding the internal consistency of the CRSP Sleepiness Scale should be noted. Specifically, Cronbach's alpha coefficient was considerably lower for Time 3 (α = .61), relative to the other time points (α = .80 & .83, respectively), as well as reports in previous publications (Meltzer et al., 2012; Poppert Cordts & Steele, 2016). Investigations into this issue failed to produce any tenable explanations or solutions. Although outside the scope of this project, an exploration of the factor structure may be warranted to determine the stability and reliability of the measure across time.

An additional limitation of the present study is the modest sample size, relative to other growth mixture models. Because statistical power cannot be calculated *a priori*, it remains unknown whether the 5-class model failed to converge because of the sample size, or because no more classes could be extracted from the data. However, the *k*-fold cross-validation procedure provides some assurance that the appropriate number of classes were specified.

Although LCGA is an innovative approach to better understand within- and between-person differences, the present study did not detect any complex growth patterns across time. Arguably, however, the eventual assignment of participants to their respected trajectories could not have been determined *a priori*. Given the general lack of significant findings in demographic characteristics distinguishing group membership (factors that are commonly used to identify and form groups; Berlin et al., 2014; Jung & Wickrama, 2008) researcher-driven decisions about class assignments may have been based on variables lacking significance in the present sample. Relatedly, LCGA considers individual behavior across time; whereas, variable-centered approaches may rely on classification based on a single event or time point. Therefore, although the patterns seem to suggest a relatively predictable split in the data, a variable-centered approach with researcher determinations about class membership assignments may not have yielded meaningful results.

Finally, an unanticipated problem with modeling a covariate and distal outcome in a growth mixture model required that Aim 2 analyses be conducted out of latent space Asparouhov & Muthén, 2014; Vermunt, 2010). Although no longer able to control for measurement error, ANCOVA is robust statistical technique that is widely used and accepted.

Findings from the present study address several gaps in the existing literature, while also generating ideas for further research. Future work with larger sample sizes would allow for more advanced statistical modeling techniques, such as latent transition analysis. More sophisticated growth mixture modeling could be used to track interindividual trajectories, while also considering intraindividual change as children could transition classes across time (e.g., Berlin et al., 2014; Jung & Wickrama, 2008; Ram & Grimm, 2009). Further, the establishment of clinical norms for the CRSP may give more context to these findings. Presently, normative scores on the CRSP Sleepiness Scale have not been reported for either clinical or community samples. Empirically derived normative data would provide researchers and clinicians reference values to assess children's sleepiness reports relative to clinical impairment. While the present study provides some data to suggest that there are both statistically and clinically meaningful differences in HRQOL as sleepiness increases, normative values would be beneficial for future use.

In summary, the findings from the present study provide further support for the chronicity or stability of sleep behavior in elementary-aged children. Previous research has focused on sleep duration and problems; therefore, this study evidences a similar trend in sleepiness, a related, albeit distinct construct in the sleep literature. Furthermore, results confirm an association between sleepiness and later HRQOL, such that children with chronic sleepiness tend to experience levels of HRQOL in line with reports by children with chronic illnesses. This relationship is both statistically and clinically significant indicating that children in the *High* sleepiness class notice subjective impairment. Results from this study may be used to inform future research through early identification of chronically sleepy children who may benefit from intervention.

References

Arand, D., Bonnet, M., Hurwitz, T., Mitler, M., Rosa, R., & Sangal, R. B. (2005). The clinical use of the MSLT and MWT. *Sleep*, *28*(1), 123-144.

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

Austin, P. C., & Hux, J. E. (2002). A brief note on overlapping confidence intervals. *Journal of Vascular Surgery*, *36*(1), 194-195.

Beebe, D. W. (2011). Cognitive, behavioral, and functional consequences of inadequate sleep in children and adolescents. *Pediatric Clinics of North America*, *58*(3), 649-665.

Berlin, K. S., Parra, G. R., & Williams, N. A. (2014). An introduction to latent variable mixture modeling (part 2): Longitudinal latent class growth analysis and growth mixture models. *Journal of Pediatric Psychology*, *39*(2), 188-203.

