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The Physical Home Environment and Sleep: What Matters Most for Sleep in Early Childhood

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The physical home environment is thought to play a crucial role in facilitating healthy sleep in young children. However, relatively little is known about how various features of the physical home environment are associated with sleep in early childhood, and some of the recommendations clinicians make for improving child sleep environments are based on limited research evidence. The present study examined how observer and parent descriptions of the child's physical home environment were associated with child sleep, measured using actigraphy and parent's reports, across a year in early childhood. The study used a machine learning approach (elastic net regression) to specify which aspects of the physical home environment were most important for predicting five aspects of child sleep, sleep duration, sleep variability, sleep timing, sleep activity, and latency to fall asleep. The study included 546 toddlers (265 females) recruited at 30 months of age and reassessed at 36 and 42 months of age. Poorer quality physical home environments were associated with later sleep schedules, more variable sleep schedules, shorter sleep durations, and more parent-reported sleep problems in young children. The most important environmental predictors of sleep were room sharing with an adult, bed sharing, and quality of both the child's sleep space and the wider home environment.

Keywords: sleep, early childhood, home environment, physical environment, machine learning

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It is widely recognized that the physical home environment plays a crucial role in facilitating healthy sleep (Pigeon & Grandner, 2013). The physical home environment can be defined as the space in which the child lives, and encompasses both physical characteristics (e.g., the number of rooms) as well as qualities (e.g., organization) of the home environment. The National Sleep Foundation provides recommendations about the aspects of the physical home environment that are most conducive to healthy sleep, including that sleep spaces be comfortable with limited light and noise (National Sleep Foundation, 2020), and improving the physical sleep environment is often a component of treatment for sleep problems in both adults and children (Pigeon & Grandner, 2013). For young children, who have little control over their sleep environment, parents play a crucial role in shaping the physical sleep environment to be conducive to optimal child sleep. However, relatively little empirical research has examined how various features of the physical home environment are associated with sleep in early childhood (Allen et al., 2016). To fill this gap in the literature, the present study examined the association between the physical home environment and sleep in early childhood, identifying which aspects of the physical home environment are the most predictive of various aspects of child sleep.

Sleep and the Physical Home Environment in Childhood

Previous research suggests that the qualities of a child's sleep space, including whether the child shares a bed or a bedroom and the quality and comfort of the bedroom, are associated with sleep across development (Allen et al., 2016). Research suggests that bedsharing, in which a child shares a bed with a parent and/or a sibling, is

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estimated to occur in between 4% and 26% of American families with young children (Barajas et al., 2011; Okami et al., 2002). However, bedsharing research has often focused on infancy/toddlerhood, with substantially less research devoted to examining the effects of bedsharing in older children (Andre et al., 2021). This is likely due, in part, to the fact that bedsharing decreases substantially after infancy (Okami et al., 2002). However, bedsharing with a parent that does persist past infancy/toddlerhood has been associated with heightened, parent-reported sleep disturbances in preschoolers and school-aged children (Kim et al., 2017; Lee et al., 2018), as well as increased internalizing and externalizing problems both concurrently and in preadolescence (Chen et al., 2021). Room sharing (i.e., sharing a sleep space, but not the same bed) has also been associated with sleep disturbances in preschoolers as reported by parents (Chung et al., 2014). Interestingly, findings suggest that room sharing with a sibling may not be as detrimental to child sleep as room sharing with an adult, suggesting that sharing a sleep space with an adult family member may have a unique, detrimental effect on child sleep (Chung et al., 2014). Various factors are thought to influence the choice to bed/room share, including practical/economic considerations, cultural considerations, child sleep problems or nighttime fears, and beliefs that bed/room sharing might have positive, developmental effects (Andre et al., 2021; Milan et al., 2007). Complicating the interpretation of this literature, many studies examine bed and room sharers as a single group or do not differentiate between "reactive" bed/room sharing (i.e., when a child has his or her own room, but moves to the parent's room) versus preplanned bed/room sharing (i.e., when the child's permanent sleeping arrangement includes bed/room sharing). Such methodological choices make extrapolations about the effects of bed/room sharing on sleep more difficult.

Reduced light and cool temperatures in the sleep space also play a key role in facilitating optimal sleep. Excess light in the sleep space has been associated with poorer parent-reported sleep in preschoolers (Chung et al., 2014; Lee et al., 2018) and school-aged children (Bagley et al., 2015). The temperature of the sleep environment also affects sleep quality (Lan et al., 2017), with sleep spaces that are uncomfortably hot or cold associated with increased parent-reported sleep problems in children (Lee et al., 2018; Wilson et al., 2014) and increased variability in children's sleep schedules as measured using actigraphy (Bagley et al., 2015). Given that both ambient light and temperature are known to serve as regulators impacting the body's circadian system (Gilbert et al., 2004; Hoyniak et al., 2019), exposure to an overly bright or warm bedroom could lead to alterations in circadian timing (Pigeon & Grandner, 2013). Similarly, the overall comfort of the sleep space (e.g., the presence of comfort items, such as plush toys or blankets) is also thought to be associated with sleep outcomes (Jacobson, 2013). Though it is important to note that the presence of comfort items/objects (e.g., toys, stuffed animals) in the sleep space has been associated with an increased risk for sudden infant death syndrome, and should be avoided in infancy (Colvin et al., 2014).

Features of the wider household including crowding, disorganization, and noise, may also be important to address when facilitating optimal sleep across development. Household crowding, often quantified as the ratio of the number of people in the household to the number of the rooms or bedrooms in the house, has been associated with parent-reported sleep disturbances in preschoolers (Milan et al., 2007). It is possible that the effects of household crowding on sleep might be mediated by factors such as increased noise, increased disorganization/chaos in the home, or increased need for room/bed sharing. Noise from both outside the home (e.g., traffic noise) and inside the home (e.g., snoring, noise from siblings or other family members) has been associated with parent-reported sleep disturbances in preschoolers (Wilson et al., 2014) and both child-reported and actigraphic sleep in school-aged children (Bagley et al., 2015). Household chaos, an index of the overall disorganization and confusion of the home, is associated with parent- and child-reported sleep disturbances across development (Billows et al., 2009; Brown & Low, 2008). Adolescents whose homes are characterized by higher levels of chaos reported getting less sleep and taking longer to fall asleep (Billows et al., 2009). Similarly, Head Start preschoolers in chaotic living conditions (e.g., crowded/noisy households; family instability) were reported by parents to have higher levels of sleep disturbances (Brown & Low, 2008).

