Sleep Patterns and Sleep Alignment in Remote Teams during COVID-19

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Working remotely from home during the COVID-19 pandemic has resulted in significant shifts and disruptions in the personal and work lives of millions of information workers and their teams. We examined how sleep patterns—an important component of mental and physical health—relates to teamwork. We used wearable sensing and daily questionnaires to examine sleep patterns, affect, and perceptions of teamwork in 71 information workers from 22 teams over a ten-week period. Participants reported delays in sleep onset and offset as well as longer sleep duration during the pandemic. A similar shift was found in work schedules, though total work hours did not change significantly. Surprisingly, we found that more sleep was negatively related to positive affect, perceptions of teamwork, and perceptions of team productivity. However, a greater misalignment in the sleep patterns of members in a team predicted positive affect and teamwork after accounting for individual differences in sleep preferences. A follow-up analysis of exit interviews with participants revealed *team-working conventions* and *collaborative mindsets* as prominent themes that might help explain some of the ways that misalignment in sleep can affect teamwork. We discuss implications of sleep and sleep misalignment in work-from-home contexts with an eye towards leveraging sleep data to facilitate remote teamwork.

Additional Key Words and Phrases: teams, remote work, distributed teams, COVID-19, sleep alignment

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1 INTRODUCTION

The closure of physical workplaces in early 2020 to curb the spread of coronavirus led millions of information workers to switch to remote work-from-home (WFH) with their teams. Studies found that the abrupt transition from working in a co-located office to WFH resulted in significant disruptions to various aspects of people's personal and professional lives [96, 120, 121, 127, 133]. One such aspect was sleep, which plays a fundamental role in overall well-being, mental health,

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and work performance [71, 81]. Several studies have indicated that WFH policies significantly impacted overall sleep patterns and sleep quality [19, 35, 115]. People also generally adopted later bedtimes and wake times (partly due to not having to commute to the office) [67, 72, 120]. Given the prospect of full-time WFH becoming a more mainstream work practice in the future [69, 120], and since much of modern work is team-based [114], it is crucial to consider how sleep is related to remote teamwork, especially in WFH configurations.

The field of CSCW has long been interested in challenges in remote teamwork [41, 90, 91]. For example, prior work on team collaboration across time zones has highlighted challenges in communication and coordination [92, 119]. Studies have also pointed to synchrony of work rhythms as an important consideration for successful team collaborations [49, 76, 116]. Yet, it remains an open question whether differences in sleep patterns affect teamwork in WFH contexts that tend to favor more fluid daily work schedules as opposed to the more regulated work schedules that employees adhere to in co-located work environments. Prior to the pandemic, showing up at the workplace at 9 am typically symbolized the start of the workday for all team members and it made colleagues visible to each other. Likewise, leaving the office at around 5 pm usually symbolized the end of the workday. Such structures may be less explicit, less uniform, and less visible in a WFH context. For example, teammates may align their sleep schedules more closely with their personal preferences and lifestyles or their particular living situations (e.g., presence of children or access to a private home office). In turn, the resulting deviations in sleep and work schedules of team members may cause conflict when schedules misalign (e.g, difficulties for teams to schedule meetings between early and late risers).

The purpose of this study was to investigate how individual sleep patterns and their differences within a team may relate to perceptions of teamwork, as represented by communication, coordination, cohesion, climate, and conflict; team productivity; and individual affect/mood. We were also interested to see if prior work can be replicated that found significant changes in sleep behaviors in the wake of the pandemic [35, 65]. The contributions of this paper are as follows:

(1) Our work extends existing inquiries into the role of COVID-19 in the context of work by assessing the degrees to which factors such as chronotype and the number of people in a given household are related to changes in individual sleep patterns and work schedules.
(2) We show how bedtime and sleep duration in particular are associated with individual affect/mood, perceived team performance, and perceived team productivity.
(3) We add a team perspective to the examination of relationships between sleep and remote work. Specifically, we provide a crucial lens into the extent to which differences between team members' sleep behaviors translate into team members' different perceptions of teamwork during the 'new normal' of WFH. We further show that differences in team members' sleep behaviors, whether aligned or misaligned, are related to their perceptions of team performance, and we discuss the practical and ethical implications for leveraging such data.

Our study is particularly timely in that the pandemic has ushered in a new phase for WFH [69]. Companies such as Salesforce, Spotify, and Twitter have already implemented permanent WFH options for their employees [1, 4].

2 RELATED WORK

The study of remote teams and their challenges is becoming more critical, not just in light of the more immediate concerns brought about by the COVID-19 pandemic [82]. In this section, we review prior work on teamwork, team alignment, and sleep, including more recent studies conducted during the pandemic.

2.1 Measures of Teamwork

The team science literature commonly distinguishes between two categories of team variables that influence teamwork: team states and team processes. For the study of team states, prior work has considered team cohesion, collective climate, team conflict, and individual affect/mood. Cohesion refers to team members' perceptions of each other, their commitment to work tasks, and their sense of group pride [7, 39]. Collective climate pertains to team members' perceptions of team processes and organizational context and it is developed through social interactions [104]. Team conflict encapsulates all the interpersonal and task-based issues that surface among team members [27]; increased task and relationship conflicts have negative effects on team outcomes [28]. Further, positive team affect is positively related to team efficiency, pro-social and citizenship behaviors, and lower turnover [58]. The study of team processes often involves examinations of team communication and coordination [58]. As a key behavioral process, team communication is an important predictor of team performance and team commitment, affecting all team-related activities including the exchange of information, the process of decision-making, the establishment of group processes, and the rapport between team members [51]. Team coordination captures how team members align their actions and create temporal patterns of work [59].

Team states and processes are influenced by the environmental contexts where work takes place [21]. Informal conversations in the office have been shown to foster team cohesion [99]. In a remote team context, however, opportunities for informal communication are more limited [58]. Co-workers who rely on computer-mediated-communication (CMC) have a lower sense of cohesion and personal rapport between team members as opposed to their co-located counterparts [128]. Recent studies conducted during the pandemic found that teams struggled with communication and cohesion [120, 133]. Miller et al. [78] found a significant decrease in feelings of social connection and cohesion in software development teams while members were working from home. Cao et al. [17] showed that multitasking during remote meetings may help boost personal productivity, though it can also relate to a loss of attention and engagement. In the absence of face-to-face interactions, teams are more prone to experience conflict as members tend to base their views of each other on other, often stereotypical assumptions that may end up being erroneously negative, create misalignment, and can affect intra-team conflict [100].

2.2 Sleep and Work Performance

Sleep plays a pivotal role for health [61] and it significantly affects quality of life [101] as well as behavior and mood [47, 53]. Studies have found that higher-quality sleep is significantly associated with both higher levels of positive affect and happiness whereas shorter periods of sleep time and later bedtimes are associated with increased repetitive, unwanted thoughts [89, 112]. According to the American Academy of Sleep Medicine and Sleep Research Society, the recommended sleep duration for healthy adults aged 18-60 years is 7-8 hours for the lowest mortality risk [95]. Anything above the recommended duration is considered oversleeping, and a sleep duration of less than seven hours is commonly considered short-sleep [42].

While sleep and wake times vary between individuals [103], they are generally determined by an internal circadian cycle that repeats roughly every 24 hours and regulates daily sleep and wakefulness [124]. A person's so-called *chronotype* is an expression of their circadian rhythm [52], and it falls on a spectrum of morning-type persons, evening-type persons, and so-called intermediate-type persons. Morning-type persons, also known as *early birds*, tend to have their peak performance times more during the first half of the day and become more distracted during the latter half [111]. In contrast, evening-type persons, or *night owls*, tend to be more productive later in the day and more disengaged in the mornings [111]. A host of endogenous and exogenous factors have been identified that contribute to circadian rhythms including lifestyle, light-dark cycle, and other socio-temporal cues [106]. Research has shown that circadian rhythms influence sleep [16], mood [85], and cognition [111].

In terms of work performance, sleep duration has been found to predict productivity loss [48]. Gingerich et al. [37] found evidence that employees who slept ten hours or more each night missed an average of 1.6 times more days of work and had an average of 2.2 times less productivity than employees who averaged around eight hours of sleep per night. In the context of WFH during the COVID-19 pandemic, the relationship between these domains may be more pronounced. While Hisler and Twenge [43] found no significant changes in the average sleep characteristics of US adults between 2018 and 2020, they documented that shorter and longer amounts than the recommended sleep duration were both more widespread during the COVID-19 pandemic. In addition, Robillard et al. [105] reported higher sleep problems during the pandemic, especially for people who went to bed later and slept less. Changes in sleep quality in the wake of COVID-19 were also associated with negative affect and worry [56]. For a systematic review of sleep problems documented during the pandemic, see [50].