Blair, P. S., Humphreys, J. S., Gringras, P., Taheri, S., Scott, N., Emond, A., & Fleming, P. J. (2012). Childhood sleep duration and associated demographic characteristics in an English cohort. *Sleep*, *35*(3), 353-360.

Blunden, S., Hoban, T. F., & Chervin, R. D. (2006). Sleepiness in children. *Sleep Medicine Clinics*, *1*(1), 105-118.

Bruni, O., Ottaviano, S., Guidetti, V., Romoli, M., Innocenzi, M., Cortesi, F., & Giannotti, F. (1996). The Sleep Disturbance Scale for Children (SDSC) construction and validation of an instrument to evaluate sleep disturbances in childhood and adolescence. *Journal of Sleep Research*, *5*(4), 251-261.

Buttitta, M., Iliescu, C., Rousseau, A., & Guerrien, A. (2014). Quality of life in overweight and obese children and adolescents: A literature review. *Quality of Life Research*, *23*(4), 1117-1139.

Carskadon, M. A., & Acebo, C. (2002). Regulation of sleepiness in adolescents: Update, insights, and speculation. *Sleep*, *25*(6), 606-616.

Celeux, G., & Soromenho, G. (1996). An entropy criterion for assessing the number of clusters in a mixture model. *Journal of Classification*, *13*(2), 195-212.

Chaput, J. P., Brunet, M., & Tremblay, A. (2006). Relationship between short sleeping hours and childhood overweight/obesity: Results from the 'Quebec en Forme' Project. *International Journal of Obesity*, *30*(7), 1080-1085.

Chervin, R. D., Aldrich, M. S., Pickett, R., & Christian, G. (1997). Comparison of the results of the Epworth sleepiness scale and the multiple sleep latency test. *Journal of Psychosomatic Research*, *42*(2), 145-155.

Chorney, D. B., Detweiler, M. F., Morris, T. L., & Kuhn, B. R. (2008). The interplay of sleep disturbance, anxiety, and depression in children. *Journal of Pediatric Psychology, 33*(4), 339-348.

Cohen, J. (1992). A power primer. *Psychological Bulletin*, *112*(1), 155-159.

Copay, A. G., Subach, B. R., Glassman, S. D., Polly, D. W., & Schuler, T. C. (2007). Understanding the minimum clinically important difference: A review of concepts and methods. *The Spine Journal*, *7*(5), 541-546.

Curran, P. J., Obeidat, K., & Losardo, D. (2010). Twelve frequently asked questions about growth curve modeling. *Journal of Cognition and Development*, *11*(2), 121-136.

Curcio, G., Ferrara, M., & De Gennaro, L. (2006). Sleep loss, learning capacity and academic performance. *Sleep Medicine Reviews, 10*(5), 323-337.

Dahl, R., & Harvey, A. (2007). Sleep in children and adolescents with behavioral and emotional disorders. *Sleep Medicine Clinics, 2*(3), 501–511.

Dahl, R., & Lewin, D. (2002). Pathways to adolescent health sleep regulation and behavior. *Journal of Adolescent Health, 31*(6), 175–184.

Dewald, J. F., Meijer, A. M., Oort, F. J., Kerkhof, G. A., & Bögels, S. M. (2010). The influence of sleep quality, sleep duration and sleepiness on school performance in children and adolescents: A meta-analytic review. *Sleep Medicine Reviews, 14*(3), 179-189.

Drake, C., Nickel, C., Burduvali, E., Roth, T., Jefferson, C., & Badia, P. (2003). The Pediatric Daytime Sleepiness Scale (PDSS): Sleep habits and school outcomes in middle-school children. *Sleep, 26*(4), 455-460.

Drotar, D. (2014). *Measuring health-related quality of life in children and adolescents: Implications for research and practice.* New York, NY: Psychology Press.

Eiser, C., & Morse, R. (2001). Can parents rate their child's health-related quality of life? Results of a systematic review. *Quality of Life Research: An International Journal of Quality of Life Aspects of Treatment, Care & Rehabilitation, 10*(4), 347-357.

Eiser, C., & Varni, J. W. (2013). Health-related quality of life and symptom reporting: Similarities and differences between children and their parents. *European Journal of Pediatrics, 172*(10), 1299-1304.