However, not all studies have demonstrated an association between the physical home environment and child sleep. In a large sample of school-aged children, Spilsbury et al. (2005) did not find an association between observed qualities of the physical sleep environment (e.g., noise, crowding, organization) and child-reported sleep. As Spilsbury et al. acknowledged, this nonfinding could be due to the limited range of physical home environments assessed in their study (Spilsbury et al., 2005). Also, most prior studies have focused on parent- or child-reported sleep, and there is a need for additional research on the association between the physical home environment and actigraphic sleep, which would allow the examination of associations with sleep variables that cannot be gleaned from parent/child reports, especially latency to fall asleep and nonsignaled nighttime awakenings. Additionally, Allen et al. (2016) concluded that the evidence base for the effect of various aspects of the physical home environment on child sleep was limited, equivocal, or insufficient for making firm conclusions, highlighting the need for additional research on the association between the physical home environment and child sleep.

The Present Study

The present study had two aims. First, we examined how the child's physical home environment, as measured using a combination of observer and parent reports, was associated with sleep in toddlerhood. Given prior research demonstrating the importance of a variety of environmental factors on child sleep (e.g., noise, household disorganization, sleep space quality), we expected to find associations between aspects of the physical home environment and child sleep. In particular, we expected that children would get worse sleep when they shared a bed or a bedroom, when their bedroom was uncomfortable (e.g., too bright, too hot, few comfort items), when their household was larger, noisier, or more chaotic, and when their household was cluttered or disorganized. Worse sleep was defined as shorter sleep durations, increased variability in sleep duration and timing from night to night, later sleep timing, more active sleep, longer sleep latencies, and more parent-reported sleep problems overall.

The second aim was to identify which particular aspects of the child's physical home environment were most meaningful in predicting the various domains of sleep. Aspects of the physical environment tend to covary to a moderate degree, presenting a challenge for identifying their relative importance in relation to sleep. To avoid issues of multicollinearity, we used elastic net regression—a supervised multivariate machine learning approach to regressing the sleep variables on the environment variables. Elastic net regression innovates on typical ordinary least squares regression by adding regularization terms, effectively removing variables that do not contribute statistically meaningful information while retaining groups of colinear and informative variables (Zou & Hastie, 2005). This approach was used to test which features of the physical home environment best predict sleep. This approach also enabled us to examine the relative importance of the various aspects of the physical home environment in predicting child sleep. Because this study is the first, to our knowledge, to compare the relative importance of various aspects of the physical home environment for child sleep, we did not have any a priori expectations about which variables would be the most predictive, so this aim was exploratory.

Method

Participants

The present study included 546 toddlers (265 females) recruited at 30 months of age and reassessed at ages 36 and 42 months. The present study included children from the Toddler Development Study ($N = 596$) who participated in at least one prebedtime observation at 30, 36, or 42 months. The Toddler Development Study is comprised of a series of substudies culminating in a multisite, longitudinal study of child development, (Hoyniak et al., 2019; see Supplemental Tables S1 and S2 for descriptions of substudies, planned missingness, and general missingness). Data were collected from 2008 to 2018, approximately equally throughout the seasons (with slightly more data collection occurring during the fall/spring of each year) and included families from two mid-sized, Midwestern cities and one mid-sized, Mid-Atlantic city. Participants were recruited using a database search based on county birth records, through partnering with community organizations (e.g., Head Start, Housing Authority), and through advertisements. Compensation was provided, and all procedures were approved by the relevant Institutional Review Boards at the three research sites. To increase the representativeness of this community sample, no exclusion criteria, beyond severe developmental delays, were imposed.

The sample included in the present study was predominantly White (87%, 4% Latinx, 2% Black, 1% Mixed Race, 4% Other, and 2% Unknown, Not Reported, or Missing), non-Hispanic (96%, 4% Hispanic), and came from predominantly two-parent households (86%; 8% Single Parent, 4% Other, 2% not reported). Primary caregivers in the samples were mostly college educated (79% college degree, 14% some college, 5% high school diploma or less, 2% not reported). Family socioeconomic status (SES) was calculated using the Hollingshead Four Factor Index (Hollingshead, 1975), which takes into account both parents' educational attainment and occupational prestige (based on U.S. Census codes). SES estimates can range from 8 to 66, with higher scores reflecting higher SES. In the current sample, SES ranged from 12.5 to 66, with $M = 48.21$ ($SD = 13.05$) indicating that the sample was predominantly middle class.

Procedure

Assessments occurred within 2 weeks of the toddler's target age. All procedures relevant to the present study were completed at each assessment. First, actigraphs were distributed to the toddler, and parents were instructed to have their toddler wear the actigraph for 1–2 weeks. Additionally, parents were given several questionnaires. Approximately 1 week later, pairs of trained research assistants visited the family's home to observe the family during the hour leading up to the toddler's reported bedtime. The observation usually began 10–15 min after the observers arrived at the home. On arrival, observers were shown the child's sleeping area and rooms where the family typically spent time before the child went to bed. Observers then found a place to stand or sit as unobtrusively as possible during the observation. As needed, observers would move quietly from one space to the next in order to keep the child in view during the observation. To discourage conversation with observers, observers made notes throughout the visit on clipboards. After initial arrival at the home, it was unusual for the child to attempt to interact with the observers. If they did, observers provided a minimal response, saying that they were unable to talk because they were doing paper work. Primary caregivers wore a microphone that enabled the observers to hear interactions occurring in rooms they did not enter. During the course of the observation, observers completed questionnaires assessing the home environment. To reduce the potential influence of observer bias, the observers were trained to maintain a nonjudgmental attitude toward families and to be highly detailed and specific in their observations and ratings. The observation ended at the end of the bedtime routine.

Measures

Physical Home Environment

Measures of the physical home environment included a combination of observer and parent reports. Descriptive statistics and correlations between these measures are included in Supplemental Tables S2–S4.

Home Checklist. During the home observation, the observers completed the home checklist, a 60-item measure assessing the quality of the physical home environment. This questionnaire, which combines items from the Home Observation for Measurement of the Environment inventory (HOME; Bradley & Caldwell, 1979) and additional items assessing the toddler's sleep space, has been used in previous research (Dodge et al., 1994; Hoyniak et al., 2021). The home checklist was completed by both observers, and items were averaged across the observers. Three different composite indexes from the home checklist, based on theoretical distinctions in the items, were used in the present study (described below). Interrater reliability for each composite index on the home checklist was calculated using interclass correlations (ICCs). All three ICCs were 0.99, indicating a high degree of reliability between observers.

Sleep Space Quality. The sleep space quality composite contained 13 items, assessing the comfort (e.g., "a stuffed animal or other toy is part of the bedtime ritual"), cleanliness of (e.g., "bedding is noticeably dirty"), and noise/light level (e.g., "overhead lights or lights that fully illuminate the sleeping space are on while the [child] falls asleep") of the toddler's designated sleep space. Items were scored as either 0 (*No*) or 1 (*Yes*), such that higher scores indicated poorer quality sleep spaces. Items were summed to create a total score.

Home Environment Quality. The home environment quality composite included 12 items assessing the general safety (e.g., "sharp objects are located within reach of the [child], [e.g., scissors, knives]") and organization (e.g., "house is uncomfortably dirty [filth, dishes, trash, etc.]") of the home. Items were scored as either 0 (*No*) or 1 (*Yes*), such that higher scores indicated poorer quality home environments. Items were summed to create a total score.

