Exploring Toddler Sleep Disparities Using Spatial Analytic Methods

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Exploring Toddler Sleep Disparities Using Spatial Analytic Methods

By: Jessica He

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Department: School of Public Health: Social and Behavioral Sciences

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Abstract

**Introduction:** Sleep health is a vital component of childhood health. However, sleep health disparities exist among toddlers from racially/ethnically diverse families living with socioeconomic adversity as early as 12 months of age. There is a gap in the current literature that includes environmental factors that may explain the factors contributing to these differences.

**Objective:** To explore associations between toddler sleep health and environmental and societal factors at the neighborhood level using spatial analysis that may help elucidate factors which contribute to the race/ethnicity differences in toddlers unexplained by socioeconomic variables.

**Methods:** A secondary analysis was performed on data collected from a longitudinal study of 110 parent-child dyads living in socioeconomically marginalized households completed in 2019 (1K23NR016277; PI: Ordway). A Geographic Information System (GIS) was used to investigate whether environmental factors at the neighborhood level influenced sleep health in the toddlers with completed actigraph-measured sleep data. ArcGIS Pro was used to conduct spatial analysis of select environmental factors and create maps to visualize these variables and their association with sleep characteristics with race/ethnicity differences identified in the larger study.

**Results:** Univariate and multivariate analysis did not result in statistically significant association between bedtime or bedtime variability with neighborhood noise exposure, light exposure, mean income, and racial/ethnic demographic composition in the study area.

**Conclusion:** Maps helped visualize clusters of participants in urban, low-income areas with high light and noise exposure. However, the socioeconomically and geographically homogeneous cohort may have limited the ability to fully examine differences in this study. Future research should include a larger sample size with varied socioecological backgrounds. The field of spatial analysis is rapidly changing and is likely to identify pathways connected to health disparities.
Acknowledgements

Many thanks to Dr. Jill Kelly for graciously accepting me as a student into her class under the most non-traditional circumstances. Her open-mindedness, creativity, and honesty simultaneously guided and grounded my learning process. I am tremendously grateful for her dedication to teaching and weathering through the highs and lows of Zoom, ArcGIS Pro, and the thesis journey with me over this year.

Words cannot convey the amount of gratitude I have for Dr. Monica Ordway. Having a mentor who is committed to my growth, as a person, and being a constant through some tumultuous years is something I cherish and will never forget. Truly, the appreciation I have for the opportunities she provided me transcend the acknowledgements of this thesis.

I would also like to extend my appreciation to the research participants and their families! Last but not least, I would like to thank my family, partner, friends, fellow research assistant colleagues, academic advisors, professors, and administrative staff at both YSPH and YSN who helped make these past four years meaningful and manageable.
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Introduction

Sleep health is a vital component of childhood health, tethered to children’s physical and mental health, growth, and development (Dewald, Meijer, Oort, Kerkhof, & Bögels, 2010). Children who do not achieve adequate sleep are placed at a higher risk for metabolic, cardiovascular, and mental health disorders in later childhood and adulthood (Dutil & Chaput, 2017; Hochadel, Frölich, Wiater, Lehmkühl, & Fricke-Oer kernmann, 2014; Sparano et al., 2019). Sleep difficulty also amplifies allostatic load, otherwise known as the ‘wear and tear’ of the body as a product of chronic stress. Existing literature demonstrates a link between those who experience early socioeconomic adversity and greater allostatic load (Friedman, Karlamangla, Gruenewald, Koretz, & Seeman, 2015), a dynamic which further exacerbates children’s health disparities.

