Toward a Family-Centered Approach to Sleep: Redefining Sleep Metrics and Interactions for Families

SUEUN JANG, KAIST, South Korea
HYE SOO PARK, KAIST, South Korea
HYUNSOO LEE, KAIST, South Korea
UICHIN LEE, KAIST, South Korea

This report introduces our family-centered approach to sleep. First, we propose redefining sleep metrics within the family context. We begin with the four foundational sleep metrics, then extend them to incorporate sleep hygiene and family environment factors, and examine them at both individual and group levels. Second, we propose designing sleep interactions for families, namely, routine visualization and co-reflection. Through these steps, we aim to develop more effective sleep interactions for families.

CCS Concepts: • **Human-centered computing** → *Ubiquitous and mobile computing design and evaluation methods.*

Additional Key Words and Phrases: Family Informatics, Family Interaction, Sleep, Reflection, Routine

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1 INTRODUCTION

Family informatics emerges as a new approach that recognizes the family as a health unit, offering a unique perspective to understand and improve health and wellbeing based on shared behaviors, needs, and responsibilities [15]. Studies like DreamCatcher [47], TableChat [39], and Spaceship Launch [53] have explored family-based needs in various health areas (e.g., sleep, meals, and physical activity) as well as the potential benefits of family informatics, such as increased healthy behaviors, active participation and collaboration toward health goals, and exchange of family support.

Sleep, in particular, is a crucial part of family health that is affected by family dynamics and the home environment [2, 12, 47, 54]. Recent studies suggest that family members influence one another's sleep through physical presence and psychological, emotional mechanisms and exhibit coregulation of sleep patterns [27]. Thus, examining the socially influenced process of sleep within the family context holds great promise.

Prior research on sleep has enabled the measurement of everyday sleep using a wide range of consumer devices (e.g., Fitbit, Microsoft Band, Luna, Withings Aura, and app-based off-the-shelf smartphones) [34, 38], and these studies on sleep data collection have further enabled research on sleep interventions (e.g., recommending sleep schedules [35], providing sleep hygiene tips [16, 17], promoting self-tracking and self-reflection [5, 14, 33, 37, 47], and guiding self-experimentation [18]) to motivate and sustain healthy behavior changes [55]. However, designing effective sleep interventions in a family context remains challenging due to the complex and multifaceted nature of sleep [9]. Factors such as meals [61, 62], physical activity [23, 52, 57], environmental conditions [10, 13], emotions [2, 22, 59], substance use [30, 44, 60], genetics [24], and life stages [28, 32, 40] all contribute to the complexity of sleep, making it difficult to find a one-size-fits-all solution [25]. This is where family informatics offers a valuable perspective. By contextualizing sleep within the family unit, family informatics allows for a deeper understanding of the unique and complex sleep experiences, while raising awareness of their mutual influence and collective responsibility [15]. To address the complexity of sleep by leveraging the family context, we approach family-centered sleep interaction design in two fold: (1) redefining sleep metrics within the family context, and (2) designing sleep interactions for families. Through effective interaction design for family sleep, we aim to help families with their collaborative efforts to improve sleep.

2 DEFINING FAMILY-CENTERED SLEEP

Prior research on sleep has relied on various metrics, ranging from minutes asleep, minutes awake, minutes to fall asleep to self-reported sleep quality or mood, to determine sleep interventions. These metrics were too confined to sleep itself for families to derive actionable insights to improve sleep. Moreover, they were provided at the individual level lacking contextual information or frame of reference.

Tailoring sleep metrics to the family context. Our approach begins with commonly used, basic sleep metrics such as total sleep time (TST), sleep onset latency (SOL), sleep efficiency (SE), and wake after sleep onset (WASO) [6, 29, 45]. These are easier for families to understand, compared to more nuanced metrics such as sleep stages [50], sleep regularity index (i.e., SRI) [46], sleep debt, social jet lag, sleep inertia [1], and circadian sleep efficiency [29] or more primitive physiological metrics such as heart rate or blood oxygen level. Furthermore, our family-centered sleep metrics go beyond sleep-specific measurements to encompass diverse sleep hygiene factors. Similar to prior research on smart homes that emphasized empowering families with control over their lives, rather than providing social engineering solutions for control over devices [19], we propose developing lifestyle-encompassing sleep metrics based on sleep hygiene [41, 56] and family routine research [31, 58]. For example, sleep hygiene literature has repeatedly emphasized sleep-specific factors like bedtime, wake time, or duration of time in bed after waking up in the morning. Also, much broader and lifestyle-related metrics like music, TV, noise, light, bed partner interaction, exercise in the afternoon or early evening, or exercise during the two hours prior to sleep have been consistently emphasized [41, 56]. By integrating diverse family-centric sleep data from multiple data sources such as mobile, wearable, and IoT devices [11, 20, 34, 38, 42], families will be able to reflect on the nuances of their sleep behaviors and identify potential causes and solutions to apply in real life [50].