España, R. A., & Scammell, T. E. (2004). Sleep neurobiology for the clinician. *Sleep, 27*(4), 811-820.

Fallone, G., Owens, J. A., & Deane, J. (2002). Sleepiness in children and adolescents: Clinical implications. *Sleep Medicine Reviews, 6*(4), 287-306.

Faul, F., Erdfelder, E., Lang, A. G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*, 175-191.

George, D., & Mallery, P. (2003). *SPSS for Windows step by step: A simple guide and reference. 11.0 update (4th ed.).* Boston, MA: Allyn & Bacon.

Graef, D. M., Janicke, D. M., McCrae, C. S., & Silverstein, J. H. (2014). Quality of life in obese youth with and without sleep problems. *Children's Health Care*, *43*(1), 39-53.

Gregory, A. M., & Sadeh, A. (2012). Sleep, emotional and behavioral difficulties in children and adolescents. *Sleep Medicine Reviews*, *16*(2), 129-136.

Grimm, K. J., Mazza, G. L., & Davoudzadeh, P. (2016). Model selection in finite mixture models: A *k*-fold cross-validation approach. *Structural Equation Modeling: A Multidisciplinary Journal*, 1-11.

Hallquist, M., & Wiley, J. (2014). *M*plus *Automation: Automating M*plus *model estimation and interpretation*. R package version 0.6-2. Retrieved from http://CRAN.R-project.org/package=MplusAutomation

Hiscock, H., Canterford, L., Ukoumunne, O. C., & Wake, M. (2007). Adverse associations of sleep problems in Australian preschoolers: National population study. *Pediatrics*, *119*(1), 86-93.

Hurvich, C. M., & Tsai, C. L. (1990). The impact of model selection on inference in linear regression. *The American Statistician*, *44*(3), 214-217.

IBM Corp. (Released 2015). *IBM SPSS Statistics for Windows*, Version 23.0. Armonk, NY: IBM Corp.

Iglowstein, I., Jenni, O. G., Molinari, L., & Largo, R. H. (2003). Sleep duration from infancy to adolescence: Reference values and generational trends. *Pediatrics*, *111*(2), 302-307.

Jedidi, K., Ramaswamy, V., & DeSarbo, W. S. (1993). A maximum likelihood method for latent class regression involving a censored dependent variable. *Psychometrika*, *58*(3), 375-394.

Jenni, O. G., Molinari, L., Caflisch, J. A., & Largo, R. H. (2007). Sleep duration from ages 1 to 10 years: Variability and stability in comparison with growth. *Pediatrics*, *120*(4), e769-e776.

Jung, T., & Wickrama, K. A. S. (2008). An introduction to latent class growth analysis and growth mixture modeling. *Social and Personality Psychology Compass*, *2*(1), 302-317.

Keller, P. S., El-Sheikh, M., & Buckhalt, J. A. (2008). Children's attachment to parents and their academic functioning: Sleep disruptions as moderators of effects. *Journal of Developmental & Behavioral Pediatrics*, *29*(6), 441-449.

Knezevic, A. (2008, October). Overlapping confidence intervals and statistical significance. *StatNews*, (73).

Little, T. D., Jorgensen, T. D., Lang, K. M., & Moore, E. W. G. (2014). On the joys of missing data. *Journal of Pediatric Psychology*, *39*(2), 151-162.

Liu, X., Liu, L., Owens, J. A., & Kaplan, D. L. (2005). Sleep patterns and sleep problems among school children in the United States and China. *Pediatrics*, *115*(Supplement 1), 241-249.

Lo, Y., Mendell, N. R., & Rubin, D. B. (2001). Testing the number of components in a normal mixture. *Biometrika*, *88*(3), 767-778.

Lubke, G. H., & Campbell, I. (2016). Inference based on the best-fitting model can contribute to the replication crisis: Assessing model selection uncertainty using a bootstrap approach. *Structural Equation Modeling: A Multidisciplinary Journal*, *23*(4), 479-490.

Magee, C. A., Gordon, R., & Caputi, P. (2014). Distinct developmental trends in sleep duration during early childhood. *Pediatrics, 133*(6), e1561-e1567.

