

# The Impact of Smartphone Usage on Circadian Cycles: A Case Study with Wearable Ring

Ella Peltonen\*, Parsa Sharmila\*, Elina Kuosmanen\*, Heli Koskimäki<sup>†</sup> and Aku Visuri\*

\**University of Oulu*  
Oulu, Finland  
{first.last}@oulu.fi

<sup>†</sup>*Oura*  
Oulu, Finland  
{first.last}@ouraring.com

**Abstract**—Smartphones are an integral part of our daily life, bringing both positive and negative impacts with them. Recent studies suggest that extensive and untimely smartphone usage directly affects circadian rhythm, i.e. alertness-sleepiness cycle. In this paper, we analyse sleep quality data collected through a wearable ring together with the smartphone interaction in bed just before falling asleep. First, we show that the sleep-tracking devices measuring sleep quality and quantity are also feasible to be used for researching circadian cycles. Second, we analyse the statistical relationships between in-bed smartphone interaction and different sleep metrics, out of which some are more prominent for future use and some present interesting negative results. Third, we present three baseline prediction models to predict sleep quality and circadian cycle based on smartphone app usage, with accuracy ranging from 31% to 67%.

**Index Terms**—Smartphone, Wearable, Sleep

## I. INTRODUCTION AND BACKGROUND

The technology-oriented world we live in provides us with both aims and means to track our internal processes, from physical training activity to the quality and effectiveness of sleep. Especially, the rise of easy-to-use and considerably cheap wearables have made it possible to self-identify users' biological processes without expenses of the medical measurements or an actual need to use medical services. People's individual goals for self-tracking can be but are not limited to optimising the performance of a particular task or improving the person's everyday lives [1].

In this paper, we analyse data collected through a wearable sleep tracking ring [2] in tandem with smartphone usage in order to detect participants' circadian cycles and sleep quality. The circadian, i.e. sleep-wake cycle, is a natural internal process of a human that regulates the rhythm of sleeping and woken periods roughly in the 24 hours periods [3]. Where some studies suggest that the early bed-time circadian cycle drives better sleep quality and efficiency [4], [5], some studies show that the regularity of the sleep-wake schedule influences sleep [6]. Many individuals aim to personalise their circadian cycle and optimise the quality of sleep, also by utilising technological self-tracking solutions [7]. However, with the best of their efforts, people can face different problems of falling asleep or disturbed sleep quality [8]. Adjustments of the sleep-wake rhythm are not only done by forcing regular bed-time earlier, but by light therapy and melatonin intake [9]. Latest studies

also suggest optimising daily habits such as nutrition, exercise, and intake of stimulants, e.g. caffeine, to manage irregular circadian cycles and preserve a good night's sleep [10].

At the same time, the ubiquitous community has paid attention to technology use, especially of smartphones, in bed before falling asleep [11], [12] and how it affects the sleep quality [13], [14], [15]. Many wearable sleep trackers focus on accelerometer data already claimed to be insufficient to detect the sleep quality but merely time in bed [16]. Some smartphone-based sleep tracking apps have received similar negative results regardless of their claims [17], [18]. The Oura ring sleep tracker, which we utilise in this study, is a wearable wellness device designed to collect data during the sleeping periods and report analysis based on its sensors to the user as sleep quality parameters [2]. When compared to the standard clinical method, polysomnography (PSF) [19], the ring gained clinically satisfactory results if not perfect capability to detect all of the tested sleep parameters [20]. This is, however, more promising than other tested sleep-tracking devices evaluated in the literature [17]. For a ubiquitous wearable device possible for people to purchase on stock and validated against PSF, usually criticised being missing validation with wearable trackers [21], motivated us also utilise it in our study.

In this paper, we put an effort to explore if a smartphone can play any role in the circadian cycles detected with wearable devices. As a novel contribution, we present a longitudinal analysis of smartphone interaction, circadian cycles, and sleep quality. We use data of 61 participants wearing the smart sleep-measurement ring for an average of 43.76 weekday nights each during a two-month study. In addition, we analyse their smartphone usage just before going asleep and combine our results to a self-assessment questionnaire to determine morningness-eveningness (MEQ) in circadian cycles [22].

## II. EXPERIMENTAL SETUP

We run a 2-month long experiment, where the following three datasets were collected: 1. Sleep quality, quantity, and individual sleep metrics through a wearable ring. 2. Smartphone app usage during the study period from the participants' personal Android devices, and 3. Morningness-Eveningness (MEQ) questionnaire [22] at the end of the study period.

TABLE I  
SLEEP METRICS COLLECTED THROUGH THE WEARABLE RING.