2.3 Team Alignment in Remote Teamwork

Team alignment is generally defined as the degree to which team members rely on other members' motivation to work together around clearly defined goals and performance-based rewards [8, 126]. Alongside communication, team alignment has been explored in a wide variety of contexts including goal alignment [38], conflict prevention [110], work-life boundaries [49], and awareness [32]. Fagerholm et al. have also shown that alignment is a continuous process that takes time and effort, and successful remote teams tend to put more effort into their internal communications [32].

The apparent shifts in work and sleep patterns in the aftermath of the COVID-19 outbreak can be regarded as a new form of team alignment. Prior work has explained this form of alignment through the notion of *temporal distance*, which has been shown to pose significant challenges for team coordination [82]. Agerfalk et al. define temporal distance as a directional measurement of the temporal displacement between at least two collaborators who want to interact with each other [3]. Traditionally, temporal distance affects teams in situations where members are located in different time zones or in the wake of explicit changes made to team members' work schedules, which results in less overlap of work hours between team members [109]. Previous work in the context of globally distributed teams also documented that fewer overlapping work hours result in communication breakdowns, such as an increased need for rework and clarifications, and difficulties adjusting to new problems [30]. Flexible work schedules can also interact with team rhythms and performance with significant effects on processes (e.g. difficulties communicating) and team states (such as causing conflict, reducing cohesion), consequently affecting team performance [77]. The COVID-19 pandemic may expand our understanding of temporal distance in team alignment by introducing differences between team members that are not guided by official work policies but by team members' chronotypes as well as their behavioral and personal lifestyle differences [13]. Räihä et al. found evidence of eveningness as a risk factor for poor work ability [107], which suggests that chronotype should be directly considered when setting up employee work schedules so that evening-type persons, for example, can work more according to their inner clock [31, 125].

3 RESEARCH QUESTIONS

In the context of WFH during the COVID-19 pandemic, sleep has emerged as an important avenue for scientific inquiry [19, 20, 115]. To better understand the role of sleep in WFH teams, we used a mixed-methods approach that combined self-reports with unobtrusive sensing using wrist-worn wearables. These kinds of sensing devices have rarely been deployed longitudinally to understand

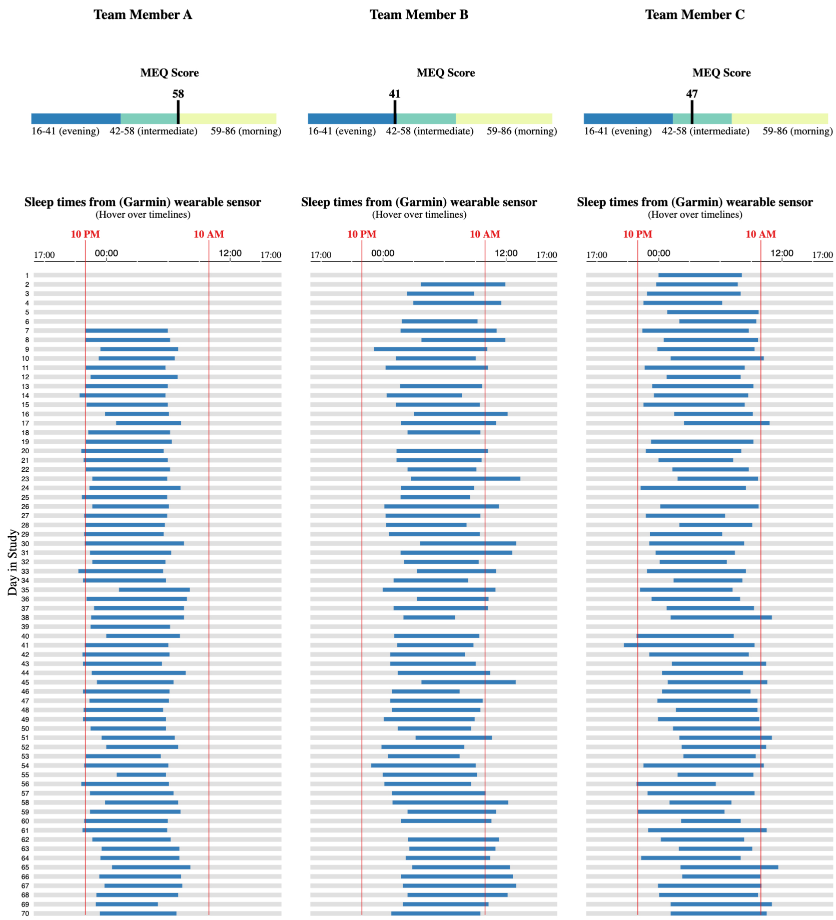

Fig. 1. Visualizations of the bed/wake times of team members along with their Morningness-Eveningness Questionnaire (MEQ) scores (lower values refer to evening-type persons and higher values to morning-types) within one team with misaligned sleep times in our study.

teamwork *in situ* other than a few exceptions; in particular, Pentland [98] deployed wearable sensors with 2,500 individuals and found that communication patterns predicted team success. Though there have been sensor-based studies of teams, their purpose was more to test the validity and accuracy of different bio-behavioral data collection methods in (often) very instrumented environments [15, 55, 135]. For example, Mundnich et al. [84] investigated the utility of off-the-shelf wearable and other environmental sensors to examine personality traits, behavioral states, job performance, and well-being in a cohort of hospital workers. Zhang et al. [135] deployed wearable sensing to track group cohesion and affect in a team of six crew members on a simulated Mars mission environment over a four-month period. To our knowledge, no study has used sensing to examine the sleep patterns of information workers and their teams longitudinally and *in situ*.

As a first step, we began by visually exploring and comparing the sleep data of study participants who belonged to the same teams. We developed interactive visualizations of the sleep times of teams computed from the wearable sensors along with relevant questionnaire measures corresponding to the team members (for additional visualizations from the larger study, see [118]). Figure 1 shows the

Morningness-Eveningness Questionnaire (MEQ) scores (used to measure chronotype, see Section 4.2.3) and a vertical visualization of the daily sleep times for each member of a three-person team over the course of ten weeks. The members in this team all identified as different chronotypes and they also exhibited different sleeping patterns: member A who tended towards a *morning-type* chronotype showed relatively consistent and early bed and wake times; member B who tended towards an *evening-type* exhibited more irregular and later sleep times compared to the other two; finally, the sleep times of member C who identified as an *intermediate type* was somewhat in between those of members A and B. To examine whether deviations in sleep patterns were reflected in perceived team states and processes we considered the following research questions:

- **RQ1:** How is the shift from co-located work to WFH related to the sleep and work patterns of information workers?
- **RQ2:** What is the relationship between individual sleep patterns and perceived team performance, productivity, and affect/mood?
- **RQ3:** What does the (mis-)alignment of team members' sleep patterns reveal about their individual mood as well as their perceptions of teamwork as measured through cohesion, communication, coordination, climate, conflict, and productivity?

4 DATA COLLECTION

This study was part of a larger longitudinal study to better understand factors that contribute to team effectiveness both in general and during the pandemic (for more information about this study, see [118]). It was approved by the Institutional Review Board (IRB) of the lead author's university with reliance agreements with the other researchers' institutions. All participants provided electronic informed consent prior to taking part in the study. Participants were assured that their data would be anonymized, not shared with their team members, and only accessible to the research team.

4.1 Participants

Participants were 75 US information workers who belonged to a total of 22 teams ranging from two to five members. Teams were recruited via email announcements, social media campaigns on Facebook and LinkedIn, and through existing partnerships with companies that had participated in prior studies. Individuals completed a screening questionnaire to determine if their teams met the eligibility criteria for participation: all members of a team had to be at least 18 years of age, work in teams of sizes two to five, and engage in cognitively demanding job tasks (i.e. data and information processing). For team sizes above two members, a team was eligible to participate if at least more than half of the members were willing to participate. For teams that consisted of six or more members but met all the other eligibility criteria, we would coordinate with team leads to meaningfully divide the whole team into smaller subgroups (e.g. project teams or work groups) of sizes two to five. We would then enroll the subgroups as separate study teams. Of the 22 teams considered for this study, two teams of sizes three and four were subgroups of a team of size seven. Demographic information for 75 participants and their teams are shown in Table 1.

The teams that participated in the study were affiliated with mid-sized technology companies, administrative offices in healthcare and academic institutions, consulting, and software development startups. Teams covered the following areas of information work: software engineering and testing, smartphone application development, e-commerce, design innovation, administrative work, and fundraising. The majority of teams were of size three (45.5%). The tenure of teams from their founding to the end of March 2021 when the data were analyzed ranged from ten months to 21 years with a mean of seven years.

Individual Level		Team Level	
Gender		Composition of Gender in Teams	
Male	64%	Majority Male	41%
Age		Distribution of Mean Age from Younger to Older Teams	
20-29	36%	20-29	32%
30-39	33%	30-39	36%
40-49	19%	40-49	27%
50-59	12%	50-59	5%
Dependents		Makeup of Teams based on Dependents	
0	32%	More than Half of the Members Have Dependents	59%
1	36%		
2	27%		
3+	5%		
Marital Status		Composition of Marital Status in Teams	
Married	61%	All Married	36%
Single	31%	Majority Married	18%
Divorced	4%	Majority Single	23%
In a Domestic Relationship	4%	All single	23%

Table 1. Participant demographics and team characteristics.