Household Disorganization. At the end of the home observation, observers reported on the overall organization of the household. Observers rated the household's confusion and disorganization on a 5-point scale, ranging from 1 (*calm, smooth*) to 5 (*confusing, chaotic*).

Bed Sharing

During the course of the home observation, the observers also recorded whether or not the child shared a bed with a parent or a sibling. Bed sharing was scored as 0 (*child does not share a bed*) or 1 (*child shares a bed with either a sibling or a parent*). Of note, this index of bedsharing does not include children who "re-locate" from their own bed to a parent's bed during the night, and instead only includes children whose primary sleeping arrangement includes sharing a bed with another member of the household.

Room Sharing

The home observers also recorded whether the child regularly shares a room with another member of their household. Room sharing with an adult versus with another child was quantified separately. Room sharing with an adult was scored as 0 (*child does not share a room with an adult*) or 1 (*child shares a room with an adult*). Room sharing with another child was scored as 0 (*child does not share a room with another child*) or 1 (*child shares a room with another child*). Similar to our index of bed sharing, our index of room sharing does not include children who "re-locate" from their own bedroom to the bedroom of a parent or sibling, and instead only includes children whose primary sleeping arrangement includes a shared bedroom.

Home Chaos

Home chaos was measured using primary caregiver reports on the Confusion, Hubbub, and Order Scale (CHAOS; Matheny et al., 1995). Households high on the construct of home chaos are those characterized by a sense of confusion, rush, and disorganization, and typically lack a sense of order or a consistent routine (Matheny et al., 1995). The CHAOS includes 15 binary items (scored as: 0—*No*, 1—*Yes*) assessing parental perception of environmental confusion in the household (e.g., "it's a real zoo in our home" and "you can't hear yourself think in our home"). Scores on each item were summed to create an overall index of home chaos, with higher scores indicating more chaotic households. The Cronbach's α value for the total summary score was 0.75.

Household Size

Household size at each age was determined based on caregiver reports of the number of individuals living in the home with the child at the time of assessment.

Purdue Home Stimulation Inventory

For a subset of the wider sample ($n = 175$ at 30 months; $n = 154$ at 36 months; $n = 162$ at 42 months), observers also completed a modification of the observation portion of the Purdue Home Stimulation Inventory (PHSI; Wachs et al., 1979). The form of the PHSI used assessed a variety of constructs related to the child's home environment (described below). The PHSI was completed by both home observers, and any scales/indexes were calculated by taking the average across the two observers. Interrater reliability for each scale/index on the PHSI was calculated using ICCs. Average ICCs ranged from 0.97 to 0.99, indicating a high degree of reliability between observers.

Stimulus Shelter. A stimulus shelter is defined as a quiet place, most often a bedroom, which is removed from the traffic and noise of the household where the child can go to nap, rest, and have quiet time. Observers reported whether or not the child had access to a stimulus shelter during the home observation. This item was scored as "child does not have access to a stimulus shelter" or "child does have access to a stimulus shelter," and then reverse scored so that higher scores reflect that the child does not have access to a stimulus shelter.

Household Noise. At 15-min intervals, the observers rated the highest noise level experienced in the home on a 5-point scale, ranging from 1 (*silent*) to 5 (*very loud*). The ratings for each 15-min interval were averaged to determine the average level of household noise during the observation.

Stimulus Sources. Observers recorded the number of stimulus sources, defined as any sources of noise in the home outside of the voices of people who were present during the observation. This could include electronics (e.g., televisions, tablets), appliances (e.g., washing machines), toys, or music. Each separate source of noise was counted once.

Household Clutter. Observers reported on whether or not the house was cluttered. Clutter was defined as disorganization of the family's belongings, including child toys, mail, clothes, and kitchen items. If household items were left out because they were in use, this was taken into consideration in the rating of this item. The observers reported on clutter, rating the household items as 1 (*put away*), 2 (*piled up*), or 3 (*scattered about*).

Household Cleanliness. Observers reported on the general cleanliness of the household, considering details such as stains on the carpets, crumbs on surfaces, dirty dishes, and trash. On the basis of this information, the observers rated the home as either "not clean" or "clean," and then this item was reverse scored so that higher scores indicated less household cleanliness.

Household Crowding. Household crowding was calculated as the ratio of the number of people living in the household to the number of rooms in the household. The number of rooms in the household was summed by the observers during the initial home tour, and included all traditional rooms, bathrooms, and the basement, but did not include closets or garage space.

Child Sleep

Actigraphy. Sleep was measured using MicroMini Motionlogger actigraphs from Ambulatory Monitoring, Inc. (Ardsley, NY), watch-like devices placed in fabric wristbands worn by children for 1–2 weeks. The number of nights of actigraphy data collected varied due to differences in protocols across substudies, family preference for scheduling lab visits, toddler noncompliance with wearing the device, and equipment failure. There were no systematic differences in the number of nights the child wore the actigraph based on family SES, child sex, or parent-reported sleep problems. To be included in analysis using actigraphy data, children were required to have at least 4 nights of usable actigraphy data, and children had an average of 10.15 nights at 30 months (*SD* = 4.02 nights), 9.86 nights at 36 months (*SD* = 4.27 nights), and 11.05 nights at 42 months (*SD* = 5.71 nights). Actigraphs measure minute-by-minute motor activity to estimate sleep/wake patterns. Sleep diaries were used when scoring the actigraphy data to determine the child's bedtime, rise time, nap times, and times when the child was not wearing the actigraph. Actigraphs were worn on the nondominant wrist, but some toddlers, who refused to wear the actigraph on their wrist (~6%), wore the device on their ankle. During actigraphy processing, time periods were excluded if they were identified by the AW2 software as "non-wear time"/bad data or identified by parents as "non-wear time" in the sleep diaries.

Actigraphy data were processed using the Sadeh algorithm (validated for use with children; Sadeh et al., 1994) by trained research assistants. A large set of raw actigraphy variables that were (a) used in prior actigraphy research, (b) consistent with major areas of sleep behavior, and (c) were not a linear combination of already selected variables, were exported from the AW2 software package. Using each child's means/standard deviations across the available days of actigraphy data, we derived four composite variables based on principal components analysis (Staples et al., 2019): sleep duration, sleep timing, sleep variability, and sleep activity (see Supplemental Table S5 for raw variables included in each composite). The four composites were formed by averaging the unweighted standardized indexes for each raw actigraphy variable exported from the AW2 software package. The sleep duration composite indexes the general length of the child's nighttime sleep period. The sleep timing composite indexes the relative lateness of the toddler's sleep schedule. The sleep variability composite indexes night-to-night variability in the timing and duration of sleep. The sleep activity composite indexes motor activity and wake episodes that occur during the sleep period. The four composites represent broad dimensions of sleep that are often examined in the child sleep literature (Meltzer et al., 2012). Composite indexes were used instead of single, raw actigraphy variables to more robustly measure the sleep constructs of interest. Descriptive values for the sleep composites are presented in Supplemental Table S6. The sleep composites had relatively high internal consistency at all ages, with an average Cronbach's $\alpha = .79$ (range: .64–.96). Sleep onset latency, a single actigraphy variable that had near-zero loadings with the four factors, was examined in addition to the composites.