Providing data analytics at individual and family levels. While individual data are the basic elements of family sleep data, they can offer valuable insights when aggregated pairwise or for the entire family. For example, individual members can initially reflect on their sleep patterns; then, they can compare their average sleep metrics with the whole family's and understand the overall picture of their family sleep; additionally, individual data can be aggregated pairwise by calculating the similarity between family members. By understanding which family member has the closest and farthest sleep pattern, families can get a more concrete comparison point within the shared sleep context and discuss collaborative efforts to improve family sleep hygiene or support each other. For instance, we can posit a scenario where a user's sleep data exhibits a sudden decrease in sleep duration. Initially, the user may feel pressured to forcefully meet the sleep target. However, if the family collectively analyzes their sleep data and discovers a similar decreasing trend across all members, they may look for potential external causes beyond individual factors, such as a recent family event or a change in the home environment. By identifying the cause within their context, they can focus on collaborative solutions, rather than focusing on meeting each individual's sleep target. As such, family-centered sleep analytics expands the solution space by encouraging families to explore the broader context that influences sleep. However, in implementing such shared data analytics systems, potential discomfort and privacy concerns regarding health data sharing within the family should be addressed.

3 DESIGNING FAMILY-CENTERED SLEEP INTERACTION

Our approach expands on fragmented, individualized sleep metrics by incorporating diverse sleep hygiene and family environment factors. To help families understand and reflect on these family-centered sleep metrics, we propose two key interaction features, routine visualization and co-reflection.

Visualizing sleep routines. Routines can help families not only communicate family health resources, but also sustain health, avoid illness, and construct family health rules when used for health contexts [21]. While prior work has provided a technical foundation to automatically extract routines from data [4, 7, 49, 63], the target audience of the routine modeling research was often professionals or researchers with existing knowledge about the domain or routine modeling techniques [3]. However, families need a more intuitive and understandable way to understand their sleep patterns [51]. People without sufficient knowledge may struggle to identify patterns from numerous combinations of features coming from multiple data sources or may misinterpret the relationship between routines and sleep metrics. Furthermore, depending on the family's sleep conditions and purposes, different models of routines will be necessary. For example, for families who want to understand their current sleep patterns, sleep itself can be viewed as a routine that consists of different sleep stages, awakenings, and interactions with the environment. On the other hand, the whole day routine can be considered when families aim to identify any obstacles and change their daytime behaviors to improve sleep quality [2, 23, 52]. In addition, pre-sleep and post-sleep routines can be considered as they are recurring themes for sleep improvement in family sleep research [8, 12, 31, 58]. To ensure the clarity and effectiveness of sleep abstraction and visualization, however, they should be tested by involving family users in the design process. This will help communicate family health data in a user-friendly way.

Prompting co-reflection through scaffolding guidance. Reflection has been highlighted as a crucial part of both personal and family informatics systems [48]. Given the importance of mutable behaviors in health [43], encouraging families to self-reflect and set actionable goals is crucial. The guiding prompts should aim to assist throughout the entire process of co-reflection, from helping them understand visualizations of both individual and family-level sleep behaviors to facilitating a conversation about the causes of good or disrupted sleep and setting potential collective actions. Prompts can be crafted based on prior research on sleep hygiene [41, 56] and sleep-related family routines [31, 58]. Promoting reflection not only fosters awareness and perceived control in the data collection and sensemaking process [36] but also unlocks access to information that might not be available or quantifiable through sensor data alone. Furthermore, extending the benefits of individual reflection, co-reflection encourages and sustains engagement, and introduces another perspective from third-party observations [26], enriching the understanding of target behaviors.

4 SUMMARY

This report proposed a family-centered approach to sleep by redefining sleep metrics and interactions for families. Firstly, building on the four foundational sleep metrics, we proposed incorporating sleep-related lifestyle data and providing data analytics at both individual and group levels. Secondly, to leverage the redefined family-centered sleep data, we proposed using routine visualizations and prompts to guide co-reflection. These approaches will empower families to understand their sleep behaviors, derive actionable insights, and work together to improve their shared sleep hygiene.

In further developing family-centered sleep informatics systems as outlined in the proposal, the following questions should be considered:

- **Target:** How should we define the target for the family-centered health interventions, considering different age ranges, developmental stages of children, and etc? How broad or specific should these targets be?
- **Theories:** Which theories or methods should guide the design of family-centered co-reflection activities?
- **Evaluation:** How should family-centered interactions be assessed? Who should evaluate: individual members, the entire family, or external observers?
- **Engagement:** What strategies can be used to ensure families' engagement in long-term in-the-wild studies?
- **Privacy:** How can we address privacy concerns from "automated disclosure" of private data (e.g., health information)?

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