The study design was for a period of ten weeks. The first two teams started their participation in late July 2020, approximately four months after the first issuance of stay-at-home orders. A total of 19 teams (n=68) completed the required ten weeks of data collection when we conducted our analyses. The remaining three teams (n=7) had already completed 8-9 weeks of data collection by that time, which was sufficient to include their data as well. Participants were compensated individually with $50 for completing the first week of data collection and $200 for completing the full study; an additional $50 was awarded if participants achieved an 80% or greater compliance score for wearing the wearable sensor and completing the surveys.

4.2 Measures and Procedures

Participants wore a fitness tracker on their wrist throughout their entire participation in the study to collect bio-behavioral data, and they completed a set of short questionnaires once each workday (i.e., Monday through Friday) about their emotional state and their perceptions of team states and processes. Participants also completed an initial questionnaire battery and a 15-30 minute semi-structured interview. Compliance was monitored remotely. We sent nudges as text messages to participants with low compliance every week and actively resolved any other device-related issues reported by the participants. The average daily compliance (excluding weekends) for wearing the fitness tracker was 77.35% (SD = 21.37%) and for the daily self-reports it was 71.95% (SD = 17.74%). Participant compliance for the initial battery was 100% because it was gathered as part of study enrollment.

4.2.1 Wearable Sensing. Each participant was mailed a Garmin vivosmart4—a commercially available health and fitness tracker—that was to be worn on the wrist (like a watch) at all times during participation (except when charging the device). As participants went about their daily lives, the wearable unobtrusively collected daily summaries of various measures related to sleep such as bedtime, wake time, and sleep duration, and other measures not used in this study [102]. A validation study with polysomnography showed that the Garmin vivosmart4 detected sleep with high accuracy (.9) and sensitivity (.98) [83]. While participants also received a Gimbal Series 21 Bluetooth beacon to track proximity information, these measures were not used in our analyses as mobility was not a focus for this study since a majority (85.24%) worked from home.

4.2.2 Ecological Momentary Assessments. As a research procedure, Ecological Momentary Assessments (EMAs) are commonly used to collect empirical data about people's behavioral and thought patterns and/or their psychological states while also accounting for potential temporal variations in the self-reports of mental processes [26]. EMAs allow for a more deeper and holistic understanding of a given study population [6], and their use has become more popular in recent years, especially in combination with the technological developments in the area of mobile smartphone apps, which allow for a simple and convenient distribution and completion of daily questionnaires *in situ* [23, 123]. We administered EMAs through a mobile survey app[1]. Participants were provided with a video tutorial as part of the enrollment process that gave guidance on how to install the survey app and enroll in their team's daily EMA schedule. The EMAs were sent to all members of a given team at the same time each day, but the time randomly varied between 10 AM and 4 PM (in each of the team members' local time zones). Study participants had six hours to complete each questionnaire.

The EMAs included the following scales with a 5-point Likert response format: the validated 10-item short-form PANAS-Short scale [129]; a 5-item questionnaire assessing team productivity focusing on efficiency, effectiveness, satisfaction, and quality [73]; and five team outcome measures. These five scales, or "5Cs", included team cohesion measured through the three-item Perceived Cohesion Scale, which indexes a sense of belonging and morale [9]; team communication and team coordination questionnaires with six item each using subscales from Eby et al. [29]; a five-item team climate questionnaire indexing trust and innovativeness from Xue et al. [132]; and a six-item measure from Pelled et al. that indexes both task and relationship conflict [97].

While the PANAS-Short scale and the team productivity questionnaire were administered each workday, participants received only three of the 5C questionnaires each day so as to not overburden them over the course of ten weeks. The distribution of the 5Cs questionnaires were balanced such that participants completed all five measures six times over a two-week cycle (for a total of five such cycles). The PANAS-Short scale questionnaire was always administered first followed by the team-related questionnaires. To prevent systematic bias in responses due to fixed ordering, we arranged the team-related questionnaires so that for each two-week cycle, the team productivity questionnaire was administered first on five randomly-selected weekdays and last on the remaining five weekdays. We also gathered information on atypical daily events from the participants such as self-reported vacation days (this information was then used to remove vacation days from the data).

4.2.3 Initial Questionnaire Battery. Participants completed an initial set of questionnaires (via Google Forms) within their first week in the study. Alongside other survey instruments deployed but not pertinent to this study, the questionnaires gathered demographic information as well as team-relevant information such as team size and tenure. The Morningness-Eveningness Questionnaire (MEQ) [45] was administered to measure participants' chronotypes [80].

4.2.4 Follow-up Questionnaire. In addition, we administered an eight-item voluntary follow-up questionnaire during the months of February and March 2021 with half of the questions asking about changes in participants' usual sleep schedules, the other half about changes in personal work schedules in the wake of the COVID-19 pandemic. Of the 75 participants, 57 (76%) completed the follow-up questionnaire, which contained the following questions (condensed from eight to two for convenience):

[1]https://www.expiwell.com/

- When [did | do] you usually [go to bed | wake up] [before | during] the pandemic?
- At what time [did | do] you typically [start | conclude] your workday [before | during] the pandemic?

Responses were recorded in the 12-hour AM/PM format. The questions concerning sleep were modified from the Pittsburgh Sleep Quality Index (PSQI) [14], which considers a one-month period of retrospection. We include the follow-up survey despite the arguably longer period of retrospection because prior studies have found retrospective self-reports of habitual behaviors to be reasonably reliable even over extended periods of time [46, 68]. For example, a study on recreational walking habits showed acceptable reliability of recall over a one-year period [36]. As habitual sleep behaviors are often scheduled with respect to other personal constraints, especially during regular working days (e.g. setting an alarm for the same time each workday morning to ensure being on time for work or going to bed right after watching a late night show), we would expect participants' recall of typical bed and wake times during workdays to be reasonably accurate over a one-year period. In a more recent study on sleep and seasonality, Mattingly et al. found consistency of sleep behaviors over the course of a year, with wake time remaining stable and bedtime only varying slightly with season [75].

4.2.5 Semi-structured Interviews. Participants completed a 15-30 minute exit interview either over *Microsoft Teams* or *Zoom* within two weeks after the last day of data collection. The interviews consisted of questions relating to: (1) each of the 5Cs team measures, (2) team productivity, (3) affect/mood, (4) work routines, and (5) work-life balance. When applicable, participants were asked follow-up questions to uncover deeper insights. We used descriptive and process coding [108] and identified the following main themes in the interview data: *team-working conventions* and *collaborative mindsets*. We revisit these themes in Section 5.3.1 to shed additional light on our main quantitative findings.

4.3 Data Analysis

To address RQ1, we examined participants' responses to the 8-item follow-up survey; sleep data from the wearable were used in a follow-up analysis. For RQ2, we examined participants' wearable sleep data to see if they predict their responses to the EMAs. To address RQ3, we calculated a measure for the deviations between team members' sleep patterns and used it to predict responses to the EMAs after controlling for pertinent covariates (detailed below). All analyses were conducted in *R* using the *tidyverse* [130], *lmerTest* [63], and *sjPlot* [70] packages.

4.3.1 Outcome Measures. To address RQ1, we excluded three participants because their responses to the follow-up survey seemed potentially invalid (e.g. one participant reported no temporal gaps at all between waking up and starting work as well as between stopping work and going to bed). We then converted survey responses of the remaining 54 participants from 12-hour time to decimal hours. Next, Shapiro-Wilk tests were used to confirm that the self-reported data were normally distributed.

To address RQ2 and RQ3, four participants were excluded due to having less than one week of EMA or sleep data in the study. For the remaining 71 participants, an average of 26.32% (SD=15.64%) of the days in the study contained missing wearable or EMA data, which is consistent with other *in situ* studies that utilized wearable sensors [11, 74]. We further excluded days that coincided with participants' self-reported vacation days as well as general U.S. holidays in 2020 including Labor day, Thanksgiving, and Christmas.