Child Sleep Habits Questionnaire. Parent-reported sleep problems were assessed using a modified version of the Child Sleep Habits Questionnaire (CSHQ; Owens et al., 2000). The CSHQ is a measure of child sleep problems that has been validated for use with young children (Goodlin-Jones et al., 2008), in which parents reported on the frequency, over the past week, of various sleep behaviors using a 3-point scale, ranging from 1 (*Rarely—0–1 times/week*) to 3 (*Usually—5–7 times/week*). All the items were averaged to create an overall score of general sleep disturbance, in which higher scores indicated more sleep problems.

Statistical Analysis

Machine Learning Approach

Data Aggregation and Preprocessing. Preprocessing, analysis, and plotting were carried out in Python v3.7.2 using the numpy v1.19.4 (Harris et al., 2020), pandas v1.1.5 (Mckinney, 2010), scipy v1.5.1 (Virtanen et al., 2020), scikit-learn v0.24.1 (Pedregosa et al., 2011), seaborn v0.9.0, and matplotlib v3.0.3 libraries. Data were organized into long format, with each visit constituting a separate sample from the same subject. Samples with largely incomplete data (e.g., if a family did not complete an entire assessment) were removed. Next, each variable was converted to standard units based on all available data at all assessments, and missing data were imputed using an iterative multivariate approach designed to converge on the most likely values for the missing entries. In this procedure, each column is predicted by the remaining variables in the data set using multiple linear regression. The missing values in each predicted variable were then estimated from the fitted regression model. This process was repeated 10 times, each time starting with a random variable and including the estimated values from the last round for the missing values in the nonselected variables. The estimated missing values from the final round were kept.

Data from a total of 1,600 visits were collected with missing data ranging from 0% to 35% for each variable. To ensure the most accurate imputation, only complete or near complete visit data (i.e., missing, at most, data from 2 of the 13 variables) were included in the final analysis. The final data set therefore included 1,410 samples (visits) for analysis, with imputed data ranging from 0% to 26% for each variable and with each child contributing, at most, three samples. For the subsample of children who were characterized further with the PHSI (i.e., 35% of the full sample, $n = 490$ visits), six additional predictor variables were included in the model (with 0%–19% imputed data per variable). A separate set of models were fit to this subsample to test if these additional variables provided more predictive insight. As our modeling approach considered multiple samples from the same child separately (up to three samples), we additionally tested if the results differed if we averaged across samples within each participant before conducting multivariate models. These results were nearly identical and are included in the Supplemental Materials (Supplemental Table S8 and Supplemental Figures 2 and 3).

Multivariate Modeling and Evaluation. To identify the best predictors of each sleep variable of interest, we employed elastic net regression using recommended cross-validation and model-fitting procedures (Nielsen et al., 2020). Elastic net models are ideal in situations in which the predictors of interest are correlated. Elastic net regression is a supervised machine learning technique that innovates on ordinary least squares regression by adding two penalty terms to the loss function—the function that models minimize in order to capture the most variance in the data being modeled, therefore minimizing "loss" of information—which combined, provide an optimal and simple solution to estimate an outcome variable from a set of potentially collinear predictors (Zou & Hastie, 2005). One term (L1) penalizes all coefficients, forcing small coefficients to zero to favor sparse results, whereas the other (L2) is a quadratic term that forces the loss function to a specific minimum, shrinking coefficient values without removing them. The combination of these two terms thus favors sparse solutions while maintaining groupings of colinear variables in the event of colinear predictors. The L1:L2 ratio is set during model fitting, with higher values indicating higher L1 and lower L2 weighting. To train the elastic net model, data were first split into training (85%) and testing (15%) data sets, with data from individual subjects grouped together across the split (i.e., not splitting individual subject data between training and testing). The model (ElasticNetCV scikit-learn class) was then trained on the training data using 10-fold cross-validation, in which the data are partitioned into 10 subsamples and each subsample is predicted by a model trained on the other nine. The 10 trained model weights are then averaged to create the overall trained model. The model was weighted toward sparser findings by limiting the L1:L2 ratio hyperparameter range for model fitting to 0.7–1. Model performance was then tested on the remaining, left-out data. To quantify the predictive power of the model, we compared the predicted sleep values to the actual values in the remaining, left-out data by computing the (a) linear coefficient from least-squares regression, (b) the mean squared error (*MSE*), and (c) the Spearman correlation coefficient. Models with good performance on these metrics were next permuted (all values for predictors were shuffled) and refit using typical permutation testing procedures (1,000 permutations) to build a null distribution and assign a p value to the model. Permuted p values were only computed for models with significant out-of-sample predictive power due to the computationally intensive nature of permutation testing. A significant p value suggests a real dependency between the predictors and the sleep variable within the model, as the model requires the data to be in an unshuffled order for a well-fitting model to be trained. This entire model-fitting procedure was conducted separately for each sleep outcome.

For each model with significant predictive power and a significant permuted p value, the coefficients, or model weights, were examined to determine which predictors remained in each of the final trained models and therefore contributed to model fit. The model weights provide insight to both the degree to which that variable was weighted in the predictor models (the magnitude of the weight) and the direction of the association with the outcome sleep variables (whether the weight is positive or negative). To further quantify the specific contribution of each predictor, importance testing was conducted. This procedure involved permuting a single predictor variable, retraining the models, then computing the change in R^2 in the left-out testing data as a result of losing that variable's covariance. Positive importance scores indicate a loss in R^2 in the permuted models, with a greater magnitude representing a greater importance to the model. These R^2 values should not be interpreted the way effect sizes are interpreted in traditional multiple linear regression because they are measured on the left-out sample, not on the training data. Instead, these values provide an indication of each variable's effect size relative to other variables within the same model. Negative importance scores indicate improved model fit when that variable was permuted, implying that inclusion of that variable was detrimental to model fitting.

This study was not preregistered. Reasonable requests for materials and analysis code for this study are available from the corresponding author.

Results

Aim 1: Associations Between the Physical Home Environment and Child Sleep

Correlations between the physical home environment variables and sleep at each age are shown in Table 1. The most robust and consistent associations emerged between child sleep and sleep space quality, home environment quality, bedsharing, and room sharing with an adult. Children with poorer quality sleep spaces, poorer quality home environments, who shared a bed, and who shared a room with a parent had shorter sleep durations, later sleep timing, more night-to-night variability in their sleep schedules, and more parent-reported sleep problems overall.