Bronfenbrenner’s Social Ecological Model (SEM) is a common framework that researchers use to study health disparities (Bronfenbrenner, 1994). This model posits that understanding contextual variables within an individual’s entire ecological system is imperative to fully appreciate the heterogeneity of human development. The SEM is comprised of four levels embedded within a chronosystem, which represents the time, historical, and maturational changes throughout all systems. Most proximal to the individual is the microsystem, which includes an individual’s immediate interactions – for instance, a child’s reciprocal exchange with their caregiver. The mesosystem is composed of various microsystems and reflect the personal interactions between the individual and their environment – like a child’s spiritual community and educational system. More distal is the exosystem, encompassing social structures with direct influences on the individual – for example, a child’s neighborhood structure. Last is the macrosystem, a category referring to sociocultural influences that are most broad and often indirectly related to the individual – such as the federal government. The SEM is closely intertwined with the recommendations put forth by the National Institute of Health. According to the NIH, multisystem interventions that integrate multiple elements of the SEM may be better suited to address disparities in children’s sleep health rather than a focus on microsystem factors alone (Warnecke et al., 2008).

Sleep health in children is multidimensional and includes sleep behaviors (bedtime routines, consistency of sleep duration and bedtime), satisfaction with sleep, alertness/sleepiness during the day, timing, efficiency (time asleep relative to time in bed), and duration of sleep (Meltzer, Williamson, & Mindell, 2021). The American Academy of Sleep Medicine recommends 1-2 year-old toddlers to have 11-14 hours of sleep in a 24-hour period while 3-5 year-old preschool children should acquire 10-13 hours of sleep (Paruthi et al., 2016). Experts also agree that the optimal bedtime for toddlers through school aged children is no later than 9 PM (Mindell, Meltzer, Carskadon, & Chervin, 2009) with regularity, meaning consistent bedtimes less than 30-60 minutes between successive nights (Allen, Howlett, Coulombe, & Corkum, 2016). Unfortunately, more than 25-40% of children experience sleep deficiency by the time they reach 2.5-5 years old (Byars, Yolton, Rausch, Lanphere, & Beebe, 2012). Consequently, sleep deficiency during early childhood years is linked with higher adiposity, poorer emotional regulation, impaired growth, and higher risk of injuries (Chaput et al., 2017).

The existing literature highlights sleep health disparities among children from varying racial/ethnic backgrounds and income class. Hispanic and Black children and those living in low-income households experience sleep deficiency at disproportionate rates compared to White children (Guglielmo, Gazmararian, Chung, Rogers, & Hale, 2018). White children report
significantly longer nighttime sleep durations (Patrick, Millet, & Mindell, 2016) and are more likely to have an established bedtime routine (Hale, Berger, LeBourgeois, & Brooks-Gunn, 2009) compared to their Hispanic and Black peers. Much more research is needed to cultivate a deeper understanding of the factors contributing to these differences, but there is a gap in the pediatric sleep literature where the samples are largely from White middle-upper income families (Gradisar et al., 2016; Hall, Clauson, Carty, Janssen, & Saunders, 2006).

Few studies neither include racially/ethnically diverse families who live with socioeconomic adversity nor consider multiple socioecological contexts, therefore limiting the application and interpretation of results (Gradisar et al., 2016). This gap in research is especially concerning since children from racially/ethnically diverse backgrounds have a higher prevalence rate of sleep deficiency (Guglielmo et al., 2018). Health disparities are often rooted in social and structural determinants of health, and the NIH calls for multilevel interventions using the Social Ecological Model that simultaneously examine influences on health at the individual, interpersonal, organizational, community, and/or societal levels to address these inequities. Currently, there is a paucity of studies investigating the environmental factors outside the individual and interpersonal levels, yet it is of critical importance in understanding the intersectional relationships linking race/ethnicity and sleep in young children. The rapidly diversifying field of geographic information science may help close this gap by providing an innovative approach to measure the environment surrounding the inner levels of the Social Ecological Model.