An analysis of correlations with Pearson r of the study-long averages the 5C measures indicated that cohesion, coordination, climate, and communication were strongly correlated (*rs* between .73

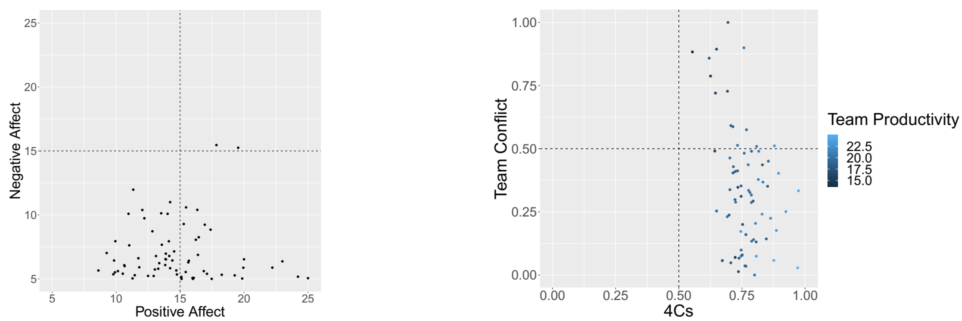

Fig. 2. Quadrant charts showing study-long trends relating to mood and perceptions of teamwork (color-shaded based on self-reported team productivity scores) across the full range of possible scores.

and .87). Therefore we combined the individual study-long average of each of these four measures into a new "4Cs" measure by first normalizing each to the [0 to 1] range (to account for differences in scales) and then averaging the four values. Team conflict was assessed separately as it was not as highly correlated with the other measures (*rs* between -.43 and -.28). Table 2 shows the means, standard deviations, and ranges of our five outcome measures. Overall, the teams' perceptions of the 4Cs and self-reported productivity were moderately high whereas conflict was low.

Variable	M (SD)	RANGE
Conflict	10.64 (3.16)	[6, 30]
4Cs (Average of Communication, Coordination, Cohesion, and Climate)	0.76 (0.08)	[0, 1]
Productivity	19.28 (2.39)	[5, 25]
Positive Affect	14.68 (3.53)	[5, 25]
Negative Affect	7.04 (2.28)	[5, 25]

Table 2. Mean (M), standard deviation (SD), and range (R) of outcome measures.

Figure 2 shows quadrant charts for the two sets of related outcome measures: positive and negative affect on the individual level as well as the 4Cs, team conflict (min/max normalized), and team productivity on the team-level. Overall, the data showed low levels of negative affect and more widely distributed levels of positive affect, suggesting that participants were generally content. When looking at the team-level chart, there was an interesting dichotomy where the 4Cs measure was generally highly reported, but so was team conflict. As expected, we see high perceptions of team productivity mostly found in the bottom-right, high 4Cs quadrant.

4.3.2 Wearable Sleep Data Calculation (RQ1 & RQ2). We used the sleep stage (light, deep, REM, and awake) information from the Garmin wearable [83] for calculating sleep. For each day, sleep was computed as the longest sleep period with interruptions of less than two hours (similar to [33]) occurring between 5 PM of the previous day to 5 PM of the target day. The 5 PM to 5 PM range was used because it covered the sleep periods for participants with differing sleep patterns and/or times in our study. To account for time zone differences among the participants, we converted all the computed bed and wake times to Eastern Standard Time (EST). We computed sleep measures only on weekdays to be consistent with the EMAs.

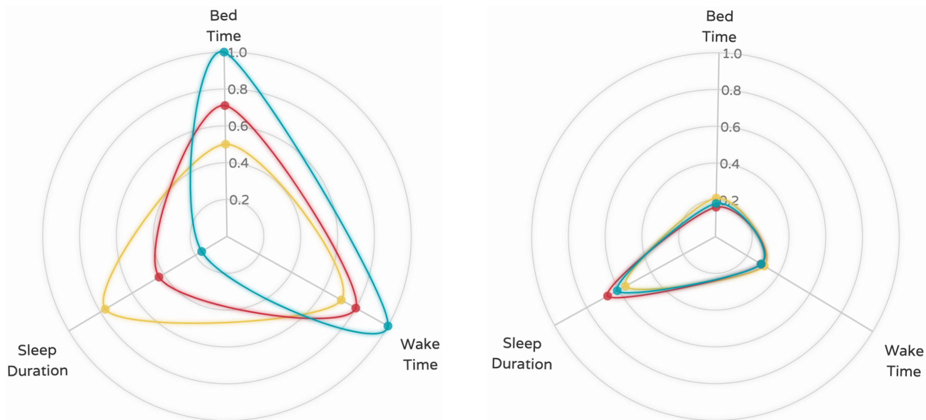

Fig. 3. Radar charts showing the misalignment (high left; low right) of sleep measures among the members of two three-member teams. The sleep measures for each participant are study-long averages which are min-max normalized. Each color in a chart represents a team member. Note that wake time is included in these charts for visualization purposes only. Only bedtime and sleep duration are considered for the calculation of sleep distance (as a measure of misalignment) since wake time was highly correlated (r = .90) with bedtime.

4.3.3 Sleep Misalignment Calculation (RQ3). To calculate the misalignment of team members' sleep patterns we computed their *sleep distance*, i.e. the sleep misalignment of a participants' sleep patterns to the rest of their team. For illustration, Figure 3 presents the average misalignment in bed time, wake time, and sleep duration among teammates from two three-member teams: high misalignment on the left and low on the right. We computed it as the average pairwise Euclidean Distance of the study-long averages of bedtime and sleep duration. That is, for each participant we calculated the Euclidean Distances to each other participant in the team and averaged them, i.e. given a participant i, for every participant j in the team T with $i! = j$, we calculated the mean of the Euclidean Distance between every pair (i, j) with the distance (i, j) defined as follows:

$$\sqrt{(bedtime_i - bedtime_j)^2 + (sleep\_duration_i - sleep\_duration_j)^2}$$

The values thus fall between 0 (i.e., no deviation in bedtimes and sleep duration) and a theoretical maximum of ~34 hours (in case any two variables of bedtime and sleep duration differ by more than 24 hours, but not both because they are interdependent). The average intra-team sleep misalignment in our sample was 1.65 hrs (SD=.86) and ranging from 3.73 hrs on average for the most misaligned team and .49 hrs on average for the members of the least misaligned team.

Figure 4 shows the distributions of study-long averages of bedtime distance and sleep duration distance (individually computed), as well as the distribution of sleep misalignment in our sample, i.e. the Euclidean Distance of bedtime distance and sleep duration distance. We also calculated a distance measure for differences in chronotype scores within teams. Chronotype (MEQ) distance was calculated as the average of the differences between an individual's chronotype score and the scores of co-workers from the same team. Overall, deviations in bedtimes among team members were relatively small at about one hour or less. There was a bit more variation in teams in regards to differences in sleep duration.

An examination of zero-order correlations for the main predictors and outcome measures for RQ2 and RQ3 showed positive correlations of sleep misalignment with both bedtime (.530) and

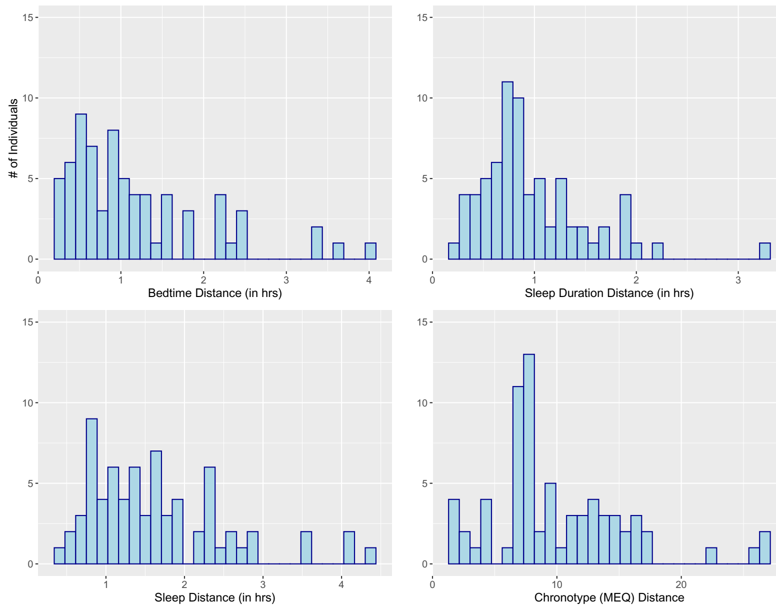

Fig. 4. Study-long averages of distance in sleep data (in hours) and chronotype.

wake time (.465) as well as with the 4Cs (.271) and positive affect (.393). The output is shown in Table 4. There was also a significant, yet low negative association between negative affect and chronotype (-.237), suggesting that the more a participant identified as an evening-type, the higher their negative affect. As to the individual sleep measures (bedtime, wake time, and sleep duration), each showed associations that were as expected; for example, we found moderate to high negative associations of both bedtime (.-515) and wake time (-.473) with chronotype (MEQ), suggesting that participants who identified as evening-types (i.e. a lower score) went to bed later and also woke up later. Other notable associations included a negative association of positive affect and sleep duration (-.327) as well as positive associations of negative affect with both later bedtime (.420) and wake time (.382).

Variable	**M (SD)**
Bedtime Distance (in hours)	1.18 (.86)
Sleep Duration Distance (in hours)	0.98 (.54)
Sleep Misalignment (in hours)	1.65 (.86)
Chronotype (MEQ) Distance	10.10 (5.56)

Table 3. Mean (M) and standard deviation (SD) of distances in sleep data (in hours) and chronotype.