Aim 2: What Matters Most for Child Sleep

To identify the best environmental predictors of each sleep variable of interest, an elastic net regression was used. Full model performance results are reported in Supplemental Table S7. Model weights for well-fitting models *only* are reported in Table 2 and visualized in Supplemental Figure 1. Weight direction (positive or negative) denotes the direction of the association between that variable and the sleep outcome, whereas magnitude denotes the degree to which that predictor was weighted in combination with the other predictor variables.

Full Sample Models

Accurate prediction models were successfully trained for five of the sleep variables: sleep duration, sleep activity, sleep timing, sleep variability, and CSHQ total scores. For the model predicting sleep duration, the variables contributing to the model in order of magnitude, in descending order, were room sharing (with an adult), sleep space quality, household disorganization, child age, and home environment quality (outside of sleep space). For the model predicting sleep activity, the variables contributing to the model in order of magnitude, in descending order, were child age, home environment quality, bed sharing, sleep space quality, household disorganization, and room sharing (with an adult). For the model predicting sleep timing, the variables contributing to the model in order of magnitude, in descending order, were household size, room sharing (with an adult), household disorganization, home chaos, sleep space quality, bed sharing, home environment quality (outside of sleep space), room sharing (with a child), and child age. For the model predicting sleep variability, the variables contributing to the model in order of magnitude, in descending order, were home environment quality (outside of sleep space), bed sharing, household disorganization, home chaos, household size, sleep space quality, room sharing (with an adult), and child age. For the model predicting CSHQ total scores, the variables contributing to the model in order of magnitude, in descending order, were room sharing (with an adult), home chaos, household size, household disorganization, sleep space quality, bed sharing, home environment quality (outside of sleep space), room sharing (with a child), and child age.

Subsample Models

For the models fitted to the subsample of children assessed with the PHSI, accurate models were obtained for two of the sleep variables: sleep timing and CSHQ total scores.

For the model predicting sleep timing, the variables contributing to the model in order of magnitude, in descending order, were sleep space quality, household disorganization, household size, PHSI average noise, room sharing (with an adult), home chaos, household crowding, PHSI stimulus sources, PHSI household cleanliness, bed sharing, PHSI household clutter, home environment quality, PHSI stimulus shelter, and room sharing (with a child). For the model predicting CSHQ total scores, the variables contributing to the model in order of magnitude, in descending order, were room sharing (with an adult), home chaos, home environment quality, household size, sleep

Table 1
Correlations Between Home Environment Variables and Child Sleep at Each Age

Age	Sample	Variable	Sleep duration	Sleep timing	Sleep variability	Sleep activity	Sleep latency	CSHQ total
30 months	Full sample	Poor quality sleep space	−.13**	.15**	.12**	.09*	.04	.21**
		Poor quality home environment	−.12*	.17**	.26**	.11*	.03	.25**
		Home disorganization	−.19**	.24**	.20**	.10*	.04	.28**
		Bed sharing	−.14**	.24**	.21**	.08^	.05	.32**
		Room sharing (adult)	−.15**	.26**	.16**	.09*	.01	.34**
		Room sharing (child)	−.07	.00	.12*	.03	.04	.09^
		Home chaos	−.12*	.13*	.13*	.02	−.09^	.18**
		Household size	.01	−.03	.01	−.03	.02	.02
	Subsample only	PHSI stimulus shelter[a]	−.14^	.08	.12	.10	.14^	.18*
		PHSI household noise	.13	−.02	.01	−.05	−.02	−.03
		PHSI stimulus sources	.02	.14^	.12	.06	.00	.04
		PHSI household clutter	−.16*	.19*	.26**	.17*	.06	.13
		PHSI household cleanliness[a]	−.08	.02	.21**	.08	−.04	.17*
		Household crowding	−.19*	.15^	−.04	.11	−.02	.04
36 monthss	Full sample	Poor quality sleep space	−.14**	.14**	.10*	.10^	.03	.25**
		Poor quality home environment	−.11*	.13*	.10*	.05	.02	.25**
		Home disorganization	−.07	.14**	.05	.03	.00	.23**
		Bed sharing	−.02	.16**	.12*	.06	.02	.27**
		Room sharing (adult)	−.13*	.20**	.06	−.03	−.04	.27**
		Room sharing (child)	−.04	−.05	−.05	−.03	.03	.03
		Home chaos	.01	.03	.00	.03	−.02	.18**
		Household size	−.01	−.13*	−.09	.12*	.02	−.08
	Subsample only	PHSI stimulus shelter[a]	.06	.03	.02	.12	−.02	−.12
		PHSI household noise	−.15^	.27**	.12	.09	.15^	.03
		PHSI stimulus sources	−.19*	.10	−.02	−.19*	−.04	.05
		PHSI household clutter	−.09	.08	.07	.19*	.11	.19*
		PHSI household cleanliness[a]	−.12	.10	.14^	.17*	−.03	.33**
		Household crowding	.02	.02	.02	.13	.01	.20*
42 months	Full sample	Poor quality sleep space	−.12*	.21**	.11^	.02	.01	.24**
		Poor quality home environment	−.03	.18**	.11*	.05	.00	.27**
		Home disorganization	.03	.11*	.08	−.05	−.03	.14*
		Bed sharing	−.12*	.15**	.17**	.04	−.03	.23**
		Room sharing (adult)	−.18**	.19**	.16**	.09	−.09	.25**
		Room sharing (child)	−.01	.02	−.01	−.03	.06	.05
		Home chaos	.08	.02	.05	−.07	.05	.10^
		Household size	.07	−.10	−.01	−.12^	.11^	−.07
	Subsample only	PHSI stimulus shelter[a]	.03	.10	.06	.08	.08	.01
		PHSI household noise	−.13	.21*	.08	.11	.20*	.21**
		PHSI stimulus sources	.05	.24**	−.02	−.13	−.01	.19*
		PHSI household clutter	−.09	.18*	.17*	.12	.10	.29**
		PHSI household cleanliness[a]	−.11	.18*	.06	.16^	.10	.32**
		Household crowding	−.01	.04	−.02	−.10	−.04	.11

Note. PHSI = Purdue Home Stimulation Inventory; CSHQ = Child Sleep Habits Questionnaire.
[a] Item was reverse scored.
^$p \leq .10$, $^{*}p \leq .05$, $^{**}p \leq .01$.