Review of Studies Relevant to the Problem

This study is a secondary analysis of the “Sleep, Biological Stress, and Health among Toddlers Living in Socioeconomically Disadvantaged Homes” study which examined the intersection among sleep, adversity, and allostatic load in toddlers (Ordway, Sadler, Canapari, Jeon, & Redeker, 2017). The study aims were trifold: to examine the extent to which socioeconomic adversity is associated with sleep characteristics, to examine the extent to which sleep characteristics are associated with allostatic load, and to explore the extent to which good versus poor sleep buffers (or moderates) the effect of adversity on allostatic load. 110 toddlers ages 12-15 months living with socioeconomic adversity were recruited and followed for one year. Among the preliminary findings in the initial sleep data analysis, statistically significant patterns in bedtime and bedtime variability were found between and within participants from different racial and ethnic groups. Non-Hispanic White toddlers had an average bedtime before the recommended guideline of 9 PM, compared to Black, Hispanic, and multiracial children who did not. Furthermore, non-Hispanic White toddlers had less bedtime variation and therefore greater bedtime regularity compared to Black, Hispanic, and multiracial children. Within group analysis identified unique patterns of socioeconomic associations in each race/ethnicity group. These findings suggest the need to look at exosystem and macrosystem variables that may help elucidate the pathway to these differences. External environments, such as neighborhoods, can be powerful mediators in exacerbating health risks among their constituents (Noah, 2015). Thus, this study aims to evaluate potential environmental and societal factors acting on individual sleep characteristics at the exosystem level (Brofenbrenner, 1994).

Geographic information systems as a novel approach to understanding sleep health disparities
Geographic information systems will be used to investigate the hypothesis that neighborhood level factors impact individual sleep characteristics, as current research contends that spatial analysis can provide greater contextual insight behind the complex union between individual attributes and the external environment (Wang, 2020). Furthermore, this innovative approach contributes to the limited literature that integrates spatial analysis with sleep research in toddlers. The extant literature suggests that neighborhood characteristics that may influence sleep include noise, light, mean income, and racial and ethnic demographic composition (Chepesiuk, 2009; Fyhri & Aasvang, 2010; Johnson, Al-Ajouni, & Duncan, 2019; Muzet, 2007).

Disparate noise exposures exist within neighborhoods – with modifying variables including commercial businesses and high capacity urban roads and also between neighborhoods affected by urbanicity, proximity to highways, and time (Seto, Holt, Rivard, & Bhatia, 2007). Moreover, varying noise levels can influence a variety of health outcomes (Fyhri & Klaebøe, 2009; Ndrepepa & Twardella, 2011). In relation to sleep duration, self-reported noise level was found to be a mediator which negatively influenced adult sleep duration and sleep issues in an urban study area (Chum, O’Campo, & Matheson, 2015).

Another physical influence is the varying light levels between neighborhoods. Even low levels of light exposure have an impact on the circadian rhythm, adversely recalibrating sleep cycles to later hours in adults (Shanahan & Czeisler, 2000). In a related cross-sectional study incorporating geocoding with light data from the Defense Meteorological Satellite Program’s Operational Linescan System, outdoor nighttime light measurements were associated with delayed bedtimes, delayed wake up times, and shorter sleep duration in the adult study population (Ohayon & Milesi, 2016).

Experts in sleep research argue that both the physical environment and social attributes influence housing conditions in neighborhoods (Johnson et al., 2019). These factors shape the living conditions of individual homes and subsequently impacts sleep hygiene in adults (Johnson et al., 2019; Xiao & Hale, 2018). Higher socioeconomic status, in particular, is repeatedly found to be associated with superior sleep characteristics in adults (Grandner et al., 2010; Stamatakis, Kaplan, & Roberts, 2007).

Race and ethnicity have also been implicated with sleep health (Johnson et al., 2019). One cross-sectional study focusing on Hispanic immigrants found a positive association between self-reported sleep disturbance and perceived racism in adults (Steffen & Bowden, 2006). Similar findings were echoed in a study conducted with ethnic minority adolescents where sleep quality was inversely associated with overt and subtle racial discrimination at school (Huynh & Gillen-O’Neel, 2016).

Research Design

Sample

Sleep data was collected as part of a prospective cohort study between 2014-2019. Primary caregivers and toddlers ages 12-15 months were recruited from childcare programs and primary care clinics in the Greater New Haven area. Parent permission and caregiver consent was completed with 110 toddler-parent dyads. Objective sleep data was collected with an actigraph, an accelerometer with a pediatric algorithm to monitor human rest and activity cycles using the Respironics Minimitter Actiwatch AW2. Caregivers were instructed to help their
toddler wear the Actiwatch, a common instrument used by sleep experts to study sleep duration and efficiency, at all times during the sleep period of at least one week (Ordway et al., 2017). Caregivers were also tasked to complete questionnaires and sleep diaries in which they recorded their toddler’s naptime, bedtime, and duration of sleep during the study period.