5 RESULTS

5.1 Association of the shift to work-from-home with sleep and work patterns (RQ1)

Table 5 presents an overview of participants' responses to the follow-up survey alongside their sleep data collected from the wearable. Generally, participants got around 8 hours of sleep, i.e. at the upper end of the commonly recommended sleep duration for adults aged 18-60 of seven to eight hours of sleep; a standard deviation of roughly one hour indicates possible oversleeping. Further,

	Sleep Misalignment	*Sleep Duration*	*Bed time*	*Wake time*	*Chronotype MEQ*	*4C*	*Conflict*	*Positive Affect*	*Negative Affect*
Sleep Misalignment									
Sleep Duration	-.223								
Bedtime	.530***	-.376**							
Waketime	.465***	.068	.899***						
Chronotype MEQ	-.276*	.172	-.515***	-.473***					
4C	.271*	-.232	.052	-.054	.147				
Conflict	.023	-.082	.299*	.283*	-.162	-.407***			
Positive Affect	.393***	-.327**	.167	.026	.126	.428***	.029		
Negative Affect	.057	-.149	.420***	.382**	-.237*	-.284*	.526***	-.005	
Productivity	.122	-.203	-.028	-.126	.039	.782***	-.304*	.422***	-.300*

Table 4. Pearson Correlations of study-long averages for each measure under consideration. (***) indicates p < .001, (**) indicates p < .01, (*) indicates p<.05.

average work duration was nine hours per day, which is also slightly elevated already. Notably, the wearable measured bed and wake times on average about 16 minutes and 18 minutes later than the self-reports, respectively, which we consider an acceptable level of alignment. Wearable sleep duration was on average only seven minutes longer than self-reported sleep duration.

Figure 5 shows density plots for the changes in sleep and work schedules with pre-COVID times represented as dashed, dotted, or solid lines, respectively. Most notably, we see how bedtimes shifted on average from before midnight (pre-COVID) to after midnight (during COVID). We also see more participants starting their workdays as late as 11 AM during the pandemic.

To answer RQ1, we used linear mixed-effects models to assess whether the changes in work-context due to COVID-19 predicted changes in participants' sleep patterns (i.e. bedtime, wake time, and sleep duration) and their work schedules (work start and end times as well as work duration). Specifically, we regressed these six measures on a pre-/during COVID-19 change measure with a random intercept for team identity to account for nesting of participants within teams as shown in Table 6. Age and chronotype scores were included to control for changes in the outcome measures attributed to normal aging processes [66] and circadian rhythms [117]. Additionally, the number of people in a household and a measure of team size (converted into a two-level factor due to the small number of teams of sizes two and five) were included to account for the idiosyncrasies of home-life in our sample as well as the potentially greater need in larger teams to coordinate schedules.

In these and subsequent analyses, we report standardized beta coefficients via the Gelman method whereby the estimates are reduced by dividing them by two standard deviations [34] in order to facilitate direct comparisons between coefficients. Pseudo R2 values for both marginal (fixed effects alone) and conditional (random and fixed effects) effects are reported using the method described by

Sleep data	From Self-reported Questionnaire		From Garmin wearable
	Before COVID Mean (SD)	During COVID Mean (SD)	During COVID Mean (SD)
Bedtime[a,c]	10:50 pm (1:02h)	11:10 pm (1:03h)	11:26 pm (1:20h)
Waketime[a,c]	6:33 AM (1h)	7:09 AM (0:39h)	7:28 AM (1:09h)
Sleep duration[d]	7:43 hours (0:54h)	7:59 hours (0:50h)	8:03 hours (0:50h)
Work start[a,c]	8:07 AM (0:37h)	8:18 AM (0:43h)	–
Work end[a,c]	5:00 PM (0:47h)	5:24 PM (1:10h)	–
Work duration[a,c]	8:54 hours (1h)	9:07 hours (1:18h)	–

[a]Bedtime, wake time, work start and work end reported here correspond to participants' local times and are not shifted to Eastern Time.

[b]For self-reported variables, n=54.

[c] Range = [5PM, 5PM].

[d] Range = [0 hours, 24 hours].

Table 5. Mean (M) and standard deviation (SD) of sleep and work schedules from both the follow-up survey and the Garmin wearable.

Fig. 5. Density plots of sleep and work schedules during COVID-19. Dashed lines indicate mean bedtime and wake time pre-pandemic. Dotted lines show pre-pandemic work schedules. The solid lines illustrate a typical 9 to 5 workday.

Nakagawa and Schielzeth [86]. Additionally, p-values were calculated using a parametric bootstrap to improve model robustness.

We found that the pre-/during COVID-19 change predictor positively predicted all the sleep outcome measures, suggesting not just a delay of roughly 20 and 36 minutes in sleep on- and offset but, importantly, a moderate increase of 16 minutes in total sleep time during the pandemic, which replicates prior work [35, 65]. Participants also started and ended their workdays by 11 and 24 minutes later, respectively, during the pandemic, without significantly increasing the hours they spent working. With respect to the demographic variables, both chronotype (MEQ) and age negatively predicted bedtime and wake time, which are expected findings. That said, chronotype showed a weak trend in predicting work start ($p = .085$), suggesting that evening-type persons may tend to start work later than the other two types. The number of people in the household and team size were not significant predictors of any of the variables.

	Bedtime		Wake Time		Sleep Duration		Work Start		Work End		Work Duration	
Predictors	*std.β*	*p*	*std.β*	*p*	*std.β*	*p*	*std.β*	*p*	*std.β*	*p*	*std.β*	*p*
(Intercept)	-.33	**.002**	-.52	**.001**	-.17	**.001**	-.30	**.001**	-.08	**.001**	.13	**.001**
COVID-19 [During]	.39	**.006**	.72	**.001**	.33	**.040**	.31	**.001**	.39	**.003**	.15	.182
Chronotype (MEQ)	-.54	**.001**	-.46	**.001**	.15	.213	-.21	.089	.01	.863	.14	.250
No. of People in the Household	-.10	.315	-.02	.891	.11	.366	-.04	.730	-.12	.332	-.08	.567
Team Size [4 to 5]	.24	.266	.28	.205	.00	.995	.25	.351	-.24	.339	-.35	.184
Random Effects												
σ^2	0.45		0.26		0.55		0.11		0.48		0.53	
τ_{00} $participant{:}team$	.30		0.37		0.22		.35		0.51		0.60	
ICC	0.40		0.59		0.29		0.76		0.51		0.60	
N	54 22_{teams}		54 22_{teams}		54 22_{teams}		54 22_{teams}		54 22_{teams}		54 22_{teams}	
Observations	108		108		108		108		108		108	
Marginal R^2	.325		.334		.058		.072		.072		.059	
Conditional R^2	.596		.724		.332		.774		.550		.628	

Table 6. Results of the analysis of the change in work and sleep schedules pre-COVID and during COVID-19. For Chronotype (MEQ), lower values refer to evening types and higher values to morning types. The reference category for Team Size is [2 to 3]. The reference category for COVID-19 is [Pre COVID-19]. Std. β gives the standardized beta coefficient. Significant coefficients are highlighted in bold. NA indicates that there is no variance due to the random effects. Note: this analysis considers a reduced sample size of n=54.

A follow-up analysis where self-reported sleep data during the pandemic were exchanged for wearable sleep data showed similar results for the pre-/during COVID-19 change predictor and the effect was overall stronger for each outcome measure (bedtime: std. β=1.07, p<.001; wake time: std. β=1.34, p<.001; sleep duration: std. β=.57, p<.003). The effect of chronotype also remained consistent for both bedtime (std. β=-.34, p<.001) and wake time (std. β=-.26, p<.001). Overall, the wearable sleep measures produced model results that are consistent with the self-report measures relating to participants' sleep during the pandemic.

5.2 Associations between individual sleep patterns and perceived team performance, productivity, and affect/mood (RQ2)

To answer RQ2, we regressed team conflict, the 4Cs, and productivity as well as positive and negative affect on the study-long averages of bedtime and sleep duration along with pertinent covariates such as age and chronotype. We further included the proportion of missing wearable sensor data per participant to account for potential effects on the outcome measures. As before, team identity was included as a random intercept.