Table 2
Elastic Net Model Coefficients for Models That Accurately Predicted Each Sleep Variable

	Full sample models N = 1,410; 9 predictors					Subsample models N = 490; 15 predictors	
Predictor	Sleep activity	Sleep duration	Sleep timing	Sleep variability	CSHQ total	Sleep timing	CSHQ total
Household disorganization	0.01	− 0.04	0.09	0.06	0.11	0.14	0.01
Home environment quality	0.05	0.00	0.04	0.12	0.07	− 0.04	0.13
Sleep space quality	0.01	− 0.07	0.08	0.03	0.11	0.15	0.12
Home chaos	0.00	0.00	0.09	0.05	0.16	0.08	0.15
Household size	0.00	0.00	− 0.15	− 0.05	− 0.13	− 0.13	− 0.12
Room sharing (adult)	0.01	− 0.11	0.13	0.01	0.17	0.09	0.26
Room sharing (child)	0.00	0.00	− 0.03	0.00	− 0.02	0.00	0.05
Bed sharing	0.03	0.00	0.07	0.09	0.10	0.04	0.00
Child age	− 0.16	0.03	0.00	− 0.01	− 0.02	0.00	− 0.05
PHSI average noise	—	—	—	—	—	0.12	− 0.03
PHSI household cleanliness	—	—	—	—	—	− 0.06	0.06
PHSI household clutter	—	—	—	—	—	0.04	0.00
PHSI stimulus shelter	—	—	—	—	—	0.01	− 0.08
PHSI stimulus sources	—	—	—	—	—	0.07	0.01
Household crowding	—	—	—	—	—	0.07	0.03

Note. Coefficients of zero did not contribute to predicting that particular variable, whereas variables with nonzero coefficients of greater magnitude were weighted more for prediction. Note that weight direction (positive or negative) denotes the direction of the association between that predictor and sleep variables within the context of the model. PHSI = Purdue Home Stimulation Inventory.

space quality, PHSI stimulus shelter, PHSI household cleanliness, room sharing (with a child), child age, household crowding, PHSI average noise, PHSI stimulus sources, and household disorganization.

Full Sample Importance Testing

Importance rankings for each predictor variable are shown in Figure 1. For the model predicting sleep duration, the predictor variables most important to the model, in descending order and irrespective of association direction, were: (a) room sharing (with an adult), (b) sleep space quality, and (c) household disorganization. For the model predicting sleep activity, the predictor variables most important to the model, in descending order and irrespective of association direction, were: (a) child age, (b) sleep space quality, (c) home environment quality, and (d) bed sharing. For the model predicting sleep timing, the predictor variables most important to the model, in descending order and irrespective of association direction, were: (a) room sharing (with an adult), (b) household disorganization, (c) household size, (d) sleep space quality, (e) bed sharing, (f) home chaos, and (g) home environment quality. For the model predicting sleep variability, the predictor variables most important to the model, in descending order, were: (a) bed sharing, (b) home environment quality, (c) sleep space quality, (d) household size, (e) room sharing (with an adult), (f) household disorganization, and (g) home chaos. For the model predicting CSHQ total scores, the predictor variables most important to the model, in descending order and irrespective of association direction, were: (a) room sharing (with an adult), (b) sleep space quality, (c) home chaos, (d) bed sharing, (e) household disorganization, (f) household size, (g) home environment quality, and (h) child age.

Subsample Importance Testing

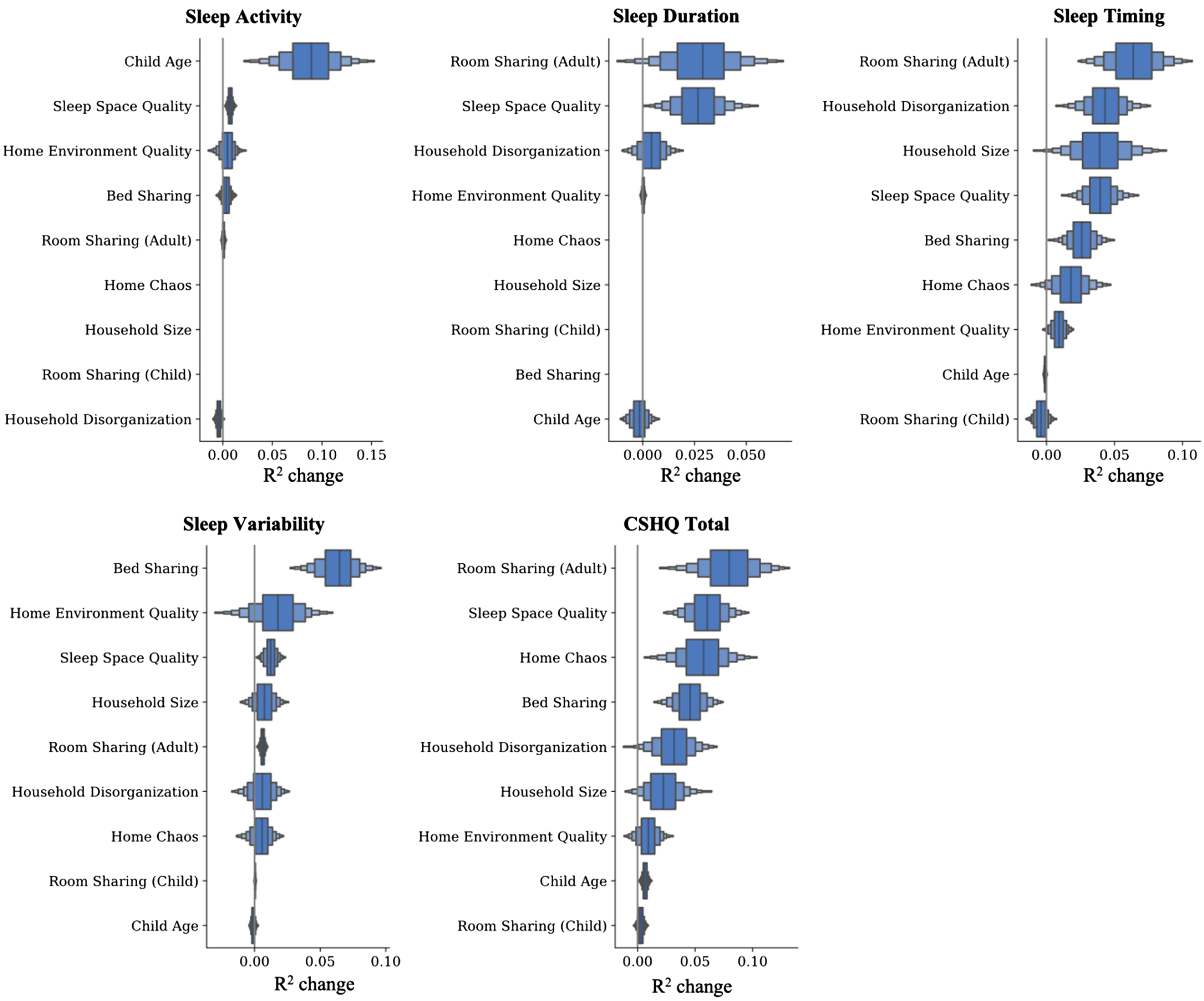
Importance ranks are presented in Figure 2. For the model predicting sleep timing, the predictor variables most important to the model, in descending order and irrespective of association direction, were: (a) sleep space quality, (b) household size, (c) room sharing (with an adult), (d) PHSI stimulus sources, (e) home chaos, (f) household disorganization, (g) household crowding, (h) PHSI household cleanliness, (i) bed sharing, (j) PHSI average noise, (k) PHSI household clutter, and (l) home environment quality. For the model predicting CSHQ total scores, the predictor variables most important to the model (in descending order and irrespective of association direction) were: (a) room sharing (with an adult), (b) sleep space quality, (c) household size, (d) home environment quality, (e) home chaos, (f) PHSI household cleanliness, and (g) room sharing (with a child).