The sample for this secondary analysis is participants who completed the primary study. Individual data was provided by Dr. Ordway. Available demographic information includes race, ethnicity, Connecticut Department of Children and Families involvement, marital status, homeowner status, annual family income, and education of the primary caregiver. Objective sleep characteristics include nap duration, nap time variability, nighttime sleep duration, nighttime sleep variability, 24-hour sleep duration, 24-hour sleep variability, wake after sleep onset, wake after sleep onset variability, bedtime, and bedtime variability. Nap duration and variability encompass all sleep periods outside of sleeping at bedtime through the night. Nighttime sleep denotes the time spent sleeping during night hours. 24-hour sleep duration was a summation of nap and nighttime sleep duration. Wake after sleep onset is the amount of time spent awake after initially falling asleep during nighttime sleep, which is also the only variable measured in minutes. All other sleep variables were measured in hours. Variability was calculated by averaging the difference between successive nights and then squaring the mean to obtain a positive value.

Only participants who completed the actigraphy collection over the study period and have recorded addresses were considered for spatial analysis. One participant was excluded on the basis of location far outside the Greater New Haven area. The final study population is 93 toddlers with their respective sleep characteristics data and demographic information.

**Preparation of Ecologic Data**

Due to the limited study population, individual level data was aggregated up into census tract spatial units, otherwise referred to here as neighborhoods, for spatial analysis. Connecticut census tract data and shape files were downloaded from the United States Census Bureau website and then imported into ArcGIS Pro. The first data table, S1901, titled “Income in the Past 12 Months in 2017 Inflation-Adjusted Dollars,” with 5-year estimates (American Community Survey, 2017b) was organized to solely include mean family income. The second data table, B03002, titled “Hispanic or Latino Origin by Race,” with 5-year estimates (American Community Survey, 2017a) was amended to calculate the rates of Hispanic or Latino individuals in each census tract using ArcGIS Pro’s Field Calculator function.

In order to analyze neighborhood level data, the two tables containing census data were joined with the 2017 Connecticut census tract shape file (United States Census Bureau, 2017). All maps and layers were reprojected to “NAD 1983 (2011) StatePlane Connecticut FIPS 0600 (Meters)” and the display units set to meters. The year 2017 was selected because it was the midpoint of the Ordway study.

Nighttime light data were retrieved from the Visible Infrared Imaging Radiometer Suite via the National Aeronautics and Space Administration website. Monthly average light rasters in 2017 for the Greater New Haven area (National Aeronautics and Space Administration, 2020) were collated using local statistics to create a raster of mean light intensity and later reprojected. This mean raster served as the estimated light intensity raster for value extraction once participant locations were geocoded in later steps.
Next, simulated noise data were retrieved from the National Park Service. Project code 2217356 modeled environmental sound levels in the United States derived from “ambient sound pressure level and non-acoustic geospatial features such as topography, climate, hydrology, and anthropogenic activity” (National Park Service, 2013). The impact level raster for the continuous United States was selected for spatial analysis, which estimated the difference between all acoustic energy and natural sound pressure levels. These estimates were given as “A-weighted hourly L50 sound pressure levels dB re 20 uPa,” approximated on a typical summer day between 2013-2015. Unlike the Chum, O’Campo, and Matheson study where participants self-reported noise levels during the data collection stage (Chum et al., 2015), the Ordway study did not gather this information during the study period. In the absence of perceived noise levels among the participants, the National Park Service simulated noise data were used to serve as a proof of concept for the purpose of this paper.