Matricciani, L., Blunden, S., Rigney, G., Williams, M. T., & Olds, T. S. (2013). Children's sleep needs: Is there sufficient evidence to recommend optimal sleep for children. *Sleep*, *36*(4), 527-534.

Matricciani, L. A., Olds, T. S., Blunden, S., Rigney, G., & Williams, M. T. (2012). Never enough sleep: A brief history of sleep recommendations for children. *Pediatrics*, *129*(3), 548-556.

Matricciani, L., Olds, T., & Petkov, J. (2012). In search of lost sleep: Secular trends in the sleep time of school-aged children and adolescents. *Sleep Medicine Reviews*, *16*(3), 203-211.

Matthews, K. A., Hall, M. H., Cousins, J., & Lee, L. (2015). Getting a good night's sleep in adolescence: Do strategies for coping with stress matter? *Behavioral Sleep Medicine*, 1-11.

Meijer, A. M., Habekothe, H. T., & Van Den Wittenboer, G. L. H. (2000). Time in bed, quality of sleep, and school functioning in children. *Journal of Sleep Research, 9*(2), 145-153.

Melendres, M. C., Lutz, J. M., Rubin, E. D., & Marcus, C. L. (2004). Daytime sleepiness and hyperactivity in children with suspected sleep-disordered breathing. *Pediatrics, 114* (3), 768–775.

Meltzer, L. J., Avis, K. T., Biggs, S., Reynolds, A. C., Crabtree, V. M., & Bevans, K. B. (2013). The Children's Report of Sleep Patterns (CRSP): A self-report measure of sleep for school-aged children. *Journal of Clinical Sleep Medicine*, *9*(3), 235-245.

Meltzer, L. J., Biggs, S., Reynolds, A., Avis, K. T., Crabtree, V. M., & Bevans, K. B. (2012). The Children's Report of Sleep Patterns–Sleepiness Scale: A self-report measure for school-aged children. *Sleep Medicine*, *13*(4), 385-389.

Mindell, J., Carskadon, M., Chervin, R., & Meltzer, L. (2004, March 1). *Summary of findings* [Fact sheet]. Retrieved from National Sleep Foundation website: Http://sleepfoundation.org/sleep-polls-data/sleep-in-america-poll/2004-children-and-sleep

Meltzer, L. J., Moore, M., & Mindell, J. A. (2008). The need for interdisciplinary pediatric sleep clinics. *Behavioral Sleep Medicine*, *6*(4), 268-282.

Mindell, J. A., & Owens, J. A. (2009). *A clinical guide to pediatric sleep: Diagnosis and management of sleep problems* (2nd ed.). Philadelphia, PA: Lippincott Williams & Wilkins Publishing.

Mindell, J. A., & Owens, J. A. (2015). *A clinical guide to pediatric sleep: Diagnosis and management of sleep problems*. Lippincott Williams & Wilkins.

Moore, M., Kirchner, H. L., Drotar, D., Johnson, N., Rosen, C., Ancoli-Israel, S., & Redline, S. (2009). Relationships among sleepiness, sleep time, and psychological functioning in adolescents. *Journal of Pediatric Psychology, 34*(10), 1175–1183.

Muthén, B. (2003). Statistical and substantive checking in growth mixture modeling: Comment on Bauer and Curran. *Psychological Methods, 8*(3), 369-377.

Muthén, B. (2004). Latent variable analysis. In D. Kaplan (Ed.), *The Sage handbook of quantitative methodology for the social sciences* (pp. 345-368). Thousand Oaks, CA: Sage Publications.

Muthén, L. K., & Muthén, B. O. (2014). *M*plus *user's guide* (7th ed.). Los Angeles, CA: Muthén & Muthén.

National Institutes of Health. (2014). National Information Center on Health Services Research and Health Care Technology: HTA: 101 Glossary. Retrieved January 8, 2016, from https://www.nlm.nih.gov/nichsr/hta101/ta101014.html.

Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural Equation Modeling*, *14*(4), 535-569.