Discussion

The present study explored the association between the physical home environment and sleep in early childhood, further examining which aspects of the physical home environment are the most important when predicting sleep outcomes. Of the aspects of sleep examined, sleep timing, sleep variability, sleep duration, and parent-reported sleep problems were the most likely to be associated with the physical home environment across ages, with poorer quality environments associated with later sleep schedules, more variable sleep schedules, shorter sleep durations, and more parent-reported sleep problems. Of the aspects of the physical home environment examined, room sharing with an adult, bed sharing, and the quality of both the child's sleep space and the wider home environment were the most important predictors of sleep in early childhood. Although we acknowledge that all aspects of the physical home environment that we examined may importantly influence child sleep, we focus our discussion on those predictors identified as *the most important* based on our importance testing approach.

Room sharing with an adult was the most important predictor in the full-sample models for sleep timing, sleep duration, and parent-reported sleep problems and, in the subsample models (i.e., the children also assessed with the PHSI) for parent-reported sleep

Figure 1
Importance Testing Results for Well-Performing Full Sample Models

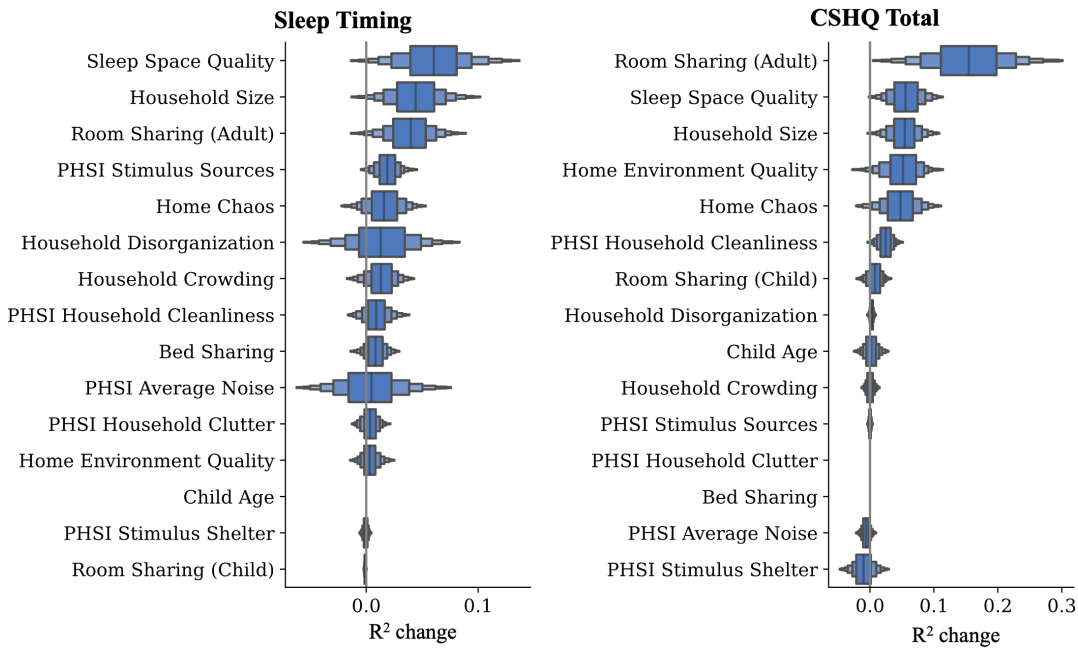


Note. Importance for each variable was operationalized as the change in model R^2 after permuting (shuffling) that variable's values and retraining the model. Graphed are distribution plots from 1,000 separate permutations. Higher, positive values indicate greater importance for model performance. Negative scores imply that inclusion of that variable in the model is detrimental to fit as the permuted variable accounted for more variance than the nonpermuted variable. Note that importance scores in this context are agnostic to direction of the association and ranks across positive and negative associations between predictor and outcome variables. These R^2 change values should not be interpreted as effect sizes are in traditional multiple linear because they are derived from the left-out data from each cross-validation fold, not the training data. Instead, they provide a relative measure of how much unique variance was captured by each variable. See the online article for the color version of this figure.

problems. Children whose primary sleeping arrangements included sharing a bedroom with a parent had shorter sleep durations overall, went to bed later, and had more parent-reported sleep problems. These findings correspond with prior research suggesting that young children in westernized countries (i.e., Australia, Canada, New Zealand, United Kingdom, and United States) get better, parent-reported sleep when they have their own room (Mindell et al., 2010). Various factors could lead to parent–child room sharing, including limitations in household space, parent beliefs about the positive benefits of sharing a room with their child, and child needs (e.g., a child who is unable to sleep alone might have their primary sleeping arrangement changed to the parent's room). Additionally, there are a number of possible reasons sharing a bedroom with a parent could lead to disrupted sleep. Children who share room with a parent may adjust their sleep schedules to match those of their parent, staying awake until the parent goes to bed or waking with the parent in the morning. Parents typically go to bed later than and wake up earlier than their children (Kouros & El-Sheikh, 2017), possibly leading children who share a room with them to have later sleep timing and to get less sleep overall. It is of course possible that children who

Figure 2

Importance Testing Results for Well-Performing Subsample Models



Note. Importance for each variable was operationalized as the change in model R^2 after permuting (shuffling) that variable's values and retraining the model. Graphed are distribution plots from 1,000 separate permutations. Higher, positive values indicate greater importance for model performance. Negative scores imply that inclusion of that variable in the model is detrimental to fit as the permuted variable accounted for more variance than the nonpermuted variable. Note that importance scores in this context are agnostic to direction of the association and ranks across positive and negative associations between predictor and outcome variables. These R^2 change values should not be interpreted as effect sizes are in traditional multiple linear because they are derived from the left-out data from each cross-validation fold, not the training data. Instead, they provide a relative measure of how much unique variance was captured by each variable. See the online article for the color version of this figure.

have sleep problems are more likely to bed/room share with a parent; indeed, the significant association between parent-reported sleep problems and parent–child room sharing supports this. However, the design of the present study does not enable us to disentangle whether parent–child room sharing *leads to* sleep disturbances, or whether sleep disturbances *lead to* parent–child room sharing. Interestingly, sharing a bedroom with a sibling, especially one with a similar sleep schedule, might be less disruptive to sleep overall (Chung et al., 2014), and in the present study, room sharing with another child was not associated with child sleep. Any effects of room sharing on child sleep were largely limited to parent–child room sharing.