**Geocoding**

Extra precautions were taken to geocode participant locations to prevent transferring sensitive information to ESRI servers. Consequently, internet service was disconnected and ArcGIS Online was logged off prior to geocoding. A data table containing de-identified participant addresses with sleep and demographic data was imported. Yale University’s Marx Library provided a local copy of the 2013 address locator to geocode the participant addresses. An older database was chosen because participants lived in well-established neighborhoods as opposed to newer neighborhoods. 92 points matched while 1 point tied – this address was then manually matched. This vector layer was reprojected to align coordinate systems. The geocoded participant addresses were spatially joined to their respective census tracts with census data.

**Mapping**

Selected census tracts were dissolved to form a study area polygon which solely included census tracts where participants lived. In order to optimize visualization of the maps, this new polygon was copied to the light and noise rasters where the tool Clip Raster was employed to limit the extent to the study area. Then, the tool Extract Values To Points was used with both rasters to sample the value of the independent variables at each participant’s location. Similarly, the Clip tool was used on both the mean income and ethnic composition feature layer with the study area polygon to optimize visualization of the study area.

The explanatory and response variables were classified using a quantile symbology for cartographic display. Dimension reduction was used to code for ethnic minority status through adding two new fields to the attribute table which served as dummy variables. The Attribute Table Field Calculator was used in the first new field to identify predominant Hispanic or Latino neighborhoods by coding all neighborhoods reporting over 50% of Hispanic or Latino individuals as, “10.” Neighborhoods with less than 50% of Hispanic or Latino individuals were coded, “0.” The Attribute Table Field Calculator was used again in the second new field to sum the first dummy variable with the value representing the participant’s ethnicity. From the Ordway study’s data, individual ethnicities were coded “1” for Hispanic or Latino and “0” as non-Hispanic or Latino. This final new field was a quaternary representation of the combination of personal and neighborhood ethnicity.
The Select By Attributes tool distinguished participants according to their neighborhood characteristics of mean income, ethnic composition, noise values, light values, and self-reported attributes such as annual family income and ethnicity. Categories such as ethnic minority status was determined by adding new fields to the attribute table, re-coding the new fields according to the self-identified ethnicity and the rate of Hispanic or Latino of each census tract, using ‘field calculator’ to mathematically add these new fields together, and lastly changing the data point symbology.

Maps created in ArcGIS Pro serve as communication tools to illustrate various neighborhood characteristics and their potential influence on individual bedtime and bedtime variability.

**Presentation and Analysis of Findings**

![Figure 1](image)

Figure 1 visualizes the state of Connecticut, the census tracts within the study area, and the locations of the participants.
Figure 2a depicts participants color coded according to the sleep recommendations from the American Academy of Sleep Medicine for toddlers within a 24-hour period (Paruthi et al., 2016). The average duration among participants was less than the recommended guidelines at 10.33 hours with a standard deviation of 0.77. Only 16% of participants met the recommended
11-14 hours for children 1 to 2 years of age. The study sample’s minimum duration was 8.32 hours while the maximum was 12.62 hours.

Figure 2b delineates the average bedtime among participants. For the entire sample, the average bedtime was 9:52 PM with a standard deviation of 1.50. The earliest bedtime was 6:11
PM and the latest was 3:00 AM. Only 27% of participants met the recommended bedtime of 9 PM (Mindell et al., 2009).

Alternatively, Figure 2c illustrates the average bedtime variability. The average bedtime variability of the whole sample was 2.40 hours with a standard deviation of 1.83. The least amount of bedtime variability was 0.01 hours and the most was 9.59 hours. Only 29% of
participants met the recommended bedtime variability of less than 60 minutes night to night (Allen et al., 2016).

Pictured in Figure 3a is the study area according to the rate of individuals who identify as Hispanic or Latino in each census tract. Participant locations are color coded by their self-reported ethnicity. 33% of participants identify as Hispanic or Latino.
Figure 3b highlights the congruency of the participant’s ethnicity against their respective census tract’s rate of Hispanic or Latino individuals. Participants who are considered to be ethnic minorities in their neighborhoods – based on the incongruency between their self-reported ethnicity and the majority ethnicity of the census tract – are denoted by larger symbols.