	Conflict		**4Cs**		**Productivity**		**Positive Affect**		**Negative Affect**	
Predictors	*std.β*	*p*	*std.β*	*p*	*std.β*	*p*	*std.β*	*p*	*std.β*	*p*
(Intercept)	-.01	.618	.00	**.001**	.01	**.001**	.02	**.016**	.00	.175
Sleep Duration	.15	.282	-.36	**.007**	-.31	**.038**	-.27	**.041**	.06	.688
Bedtime	.43	**.034**	-.23	.287	-.29	.195	.23	.298	.35	**.049**
% of Missing Data	.16	.257	.04	.836	.11	.359	.04	.762	.26	**.041**
Chronotype (MEQ)	-.01	.912	.18	.223	-.03	.962	.27	**.045**	-.07	.555
Age	.23	.166	-.37	**.035**	-.14	.405	.09	.612	.07	.631
Random Effects										
σ^2	8.46		0.01		4.71		9.28		4.31	
τ_{00}	0.91_{team}		0.00_{team}		0.50_{team}		2.04_{team}		0.00_{team}	
ICC	0.10		0.01		0.09		0.18			
N	22_{team}		22_{team}		22_{team}		22_{team}		22_{team}	
Observations	71		71		71		71		71	
Marginal R^2	.129		.158		.080		.160		.217	
Conditional R^2	.214		.164		.159		.311		NA	

Table 7. Predicting teamwork and affect from bedtime and sleep duration. For chronotype (MEQ), lower values refer to evening-types and higher values to morning-types. Std. β gives the standardized beta coefficient. Significant coefficients are highlighted in bold. NA indicates that there is no variance due to the random effects.

Results of the modeling are shown in Table 7. We found that sleep duration predicted the 4Cs measure suggesting that participants who slept longer had a lower perception of team processes and states. Longer sleep duration was also associated with lower perceptions of team productivity and positive affect. These results may point to the potential hampering effects of oversleeping in WFH teamwork. At the same time, participants who went to bed later between regular workdays reported higher team conflict and negative affect, which can point to the emotional and psychological effects of sleep deprivation [79]. Another finding of note is that younger participants had on average better communication, coordination, cohesion, and trust than older participants; given that team interactions during the pandemic happened (almost) exclusively via software tools, this finding may point to generational differences in regards to software literacy in our sample.

As a follow-up, we tested the sleep measures as curvilinear predictors. We found moderate curvilinear effects for sleep duration when predicting the 4Cs (p=.022) and positive affect (p=.032). As shown in Figure 6, the 4Cs measure and positive affect decrease as sleep duration increases, but then both plateau when participants sleep slightly longer than eight hours. Despite the lack of samples below seven hours of recorded sleep duration, the curvilinear trends of sleep duration in the data further support the finding in RQ1 that oversleeping may have likely been a problem for participants in the study.

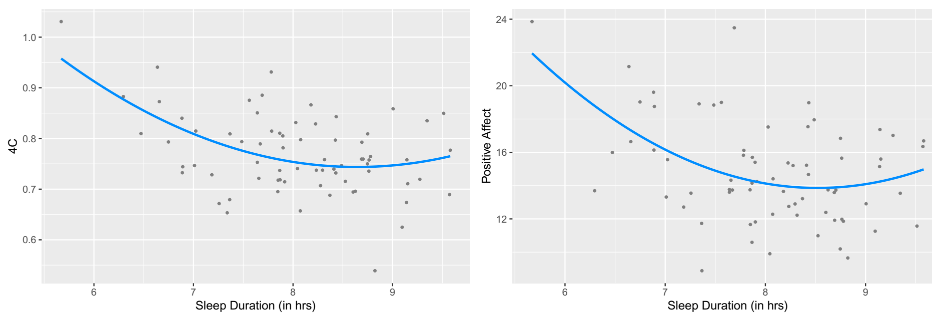

Fig. 6. Curvilinear effects of sleep duration on the 4Cs and positive affect with slightly expanded ranges for the focal predictor.

5.3 Associations between sleep misalignment and perceived team performance, productivity, and affect/mood (RQ3)

An examination of the five teams with the highest average sleep misalignment (n=14, *M*=2.91 hrs, *SD*=.85 hrs) and the five teams with the lowest average sleep misalignment (n=15, *M*=.81 hrs, *SD*=.25 hrs) showed significant group mean differences for bedtime (p=.004) and positive affect (p=.017). On average, participants in teams with high misalignment went to bed about 2.4 hours later and scored 3.8 points higher on positive affect than those in the least misaligned teams (top five: *M*=17, *SD*=3.78, bottom five: *M*=13.2, *SD*=4.22). Considering that we found no significant difference relating to the average number of dependents in either group—which could have indicated an influence of family schedules on sleep schedules—the findings suggest that teammates in highly misaligned teams have much greater personal scheduling freedom compared to those in the most aligned teams. The difference in positive affect score between the two groups could indicate that participants in highly misaligned teams were on average more content with the WFH context and also more engaged.

Next, we examined what factors in the makeup of a team may contribute to sleep misalignment. We used a linear mixed effects model to predict sleep misalignment from individual sleep measures (bedtime, wake time) and relevant team-level covariates. We added team as a random intercept. While team size, the distribution of gender, mean age, and the average proportion of team members with dependents did not factor into sleep misalignment, we found that teams with differences in chronotype scores positively predicted sleep misalignment (p<.001). We then repeated the same models as in RQ2 with sleep misalignment as the focal predictor along with additional team-level covariates including chronotype (MEQ) distance to examine the incremental validity of sensor-based sleep behaviors over self-reported preferences. We further included team size (again as a binary factor) to account for its influence on teamwork.

As shown in Table 8, we found that teams that were more misaligned in their sleep patterns reported higher 4Cs (i.e. team communication, coordination, cohesion, and climate); higher positive affect; but not higher productivity. The addition of the new covariates resulted in later bedtimes being negatively associated with higher team conflict, lower 4Cs, and lower team productivity. Further, sleep duration remained a consistent predictor of the 4Cs, positive affect, and productivity, thus replicating the results from RQ2 after accounting for misalignment and the other team-level covariates.

	Conflict		4Cs		Productivity		Positive Affect		Negative Affect	
Predictors	*std.β*	*p*	*std.β*	*p*	*std.β*	*p*	*std.β*	*p*	*std.β*	*p*
(Intercept)	-.15	.781	.15	**.001**	.26	**.001**	.01	**.009**	-.04	.115
Sleep Misalignment	-.12	.425	.34	**.027**	.18	.276	.37	**.011**	-.26	.068
Sleep Duration	.19	.170	-.41	**.003**	-.35	**.013**	-.28	**.017**	.04	.740
Bedtime	.73	**.005**	-.58	**.017**	-.59	**.031**	-.07	.736	.42	**.046**
% of Missing Data	.14	.311	.07	.578	.14	.262	.06	.679	.24	**.041**
Chronotype (MEQ)	.07	.668	.13	.391	-.08	.589	.22	.088	-.11	.431
Team Size [4 to 5]	.27	.265	-.26	.306	-.45	.144	.00	.975	.07	.854
Age	.24	.137	-.38	**.016**	-.15	.343	.05	.783	.07	.592
Chronotype Distance	-.25	.100	.14	.344	.20	.231	.13	.400	.10	.524
Random Effects										
σ^2	8.05		0.00		4.71		8.88		4.26	
τ_{00}	1.02_{team}		0.00_{team}		0.94_{team}		1.00_{team}		0.00_{team}	
ICC	0.11		0.12		0.17		0.10			
N	22_{team}		22_{team}		22_{team}		22_{team}		22_{team}	
Observations	71		71		71		71		71	
Marginal R^2	.194		.276		.168		.277		.250	
Conditional R^2	.284		.363		.306		.351		NA	

Table 8. Predicting teamwork and affect from sleep misalignment. For chronotype (MEQ), lower values refer to evening types and higher values to morning types. Std. β gives the standardized beta coefficient. Significant coefficients are highlighted in bold. NA indicates that there is no variance due to the random effects.

As a follow-up, we tested sleep misalignment as a curvilinear predictor (see Figure 7). We found moderate curvilinear effects for misalignment when predicting positive affect (p=.023). An average sleep misalignment of about 2-2.5 hours showed the highest association with positive affect. This may indicate a sweet spot below and above which positive mood may be dampened by contributing factors such as too rigid or too lax work schedules; however, we note the lack of samples in the range of greater sleep misalignment.