Owens, J. A., Spirito, A., McGuinn, M., & Nobile, C. (2000). Sleep habits and sleep disturbance in elementary school-aged children. *Journal of Developmental & Behavioral Pediatrics, 21*(1), 27-36.

Paavonen, E. J., Aronen, E. T., Moilanen, I., Piha, J., Rasanen, E., Tamminen, T., & Almqvist, F. (2000). Sleep problems of school-aged children: A complementary view. *Acta Paediatrica*, *89*(2), 223-228.

Paavonen, E. J., Porkka-Heiskanen, T., & Lahikainen, A. R. (2009). Sleep quality, duration and behavioral symptoms among 5–6-year-old children. *European Child & Adolescent Psychiatry*, *18*(12), 747-754.

Paavonen, E. J., Räikkönen, K., Pesonen, A. K., Lahti, J., Komsi, N., Heinonen, K., ... & Porkka-Heiskanen, T. (2010). Sleep quality and cognitive performance in 8-year-old children. *Sleep Medicine*, *11*(4), 386-392.

Palermo, T. M., Long, A. C., Lewandowski, A. S., Drotar, D., Quittner, A. L., & Walker, L. S. (2008). Evidence-based assessment of health-related quality of life and functional impairment in pediatric psychology. *Journal of Pediatric Psychology*, *33*(9), 983-996.

Payton, M. E., Greenstone, M. H., & Schenker, N. (2003). Overlapping confidence intervals or standard error intervals: What do they mean in terms of statistical significance? *Journal of Insect Science*, *3*(1), 34.

Pilcher, J. J., Ginter, D. R., & Sadowsky, B. (1997). Sleep quality versus sleep quantity: Relationships between sleep and measures of health, well-being and sleepiness in college students. *Journal of Psychosomatic Research*, *42*(6), 583-596.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879.

Poppert Cordts, K., & Steele, R. G. (2016). An evaluation of the Children's Report of Sleep Patterns using confirmatory and exploratory factor analytic approaches. *Journal of Pediatric Psychology*, *41*(9), 993-1001.

Price, A. M., Quach, J., Wake, M., Bittman, M., & Hiscock, H. (2016). Cross-sectional sleep thresholds for optimal health and well-being in Australian 4–9-year-olds. *Sleep Medicine*, *22*, 83-90.

Price, A. M., Wake, M., Ukoumunne, O. C., & Hiscock, H. (2012). Outcomes at six years of age for children with infant sleep problems: Longitudinal community-based study. *Sleep Medicine*, *13*(8), 991-998.

Quach, J., Hiscock, H., Canterford, L., & Wake, M. (2009). Outcomes of child sleep problems over the school-transition period: Australian population longitudinal study. *Pediatrics*, *123*(5), 1287-1292.

Quach, J., Hiscock, H., & Wake, M. (2012). Sleep problems and mental health in primary school new entrants: Cross-sectional community-based study. *Journal of Paediatrics and Child Health, 48*(12), 1076-1081.

R Core Team. (2014). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing. Retrieved from http://www.R-project.org/.

Ram, N., & Grimm, K. J. (2009). Methods and measures: Growth mixture modeling: A method for identifying differences in longitudinal change among unobserved groups. *International Journal of Behavioral Development*, *33*(6), 565-576.

Reynolds, M. M., & Mallay, H. (1933). The sleep of young children. *The Pedagogical Seminary and Journal of Genetic Psychology, 43*(2), 322-351.

Riley, A. W. (2004). Evidence that school-age children can self-report on their health. *Ambulatory Pediatrics, 4*(4), 371-376.

Rothrock, N. E., Hays, R. D., Spritzer, K., Yount, S. E., Riley, W., & Cella, D. (2010). Relative to the general US population, chronic diseases are associated with poorer health-related quality of life as measured by the Patient-Reported Outcomes Measurement Information System (PROMIS). *Journal of Clinical Epidemiology*, *63*(11), 1195-1204.

Sadeh, A. (2007). Consequences of sleep loss or sleep disruption in children. *Sleep Medicine Clinics, 2*(3), 513-520.

Sadeh, A., Gruber, R., & Raviv, A. (2002). Sleep, neurobehavioral functioning, and behavior problems in school-age children. *Child Development*, *73*(2), 405-417.