Bed sharing was the most important predictor in the full-sample model for sleep variability, and findings suggested that young children whose primary sleeping arrangements include sharing a bed had more variable sleep schedules from night-to-night. Bed sharing is a complex topic, and family decisions to bed share often encompass both cultural, economic, and familial considerations (Andre et al., 2021). Although it is beyond the scope of the present study to fully assess the impact of bedsharing, our findings do suggest that routine bedsharing in early childhood is associated with more variable sleep. Similar to room sharing, children who bedshare with a parent or a sibling may adjust their sleep schedules to match those of their parent/sibling, staying awake until the parent/sibling goes to bed and waking with the parent/sibling in the morning. Parental sleep tends to be more variable than children's sleep (Matricciani et al., 2019), and children who share a bed with their parent may be more likely to match their parent's variable sleep schedules. Given research suggesting that cosleeping with a toddler may also negatively impact parent sleep (Covington et al., 2018), perhaps both parents and children may benefit from having separate beds. Similar to our parent–child room sharing findings, it is possible that children who have sleep problems are more likely to room or bed share with a parent. Our findings of a significant association between parent-reported sleep problems and bedsharing supports this. As with parent–child room sharing, the design of the present study does not enable us to disentangle whether bedsharing *leads to* sleep disturbances, or whether sleep disturbances *lead to* bedsharing, and future research on this topic will be essential. Additionally, we did not assess parental rationale for bed/room sharing, which could impact whether or not bed/room sharing is disruptive to child sleep.

Quality of the child's sleep space and the wider home environment were both found to be important for the prediction of sleep duration, sleep timing, sleep variability, and parent-reported sleep problems in the full-sample models, and for sleep timing in the subsample models (i.e., the children also assessed with the PHSI). Our measure of sleep space quality included observer reports of the relative lack of comfort and cleanliness of the child's room, as well as exposure to excess light and noise in the child's sleep space. These findings correspond with prior research highlighting the importance of sleep space conditions, including light, noise, and temperature, on sleep in childhood (e.g., Bagley et al., 2015; Lee et al., 2018). The present study is unique in that we had separate scales to quantify quality of the sleep space and the quality of the wider home environment. Sleep space quality was especially important for predicting sleep duration in the full sample model and sleep timing in the subsample model. It is possible that poorer quality sleep spaces, such as those that are bright, loud or uncomfortable, might interfere with sleep throughout the night, leading to shorter sleep durations overall, and may additionally interfere with circadian rhythms, leading children to have later than optimal sleep schedules. Home environment quality, a measure of the organization, safety, and cleanliness of the home outside the child's room, was especially important for predicting sleep variability in the full sample model. Overall, household disorganization may interfere with the family's ability to adhere to a consistent sleep schedule, or, possibly, parent characteristics (e.g., psychopathology) could be an underlying variable causing both household disorganization and variable sleep schedules.

In the full-sample model of sleep activity, child age was found to be the most important predictor, with sleep activity decreasing with age. The central role of child age in predicting sleep activity is consistent with longitudinal research suggesting that parent-reported nighttime awakenings decrease across early childhood (Reynaud et al., 2018) and sleep efficiency increases across early childhood (Tétreault et al., 2017). The age-related decline in movement after sleep onset observed in the present study is likely reflective of maturational changes in sleep architecture and patterns (Lopp et al., 2017).

The present study has several important strengths, including that we incorporated parentand observer reports, and actigraphy data, allowing us to reduce measurement bias due to shared method variance. Next, given the large sample size and repeated-measures design, we were able to use a machine learning approach, enabling us to examine the relative importance of several aspects of the physical home environment in predicting children's sleep. Finally, we quantified multiple domains of sleep (e.g., duration, timing), enabling us to test the specificity of the effects of various environmental features on different aspects of sleep. Importantly, our findings suggest that different aspects of sleep might have different environmental determinants.

Several limitations are worth noting. First, our sample was predominately White and middle class and our results may not generalize to samples of more marginalized families and/or those living in more disadvantaged households. The direct observation portion of the PHSI was only completed on a subset of participants. Thus, conclusions regarding the relative importance of PHSI variables for child sleep are based on a smaller number of samples and are less likely to generalize than the full sample models. Our index of sleep latency could not be fit by the elastic net regression models, suggesting that the model trained on one portion of the data did not generalize to the rest of the sample. This suggests that the association between the environmental predictors and sleep latency may be weak/not generalizable, or this could be due to the fact that sleep latency calculations, which are dependent on sleep diaries in addition to actigraphy data, are less reliable than other actigraphy-only based measures of sleep. This could also indicate that the association between the physical home environment and sleep latency is nonlinear, a possibility especially given that both too short and too long sleep latencies are problematic (Alexandru et al., 2006). More generally, nonlinear associations and interactions among predictors of sleep deserve further research, especially given the modest amounts of variance accounted for by the correlations and machine-learning regression analyses.

Next, although family routines, specifically bedtime routines, are an important contextual factor for understanding child sleep; in the present study, we did not examine bedtime routines as a part of the physical home environment. Given that ample research has examined the effects of bedtime routines on child sleep (Mindell & Williamson, 2018), including research from our own group (Hoyniak et al., 2021), we chose not to consider bedtime routines here. Similarly, prior research from our group using this sample has examined how screen use prior to bedtime affects toddler sleep (Staples et al., 2021). Thus, despite established effects of screen engagement before bedtime on child sleep, we opted not to include a screen use variable in the present study given overlap with this prior research. Another limitation is that we had only one home observation at each age. Collecting repeated observations of the home environment at each age would likely lead to a more reliable measure of the child's environment. However, it would also have increased participant burden and decreased our sample size. Additionally, observer bias in our home observation measures was likely unavoidable, but we tried to minimize the effect of observer bias with thorough observer training, requiring two observers per visit, using a number of different observers who generally reflected the racial and sociodemographic backgrounds of our sample, and having specific and detailed measures for the observers to complete during the observation. Next, although we focused on the observable, physical aspects of the home environment, we did not address plausible links between the physical environment and psychological factors. For example, children sharing parents' beds may be doing so at least in part for psychological reasons, such as fear of the dark or of being by themselves, and similarly, parents' own anxieties/mood difficulties could influence parent behaviors and qualities of parent–child interaction around bedtime and subsequent child sleep (e.g., Teti & Crosby, 2012). Future research should examine links between the physical environment and psychological factors.

Conclusion

This study is among the first to explore how specific aspects of the physical home environment are associated with sleep in early childhood. Findings suggest room sharing with an adult, bed sharing, and the quality of both the child's sleep space and the wider home environment were all important predictors of child sleep. Given the importance of these factors in predicting young children's sleep, clinicians may consider recommending adjustments to lighting and temperature in the child's sleep space, decreasing household noise, and encouraging independent child sleep, in order to improve sleep. These modifications may be useful in preventing and treating early childhood sleep problems. Additionally, general parental education about sleep benefits, healthy sleep environments, the potential detriments of bedsharing/room sharing with an adult, and overall sleep hygiene may help to prevent the occurrence of sleep problems in early childhood.

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