Metric	Description
Total time in bed	Total time (in minutes) in bed, from going to bed to getting up
Total time of sleep	Total duration (in minutes) of sleep
Sleep latency	Time (in minutes) it took to fall asleep on the onset of bedtime
Sleep efficiency	Time (in percentages) spent asleep during bedtime
Sleep quality	The quality (bad, medium, good) of sleep based on the sleep score (1-100) provided by the ring's algorithm
Restfulness	A score (0-100) based on restless events and actions during the night
Light sleep	Total amount of light sleep registered during the sleep period (in seconds)
REM sleep	Total amount of REM sleep registered during sleep period (in seconds)
Deep sleep	Total amount of deep sleep registered during the sleep period (in seconds)
Total amount of sleep	Total sleep = REM + light sleep + deep sleep
rMSSD	The average heart rate variability (HRV) calculated with rMSSD method [24]
Average heart rate	The average heart rate registered during the sleep period (beats per minute)

**Recruitment.** Participants were attracted through mailing lists and word of mouth. The participants received no monetary awards or other compensations for participation. Participants were borrowed Oura sleep tracking ring [2] to be used during the study period and an Android smartphone if they did not possess one or had a model which is incompatible with the used tracking applications. All the devices were returned at the end of the study period.

**The wearable ring** consists of an infrared photoplethysmography (PPG) sensor for heart rate, negative temperature coefficient (NTC) sensor for body temperature, and a 3D accelerometer, and can measure daily activity and performance, as well as detailed sleep-related metrics, e.g., amount of deep and REM sleep, sleep disturbances, and sleep latency and efficiency. Table I provides a summary of the sleep-related metrics collected through the wearable ring.

**Smartphone usage** was collected through the AWARE framework [23], used extensively in similar HCI research. AWARE enables background logging of different data from the users' personal smartphones, which are then stored on a remote server anonymously. The smartphone usage, wearable data, and MEQ questionnaire are linked together with an anonymous ID.

**Ethical considerations.** The study design and data collection are subject to the IRB process of the University of Oulu, Finland. In the initial meeting, the participants were informed of their consent and signed a consent form authenticated by the IRB. Participation in the study has been voluntary, and the users have been informed about the data collection and management procedures.

### III. DATA OVERVIEW

**Sleep dataset.** The ring has an average battery life of 3-5 days and thus enables continuous tracking. Participants were asked to wear the ring as it best suits their everyday life. Some participants reported that they did not always wear the ring during the day because of their sports activities and that they did not always wear it during the night - mostly due

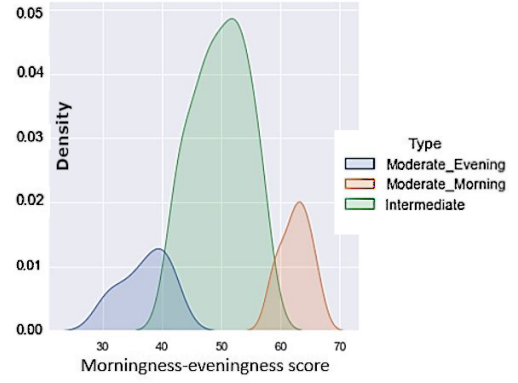


Fig. 1. User density distribution of MEQ scores.

to sometimes forgetting the ring. Typically the gaps in our sleep dataset last for 1-2 nights. Two users had personal issues regarding sharing their sleep data for research and did not opt-in to share their sleep data through the wearable vendors cloud service. 86 participants provided their sleep data on a total of 3764 unique nights. Participant's shared an average of 43.76 nights with a standard deviation of 10.5. The largest sample comes from a participant who shared 68 nights' data.

**Smartphone app usage.** We collected foreground and active apps used during the day and night. Whenever the foreground app changes, an item was stored containing the timestamp, app package name, and its Play Store category. We use these categories and total interactions with them, i.e. the number of times the app has recorded to be active in a given time. In total, we collected 1.39M items from 89 unique users, consisting of 951 different apps belonging to 33 categories.

**MEQ questionnaire** outputs a score (16-86), which determines the participants on a five-point scale: definite morning, moderate morning, intermediate, moderate evening, and definite evening. Figure 1 shows the distribution of the MEQ categories in our participant pool; most of the participants fall into the intermediate category, with considerable presentation also in the moderate evening and moderate morning categories. No participants identified to be exclusively morning or evening person; however, the MEQ criteria are quite strict, and the score typically follows the normal distribution ( $M=50$ ). Indeed, some studies in psychology only use classification in its reduced form, including morning, evening, and intermediate types [25]. In this paper, we use these three categories.

**To summarise,** our study participants (the final 61 in total from all the datasets were successfully gathered) were: 33 of the participants (55%) recognised as female, 28 (45%) as male, the mean age of participants was 28.08 years (median of 25 years), with a standard deviation of 8.56 years, minimum of 19 and maximum age of 61 years.