Sadeh, A., Raviv, A., & Gruber, R. (2000). Sleep patterns and sleep disruptions in school-age children. *Developmental Psychology, 36*(3), 291.

Schenker, N., & Gentleman, J. F. (2001). On judging the significance of differences by examining the overlap between confidence intervals. *The American Statistician*, *55*(3), 182-186.

Segura-Jiménez, V., Carbonell-Baeza, A., Keating, X. D., Ruiz, J. R., & Castro-Piñero, J. (2015). Association of sleep patterns with psychological positive health and health complaints in children and adolescents. *Quality of Life Research*, *24*(4), 885-895.

Shochat, T., Cohen-Zion, M., & Tzischinsky, O. (2014). Functional consequences of inadequate sleep in adolescents: A systematic review. *Sleep Medicine Reviews, 18*(1), 75-87.

Smaldone, A., Honig, J. C., & Byrne, M. W. (2007). Sleepless in America: Inadequate sleep and relationships to health and well-being of our nation's children. *Pediatrics, 119*(Supplement 1), S29-S37.

Smedje, H., Broman, J. E., & Hetta, J. (2001). Associations between disturbed sleep and behavioural difficulties in 635 children aged six to eight years: A study based on parents' perceptions. *European Child & Adolescent Psychiatry*, *10*(1), 1-9.

Spieth, L. E., & Harris, C. V. (1996). Assessment of health-related quality of life in children and adolescents: An integrative review. *Journal of Pediatric Psychology*, *21*(2), 175-193.

Streiner, D. L. (2003). Starting at the beginning: An introduction to coefficient alpha and internal consistency. *Journal of Personality Assessment*, *80*(1), 99-103.

Theunissen, N. C. M., Vogels, T. G. C., Koopman, H. M., Verrips, G. H. W., Zwinderman, K. A. H., Verloove-Vanhorick, S. P., & Wit, J. M. (1998). The proxy problem: Child report versus parent report in health-related quality of life research. *Quality of Life Research*, *7*(5), 387-397.

Tsiros, M. D., Olds, T., Buckley, J. D., Grimshaw, P., Brennan, L., Walkley, J., ... & Coates, A. M. (2009). Health-related quality of life in obese children and adolescents. *International Journal of Obesity*, *33*(4), 387-400.

Vandekerckhove, M., & Cluydts, R. (2010). The emotional brain and sleep: An intimate relationship. *Sleep Medicine Reviews*, *14*(4), 219-226.

Varni, J. W., Burwinkle, T. M., & Seid, M. (2006). The PedsQL™ 4.0 as a school population health measure: Feasibility, reliability, and validity. *Quality of Life Research*, *15*(2), 203-215.

Varni, J. W., Burwinkle, T. M., Seid, M., & Skarr, D. (2003). The PedsQL™ 4.0 as a pediatric population health measure: Feasibility, reliability, and validity. *Ambulatory Pediatrics*, *3*(6), 329-341.

Varni, J. W., Seid, M., & Kurtin, P. S. (2001). PedsQL™ 4.0: Reliability and validity of the Pediatric Quality of Life Inventory™ Version 4.0 Generic Core Scales in healthy and patient populations. *Medical Care*, *39*(8), 800-812.

Vella, S. A., Magee, C. A., & Cliff, D. P. (2015). Trajectories and predictors of health-related quality of life during childhood. *The Journal of Pediatrics*, *167*(2), 422-427.

Vermunt, J. K. (2010). Latent class modeling with covariates: Two improved three-step approaches. *Political Analysis*, 450-469.

Vingilis, E. R., Wade, T. J., & Seeley, J. S. (2002). Predictors of adolescent self-rated health: Analysis of the National Population Health Survey. *Canadian Journal of Public Health/Revue Canadienne de Sante'e Publique*, *93*(3), 193-197.

Vuong, Q. H. (1989). Likelihood ratio tests for model selection and non-nested hypotheses. *Econometrica: Journal of the Econometric Society*, 307-333.

World Health Organization [WHO] (1947). The constitution of the World Health Organization. *WHO Chronicles, 1*, 29.