45% of participants who are not Hispanic or Latino live in census tracts where the majority is likewise non-Hispanic or Latino. This group had an average bedtime of 9:50 PM with
a standard deviation of 1.70, which was consistent with the overall average. The mean bedtime variability was 2.16 hours with a standard deviation of 1.79, denoting better bedtime consistency night-to-night compared to the overall average by approximately 14 minutes.

13% of participants who are Hispanic or Latino reside in census tracts where the majority are non-Hispanic or Latino, implying that they are considered ethnic minorities in their neighborhoods. This group had an average bedtime of 10:03 PM with a standard deviation of 1.46, which was 11 minutes later than the overall average. However, their mean bedtime variability was 1.90 hours with a standard deviation of 1.11, indicating this subset had the most consistent bedtimes compared to others. This group’s bedtime variability was 30 minutes less than the overall average.

Conversely, 22% of participants who are not Hispanic or Latino live in census tracts where the majority are Hispanic or Latino. This subset had an average bedtime of 9:34 PM with a standard deviation of 1.29, which is 18 minutes earlier than the overall average and also the earliest bedtime of all the groups. The average bedtime variability was 2.21 hours with a standard deviation of 1.82 – approximately 11 minutes less than the overall average.

Lastly, 20% of participants who are Hispanic or Latino reside in census tracts where the majority is also Hispanic or Latino. This group had the latest average bedtime at 10:08 PM with a standard deviation of 1.25. This group also saw the greatest amount of bedtime variability at 3.42 hours with a standard deviation of 2.76, which exceeds the overall average by one hour and two minutes.
Figure 4a exhibits a gradient of census tracts based on mean income. 37% of participants live in census tracts with the lowest mean income, 32% in those with the second lowest mean income, and 20% with the middle-income. 7% of participants resided in the second to highest income neighborhoods while 3% lived in the highest income bracket.

Figure 4a concurrently shows the locations of participants color coded by self-reported annual family income, although two participants did not provide this measure. Table 1 displays
the average bedtime and bedtime variability among the participants categorized by annual family income.

Table 1. Average Bedtime and Bedtime Variability by Annual Family Income

<table>
<thead>
<tr>
<th>Annual Family Income</th>
<th>Percentage of Participants</th>
<th>Average bedtime (standard deviation)</th>
<th>Average bedtime variability (standard deviation)</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;$10,000</td>
<td>43%</td>
<td>9:56 PM (1.58)</td>
<td>2.61 hours (2.18)</td>
</tr>
<tr>
<td>$10,001-$20,000</td>
<td>15%</td>
<td>10:26 PM (1.23)</td>
<td>3.00 hours (2.08)</td>
</tr>
<tr>
<td>$20,001-$30,000</td>
<td>14%</td>
<td>9:44 PM (1.50)</td>
<td>1.50 hours (0.91)</td>
</tr>
<tr>
<td>$30,001-$40,000</td>
<td>11%</td>
<td>9:44 PM (1.17)</td>
<td>3.15 hours (2.40)</td>
</tr>
<tr>
<td>$40,001-$50,000</td>
<td>5%</td>
<td>10:18 PM (1.24)</td>
<td>3.15 hours (3.37)</td>
</tr>
<tr>
<td>&gt;$50,000</td>
<td>10%</td>
<td>8:30 PM (1.29)</td>
<td>0.93 hours (0.66)</td>
</tr>
</tbody>
</table>
Figure 3b presents the bedtime associated with each participant with respect to their census tract’s mean income. Among the 37% of participants residing in census tracts with the lowest mean income, the average bedtime was 10:01 PM with a standard deviation of 1.62. 32%
of participants live in neighborhoods with the second to lowest income category and had an average bedtime of 9:52 PM with a standard deviation of 1.41. 20% live in neighborhoods within the middle-income bracket and had an average bedtime of 9:57 PM and a standard deviation of 1.64. Among the 8% in the second to highest income neighborhoods, the average bedtime was 9:19 PM with a standard deviation of 0.60. Only 3% of participants live in the highest income bracket neighborhoods; they had the earliest average bedtime of 8:59 PM with a standard deviation of 1.71.
Figure 4c displays the bedtime variability of each participant in the context of their respective census tract’s mean income.
Among the 37% of participants residing in census tracts with the lowest mean income, the average bedtime variability was 2.77 hours with a standard deviation of 2.47. 32% of participants live in neighborhoods with the second to lowest income bracket, this group saw an average bedtime variability of 2.30 hours with a standard deviation of 1.71. 20% are located in neighborhoods in the middle-income bracket and had an average bedtime variability 2.37 hours and a standard deviation of 1.64. 8% reside in the second to highest income neighborhoods and had the average bedtime variability of 1.65 hours with a standard deviation of 1.42. 3% of participants live in the highest income bracket neighborhoods and had an average bedtime variability of 1.03 hours with a standard deviation of 1.15.
Figure 5a visualizes the bedtime of each participant against the average light values obtained from NASA. At the individual level of the participants, the light values range from 7.14 to 121.51 units with a mean of 37.93 units and a standard deviation of 24.17. 19% of participants live in residences with the least light exposure; their average bedtime was 10:05 PM with a standard deviation of 1.45. 61% of participants reside in areas with moderate light...
exposure and saw average bedtime of 9:43 PM with a standard deviation of 1.53. 20% of participants are located in areas with the most light exposure. This group had the latest average bedtime at 10:09 PM with a standard deviation of 1.39.