5.3.1 Qualitative Analysis for the 4Cs and Positive Affect models: We turned to the interview data to explore the counter-intuitive findings of sleep misalignment with the 4Cs and positive affect further. Given the positive direction of the association, we focused our analysis on sample of 29 interviews with participants who belonged either to the five teams with the highest sleep misalignment (n=14, misalignment in hours: M=2.91, SD=.85) and the five teams with the lowest (n=15, misalignment

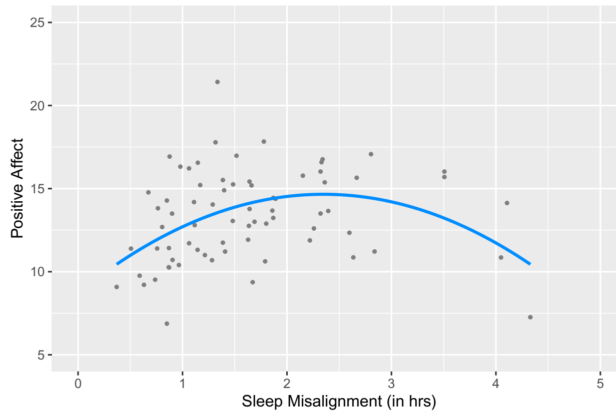

Fig. 7. Curvilinear effect of sleep misalignment on the full range of possible positive affect scores [5, 25] with expanded ranges for the predictor.

in hours: *M*=.81, *SD*=.25). Participants in highly misaligned teams worked either in consulting capacities (three teams) or in startups; notably, members in both startups reported that their startups were founded specifically as full-time remote startups, which may suggest that more misaligned teams were also more likely to have pre-existing knowledge and experience not just with asynchronous teamwork but with WHF remote work. For comparison, participants from the five teams with the lowest misalignment came from areas such as software engineering, software testing and quality control, and one tech startup. Aside from work context, members from teams with the highest misalignment were on average also 11 years younger (*M*=28.18, *SD*=9.1) than those in with the lowest misalignment (*M*=39.72, *SD*=7.4). A thematic analysis of interviews from members of the five most misaligned teams revealed the following themes which are based only on alignment-related responses that emerged organically during the interviews: *team-working conventions* and *collaborative mindsets.*

There were two members from one team whose responses most closely revealed fluctuations in alignment, albeit only in their work schedules, which suggests different sleep patterns that affect availability of team members during the day. As one participant shared: *"I don't really know when someone's workday begins and ends. I know, the general expectation is like, you know, eight to five kind-of-thing" (P16).* The other member of this team responded when asked about coordination during remote WFH: *"How does that jive? I think everyone sort of has a more casual, just about everyone has a more casual timeline, though. It slides a little bit. Maybe you don't come in until nine but yet you're staying 'til 6 or 6:30 pm because you work at home, right? You can work a little longer because you don't have to say 'Oh, so to drive home. It's going to take a half hour.' I am home so I can spend that half hour being productive. I think everyone has, I think, most of the team has that same rhythm" (P17).*

Half of all participants from highly misaligned teams talked about different types of agreed-upon and/or explicitly specified *team-working conventions* to help prevent (or lessen the impact) of challenges stemming from asynchronous remote teamwork. Two participants from the same startup team discussed these mechanisms in terms of adapting to already-established routines and workflows that are conducive to asynchronous teamwork as part of the on-boarding experience: *"When people recently join and get integrated, I think that process is a little difficult because they need to get used to how we operate our little community, our work space, our flex hours, asynchronous work. Those are all concepts that even I had trouble getting used to at first" (P9)*; *"When I first got in, and then* *they taught me how to work, like, in this [asynchronous] way" (P8).* One team lead (P1) emphasized that sanctioning and encouraging highly flexible work schedules only works in his team because team members also (a) commit to being *"very punctual"* when meetings do happen, and (b) to always support comments, statements, and suggestions with additional evidence and examples both during meetings and in the context of asynchronous text-messaging. Aside from this, one participant also reported that their team had adopted an agreed-upon rule to always reference times in their correspondence against Pacific Time (PT). Awareness and use of project management tools such as *Asana* or *Trello* to support asynchronous work was also more common for respondents from highly misaligned teams when we asked them about how they coordinated their activities with teammates. Members from teams with low misalignment either did not reference the use of a project management tool or they reported that their teams had incorporated a project management platform into their day-to-day workflow only recently, i.e. after their shift to remote work during the pandemic. Naturally, managing these team-working conventions requires a certain degree of existing familiarity with asynchronous work, which is commonly the case for startups and consulting teams, especially when teamwork is conducted remotely. These circumstances may help to explain the positive association with sleep misalignment.

Among the same group of highly misaligned participants, two participants from two teams also reflected about their dedication toward *collaborative mindsets.* One respondent talked about helping others adapt to a new communication platform: *"They weren't used to using the Slack communication platform. And so they've never had their notifications on. I often checked it until they got into, like, the flow of things, which took quite a while" (P4).* Another participant from a different team expressed a more general mindset and approach relating to remote teamwork: *"I want to make sure that I kind of am working with the other person at a time when they're the most productive and they're most available. Usually, for my co-workers that is, like, in the morning even though I'm most productive during the night. I think that kind of leads well for me because I can kind of do all my meetings and get all my collaboration/communication work done in the morning. And then in the night, I can kind of, you know, put my head down and start working on, you know, a new code, or push something that I just seem to do independently to get something done. I think that that really works well" (P3).* While we cannot say whether participants from teams with the lowest misalignment lacked a collaborative mindset, they were more likely to frame their remote team collaborations vis-à-vis external operational factors such as increased frequency of meetings during the week rather than as a characteristic of their professional approach to team-working. These responses suggest that participants in teams with the highest average sleep misalignment were also more likely to have cultivated a mindset that is compatible with remote work from home. Thus, despite the increased workload to manage communication and coordination and maintain cohesion, participants may have considered remote work positively because of the increased autonomy and flexibility it provides. It is, thus, possible to attribute the positive association between sleep misalignment and positive affect either to already existing friendships in teams cultivated prior to the pandemic or to the individual satisfaction of participants with remote WFH in general.

6 DISCUSSION

The onset of COVID-19 and the switch to WFH has raised many questions about how such a radical and abrupt change in work context might affect teamwork. Our study offers insights that distinguish it from other COVID-related studies. Rather than considering only individual participants, we used unobtrusive sensing of bio-behavioral data and daily EMAs (among other methods) to collect data simultaneously from (at least the majority of) members belonging to the same team and *in situ.* This is important since studying individuals in isolation might not reveal the array of potentially novel factors influencing remote teamwork in a WFH context. In what follows, we summarize main findings, consider their implications, and suggest ideas for future research.

6.1 Main Findings

Turning first to the results of our analyses on the participant-level, our findings replicate prior work that has identified significant delays in sleep on- and offset as well as longer sleep duration during the COVID-19 pandemic [19, 43]. As far as work schedules are concerned and contrary to other recent work [120], we did not find a trend towards overworking during WFH, potentially due to the arguably long pre-COVID daily total work duration of nine hours that participants reported working even before the transition.

We also found an association of sleep misalignment and the 4Cs. This may suggest several things: for example, it could indicate that team members in misaligned teams may have to work harder or go to greater lengths to collaborate with one another asynchronously. Somewhat unexpected was that sleep misalignment also positively predicted positive affect/mood; it is possible that high misalignment is easier to manage for teams where members have already developed and cultivated asynchronous collaboration working styles and routines. Since both affect measures operate on the participant and not the team level, it is possible that a greater misalignment in teams may represent greater individual autonomy in personal work scheduling and, potentially, higher satisfaction; this expands findings from a recent survey administered during the pandemic where more than half of respondents indicated that they would consider quitting their job over insufficient flexibility when it comes to personal work schedules [2].

The curvilinear effects of sleep duration on the 4Cs and on positive affect revealed higher reported scores for either outcome measure when sleep duration was eight hours or less. It is possible that traditional sleep duration recommendations may need to be reevaluated when more traditionally recognized temporal cues in the daily lives of working adults such as organizing a commute, arriving and leaving an office at relatively set times each day, or setting specific times for meals during the day [10, 22] become less strict in a WFH setting. Future research is needed since the majority of work in this area has highlighted the negative effects of sleep deprivation rather than the role of longer sleep [54, 94, 101].

We further found that later bedtimes were associated with team states and processes. It is possible that participants who went to bed later engaged in more off-hour work and had more difficulty coordinating their work with other team members asynchronously. Another explanation may be found in the phenomenon of bedtime procrastination, which is commonly defined as the act of needlessly and voluntarily delaying going to bed, despite knowing that one is going to feel worse the next morning [22, 87]. Bedtime procrastination is often tied to engaging in some form of rewarding activity to unwind after a stressful day such as watching TV or playing video games [62]. However, prior work has shown that later bedtimes alleviate negative mood only in the short-term [87]. During the pandemic, later bedtime was also found to be associated with greater negative affect [134]. For example, Conroy et al. [24] showed that later bedtimes were associated with worse mood during the pandemic. More work is needed to address these questions.

In all of these findings, it is important to emphasize the relatively low correlation of bedtime and sleep duration (-.376), which means that these two measures operated largely independently from one another. Against the backdrop of different degrees of personal scheduling latitude afforded to employees during the pandemic and potentially different daily presence requirements, the data may both show oversleeping as well as sleep deprivation. In other words, participants could have gone to bed later and slept either more or fewer hours, and vice versa. In either case, our findings overall suggest problematic sleep behaviors that negatively affected both teamwork and individual mood.