Figure 5b displays the bedtime variability of each participant against the average light values obtained from NASA. Those living in residences with the least light exposure had an average bedtime variability of 1.93 hours with a standard deviation of 2.19. Participants exposed
to moderate light exposure had an average bedtime variability of 2.52 hours with a standard deviation of 2.24. Comparatively, participants living in areas with the most light exposure had the most average bedtime variability of 2.87 hours with a standard deviation of 2.09.
Figure 6a illustrates the bedtime of participants against the estimated noise value at their location. At the individual level of the participants, the noise estimates range from 11.44-19.71 dB with a mean of 14.59 dB and a standard deviation of 1.66. 20% of individuals live in areas with the least amount of estimated noise exposure and their bedtime was 9:49 PM with a standard deviation of 1.49. 61% reside in areas with moderate noise exposure and their average bedtime was 9:53 PM with a standard deviation of 1.53. In comparison, 19% of participants or located in areas with the most estimated noise exposure and their average bedtime was approximately 9:56 PM with a standard deviation of 1.43.
Figure 6b depicts the bedtime variability of each participant against the estimated noise value at their location. Those living in areas with the least amount of estimated noise exposure had a bedtime variability of 2.00 hours with a standard deviation of 1.38. Participants residing in places with moderate noise exposure had a bedtime variability of 2.47 hours with a standard deviation of 2.30. Among the participants located in areas with the most noise exposure, the average bedtime variability was 2.53 hours with a standard deviation of 2.06.
Table 2. Univariate Analysis (correlation coefficient)

<table>
<thead>
<tr>
<th></th>
<th>Noise</th>
<th>Light</th>
<th>Mean income</th>
<th>Rate Hispanic/Latino</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bedtime</td>
<td>0.005</td>
<td>0.016</td>
<td>0.008</td>
<td>0.003</td>
</tr>
<tr>
<td>Bedtime Variability</td>
<td>0.003</td>
<td>0.007</td>
<td>0.025</td>
<td>0.020</td>
</tr>
</tbody>
</table>

Table 3. Multivariate Analysis (p-value of regression coefficients)

<table>
<thead>
<tr>
<th></th>
<th>Noise</th>
<th>Light</th>
<th>Mean income</th>
<th>Rate Hispanic/Latino</th>
<th>Participant ethnicity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bedtime</td>
<td>0.785</td>
<td>0.362</td>
<td>0.165</td>
<td>0.111</td>
<td>0.136</td>
</tr>
<tr>
<td>Bedtime Variability</td>
<td>0.980</td>
<td>0.734</td>
<td>0.319</td>
<td>0.847</td>
<td>0.204</td>
</tr>
</tbody>
</table>

Regression analyses were performed and determined that none of the predictor variables were significantly predictive to bedtime or bedtime variability.

Conclusions

The purpose of this exploratory study was to use spatial visualization to evaluate potential environmental and societal factors at the neighborhood level influencing individual sleep characteristics. In summary, there was no statistically significant association between bedtime or bedtime variability with neighborhood attributes such as noise, light, mean income, and racial and ethnic demographic composition.

Although the Chum et al. (2015) study found that noise levels mediated sleep duration and sleep issues, this study did not find significant associations between noise exposure and sleep characteristics. It must be underscored, however, that the Chum et al. study used self-reported noise data whereas this study relied on a model estimating noise levels in the absence of self-reported measures. Therefore, this estimate may not accurately capture perceived noise levels and future investigation should ask for self-reported noise exposure before ruling out this variable in relation to bedtime and bedtime variability.

While delayed bedtimes were seen among participants with greater light exposure similar to the Ohayon & Milesi (2016) study, this finding was ultimately deemed not significant. After conducting home visits and gaining in-person insight, the results can possibly be explained by the purposeful darkness experienced inside participant homes. At one point during the primary study, a headlamp was required to complete the home visit questionnaires. For privacy, participants often obscured windows with barriers to shield their homes from onlookers. Therefore, the results confirm that light intensity of the external environment did not play an influential role in participant sleep characteristics and this variable can be ruled out.

The maps produced by ArcGIS provide a possible reason behind the lack of significant association between mean income and sleep characteristics. Participants were clustered in fairly homogenous urban areas with respect to mean income level – with 69% living in neighborhoods with either the lowest income bracket of less than $50,000 or second to lowest category between
$50,000-$70,000. In the same vein, the participants themselves were financially alike with 43% reporting an annual family income of less than $10,000 and all participants reporting an amount considerably less than Connecticut’s median household income of $78,000 (United States Census Bureau, 2019). It stands to reason that the lack of significant correlation can be attributed to the nature of the spatial distribution of participants. Future research should deliberately focus on locations outside the primary study area to add variety to the independent variables. For example, recruiting new participants from financially wealthier families, neighborhoods with higher mean income, places with less light or noise pollution, or rural areas may elucidate associations that this study was unable to produce.

Ethnic demographic composition of the neighborhoods was likewise not significantly associated with bedtime or bedtime variation among participants. Statistical power notwithstanding, later bedtimes and greater bedtime variability were still observed between participants who identify as Hispanic or Latino regardless of the ethnic composition of their neighborhood. Race was not analyzed in this study and is a potential variable in future research. The maps generated in this secondary analysis inspires further questions about influential environmental factors impacting sleep health such as the congruency between individual attributes and neighborhood characteristics, a potential factor to consider in future investigations.

In addition to a homogenous study sample and the aforementioned constraints, the study size is also limited. It is equally important to address ecological fallacy in this study, which is the erroneous practice of assigning statistics about a group to individuals within the group (Piantadosi, Byar, & Green, 1988). For example, if the mean income of the neighborhood is between $50,000-$70,000, this does not mean every individual family in the neighborhood falls in the same income bracket. Consequently, it is illegitimate to comment about toddler sleep behavior at the neighborhood level. This study assessed the influence of neighborhood on the individual rather than attributing the neighborhood characteristics to the individual.

This paper contends that neighborhood characteristics do exert an effect on individual sleep health, and further investigation should be considered to examine other external influences. While this secondary analysis may not meet publication criteria due to the limited sample size, it does offer insight into future research opportunities and innovative methods in understanding sleep hygiene in toddlers. Although light is not recommended to be part of future analysis due to clinical insight during home visits, participant’s racial identity and the congruency of individual attributes relative to their neighborhood characteristics should be examined. Expanding upon this current study, a deeper consideration into crime rates of neighborhoods, policing, and discriminatory housing policies (Johnson et al., 2019) may also be worth investigating with respect to toddler sleep health.
References