At the team-level, we found two interesting but also quite counter-intuitive associations of sleep misalignment with teamwork and self-reported positive mood. Specifically, teams that were more misaligned in sleep reported higher 4Cs and higher positive affect even though one might reasonably assume an association moving in the opposite direction: more misalignment in sleep may facilitate more misaligned work schedules, which in turn may then create more difficult conditions for communication and coordination, which prior studies on remote work have also documented [120, 133]. In the case of our collected data, however, the more misaligned teams reported on average better communication and coordination as well as stronger cohesion and climate (as a measure of trust). Future work should investigate whether higher reported scores for the 4Cs may indicate that teams with high sleep misalignment also have to put more effort into communication and coordination in their teams. For example, a handful of participants shared during their interviews that communicating with teammates remotely would also necessitate a mindset of *over-communicating*, i.e. to enrich comments, feedback, and statements with supporting evidence or examples. Such an approach likely requires additional time and effort from team members in situations such as composing and reading text messages, finding times to meet, creating and sharing video conferencing links, among others. Yet, a recent study has shown positive associations of good quality meetings and effective communication with better perceived productivity [113].

At this point in time, however, there is not a clear and comprehensive explanation for these observed dynamics as misalignment was only considered against a limited, albeit well-considered and relevant selection of covariates. More work is needed to identify other relevant covariates. That said, the curvilinear effect of sleep misalignment when predicting positive affect may already indicate certain optimal ranges of sleep misalignment in a given team. Specifically, the curvilinear effect could indicate that there are *sweet spots* of sleep misalignment to consider where teamwork either improves or worsens. In the case of the teams in this study, a sleep misalignment below two hours may imply a more rigid work schedule characterized by closer alignment of sleep, and reduced positive mood; at the same time, a sleep misalignment above 2.5 hours and the corresponding lower positive mood may indicate work schedule policies in the team that are too loosely defined which may make it more difficult for team members to collaborate. In either case, lower positive affect as an indicator of engagement may suggest lower active engagement among teammates and, thus, less viability [18]. Staying in or close to the *sweet spot* of sleep misalignment could potentially indicate a satisfying blend of flexibility and structure that is unique to each team. Therefore, staying within a certain range of sleep misalignment may benefit teamwork which could be tested in future research. As Omondi [93] showed, flexible work allows people greater control over their personal lives, which may boost positive mood. In the context of COVID-19, it is likely that the increased control manifests in being able to negotiate work schedules and personal schedules without hassle; participants with families may also be able to spend more time with other family members. Hence, our findings indicate that sleep misalignment of team members is not necessarily associated with a perception of poorer collaboration in a WFH context. Rather, the findings expand upon prior work that has documented the positive aspects of increased flexibility in personal scheduling [5, 57], by showing how different degrees of flexibility may support or undermine teamwork. While this study did not concern work breaks, the WFH context could affect other team behaviors such as desynchronizing team members' break-taking behaviors which may impact availability. However, in all these cases we cannot assess causality concerning the relation of flexible sleep patterns, mood and teamwork which future research could address.

Sleep misalignment may emerge in the future as a more distinct construct in remote teamwork that contributes to the success or failure of remote teams. In light of this, it is important to consider how data as sensitive and personal as sleep may be leveraged to support teams.

6.2 Practical Implication and Ethical Considerations

If the goal is to prevent too much misalignment in teams, then maintaining good sleep hygiene may be more difficult to maintain in WFH contexts with more fluid work schedules: on the one hand it empowers individual employees to organize and manage their sleep/wake cycles and schedules, on the other it puts the onus more on individuals to manage their sleep, which they can monitor with tools similar to those used in task management [131]. Sleep can be tracked reliably with off-the-shelf wearable devices such as the one used for this study. Personal sleep monitoring can help employees to create daily work routines suitable for the context of their WFH. In co-located work configurations, temporal cues such as the 9 to 5 workday or leaving one's home at the start of the commute implicitly constrain the daily hours reserved for sleeping. Recent work has shown that remote workers find it difficult to manage work/leisure boundaries [25]. At first glance and given the importance of employee well-being in organizational contexts, it may be prudent in the interest of well-being and team performance to collect sleep information from WFH employees, possibly with a sensing device similar to and as reliable as the wearable used in this study.

However, bio-behavioral data such as sleep are very personal and sensitive data—a circumstance which raises significant privacy issues and concerns even before questions on how such data may be collected in organizational contexts can be posed [40, 44, 122]. While the use of wearable sensors in the workplace is not new and has, in fact, steadily increased in recent years [64], privacy and ethical considerations have been frequently raised [60, 88]. For example, when wearables were used with a group of New Zealand forestry workers to address potential health and safety concerns by tracking their patterns of fatigue, the workers felt that their jobs were at risk if managers had access to the data, even if the data were aggregated and only tracked voluntarily on an opt-in basis [12]. Interviews conducted with employees of a manufacturing company after their sleep had been tracked to create educational materials regarding sleep deprivation showed that employees were generally open to the premise, but believed that such data should be controlled by someone who is external and impartial rather than a manager.

That said, there are a few avenues that companies and organizations can pursue to promote better sleep habits without violating data privacy. For example, companies can promote healthy sleep habits via company wide communication channels such as blogs, newsletters, presentations, and workshops. Another option would be to offer full-time WFH employees a personal health and fitness tracker used strictly for personal use. Such an approach may circumvent any issues related to data privacy as no actual data would be collected on the organizational level.

When it comes to collecting sleep data for the purpose of improving collaborations in teams, the situation becomes more complicated. For one, data inference problems are ever-present in smaller-sized teams even if misalignment is only represented as the average sleep misalignment in a team. If data are then collected across teams instead, the resulting average of sleep misalignment as well as potentially *optimal* ranges and corresponding *sweet spots* may not apply, as we have seen, to every team as each team's average sleep misalignment is unique and changing due to factors such as team make up and member turnover. If data were still to be collected, there need to be basic and hassle-free opt-in/opt-out requirements; actionable information would vary based on the comfort and privacy of team members as well as the security of collecting such sensitive data. In practice, anonymized data could be collected first over a period of time to stake out particular ranges and identify sweet spots where misalignment best synergizes with teamwork. An average sleep misalignment score for the whole team could then be communicated to team members on a regular basis (e.g. weekly, quarterly, etc.) to create opportunities for reflection. Alternatively, a system could inform team members in situations where sleep misalignment lies outside the team's ideal range or sweet spot and negatively influences WFH collaborations. However, more work is needed to develop optimal privacy practices for bio-behavioral data collected in the workplace, especially as tracking in the workplace becomes more ubiquitous in the future.

7 LIMITATIONS

Our study also has limitations. First, we only collected data for teams of sizes two to five. Although we focused on small teams as these provide sufficient complexity without being intractable, the results of this research may not apply to larger-sized teams. However, a team of three still offers seven interacting units (three individuals, three dyads, and the triad); 15 interacting units for teams of four (four individuals, six dyads, four triads, the entire team); and 30 for teams of five. Future research can address the role of sleep patterns on collaboration in larger remote teams. Also, our results can only generalize to information workers.

Second, the survey to collect the work schedule and sleep pattern information was administered in early 2021. Although we believe that there is sufficient reason to consider pre-COVID sleep and work schedules as biographical information, we must acknowledge the possibility of memory bias regarding participants' perceptions of their typical bedtimes prior to the COVID-19 pandemic. That said, the wake times of participants prior to COVID-19 are likely more accurate given the widespread use of alarm clocks for personal sleep regulation on workdays.

Third, we must also note that the response rate to the follow-up survey was 76%. There is the possibility of social desirability bias as participants who did not respond may have been reluctant to disclose habits that could be perceived negatively during the pandemic (e.g. that they would sleep longer). That said, the model using the sensor data for pre-/during COVID-19 wake time, bedtime, and sleep duration produced results that were similar to the self-reports. In fact, the results using sensor data for RQ1 showed even stronger differences of sleep patterns before and during the pandemic. We note though the low correlations that we found between participants' self-reported typical bedtimes during COVID-19 and the mean bedtimes we computed from the sensors (.261) as well as the correlation between sleep duration during COVID-19 gathered from the work/sleep survey and the mean sleep duration computed from the sensor data (.182). By contrast, the correlation between self-reported and objectively measured wake time during COVID-19 is comparatively higher (.565). It is not clear whether participants underestimated their bedtimes and wake times or whether the Garmin wearable overestimated them—a tendency documented in a validation study [83].

Fourth, the four questions related to self-reported sleep schedules before and during COVID-19 did not specifically reference workdays. While it is likely that participants assumed that the sleep questions related solely to workdays due to (a) the placement of the question immediately after the work-related questions and (b) the knowledge of having participated in a workplace study, we cannot say if participants also considered weekends in their responses—though we feel it is unlikely.

Finally, a key limitation in our work is that our sample was somewhat skewed toward men (64%). However, we found no significant differences between men and women in wake time, sleep time, or sleep duration. In future research we plan to study a more gender-balanced sample.

8 CONCLUSION

Our study is a first step into examining how sleep affects teamwork in the context of WFH. With the help of unobtrusive sensing and daily questionnaires we showed that several sleep measures as well as a measure capturing deviations in sleep patterns within a team predict team outcomes and individual affect/mood. In addition, our study highlights the value that wearable sensors can provide in capturing bio-behavioral data. With more research, individuals as well as teams and, by extension, organizations can leverage findings from this study to support the well-being of information workers in full-time WFH.

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