### IV. DATA PRE-PROCESSING AND ANALYSIS

The sleep data collected by the sleep tracker ring, app usage data collected from the participants' smartphones, and self-reported morningness-eveningness survey are merged by participant identifiers and date. The data is preprocessed to consist

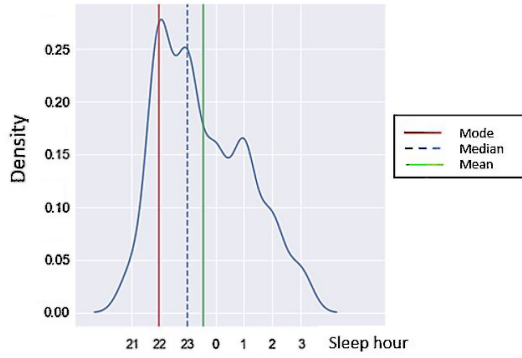


Fig. 2. Data distribution after balancing.

of each app's hour-wise app usage and interaction count. Hour-wise total app usage and interaction count for each participant is then merged with a value of sleep parameters mentioned in Table I for respective participants. Previous research suggests that sleep parameters tend to respond differently for weekends and weekdays [26] and circadian cycles are heavily led by our everyday social and temporal organisation [27]. As we are interested in people's daily lives, we choose only to consider weekdays (Monday to Friday).

**Data Categorisation.** We categorise the numeric parameters for categorical analysis. Sleep hour is mapped into three categories, with the influence of the morningness-eveningness self-assessment questionnaire (MEQ) [28], which categorises the sleep onset time by "morning types", "intermediate types", and "evening types" based on hours. We use the following categories: hours 21 to 22 as morning people (21:00-22:45 in MEQ), hours 23 to 0 (22:45-00:45 in MEQ) as intermediate people and hours 1 to 3 (00:45-03:00 in MEQ) as evening people. We label this variable as the *measured circadian cycle (MCC)*, as it is derived from participants' current sleep-awake schedule. We *emphasise* the variable within the text to prevent misunderstanding the variable with the term circadian cycle.

We calculate the hourly total app interaction count by adding all the app category interactions for each hour. Average hourly interaction count is 12.47 (min = 0, max = 40, IQR = 3.5-17). Considering interaction count rarely increases beyond 20, and the majority are divided equally above or below 10, we divide our data into four categories: 0, 1-10, 11-20, 21+. Hours from going to bed till falling asleep and wake-up hours are classified by hours: 0-3, 4-6, 7-9, 10-12, 13-15, 16, 17-21, 22-23. These classifications are an adaption from the original MEQ questionnaire and similar hourly classification used in previous literature [29].

**Balancing the circadian cycle distribution.** To make our further analysis non-biased towards any particular sleep cycle, we balance the data considering the distribution of "morning", "intermediate", and "evening" types of circadian cycles. The number of participants with an "intermediate type" is significantly higher than the other two types (morning and evening). Among the total data, 23.35% data is of "evening types", 24.89% data is of "morning types", and 51.98% data is

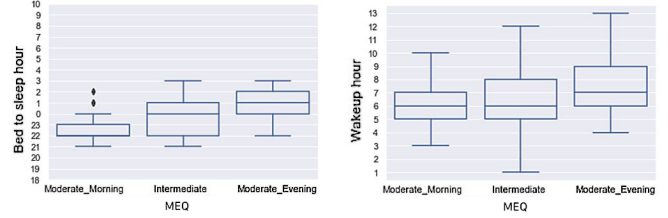


Fig. 3. MEQ results associated with bed to sleep and wake-up hours.

of "intermediate types". We sample down the largest category (intermediate) by variance, where we keep samples that ensure higher variance (more variety remains in the dataset). We settle for a threshold of 50 for variance. After preprocessing, we have a total sample of  $N=597$ , where "morning type" *measured circadian cycle* has  $N=201$ , "intermediate types" has  $N=185$ , "evening types" has  $N=211$ . Figure 2 shows the data distribution after sampling down intermediate types. The red line represents mode, blue dotted line median, and green line mean of the distribution. The skewness of the distribution is  $-0.239$  ( $-0.25 < -0.239 < 0.25$ ) and kurtosis of the distribution is  $-1.922$  ( $-2.25 < -1.922 < -1.76$ ), meaning the data is approximately symmetrically distributed and right-tailed [30].

## V. CIRCADIAN CYCLES IN SMARTPHONE INTERACTION

We first study if our participants behave correspondingly to their MEQ results regarding when they go to sleep and wake up. Figure 3 shows the percentiles of MEQ moderate evening, moderate morning, and intermediate type based on hours they spend from going to bed till falling asleep (3(a)) and hours when they wake up (3(b)). Moderate morning-type of people, indeed, seem to go to bed earlier (around 22-23pm) and correspondingly, also wake up earlier in the morning (5-7am). Moderate evening people tend to go to bed later (0-2am) and wake up later (6-9am). Extremely late (that are not, however, considered as outliers) moderate evening people do not go to sleep before 3am and wake up at the latest 13pm. Corresponding values for moderate morning people being 21pm to bed and 10am wake-up time. Intermediate people, as expected, fall between all of these ranges without a clear morning or evening profile in their data. From Figure 4(a) we can see the association of *measured circadian cycle* and MEQ results. **Highest frequency of users who assessed themselves as a moderate morning or moderate evening type, their measured circadian cycle is also morning and evening type respectively.** The intermediate association is more flexible, which is also seen in comparison to bed and wake-up hours as seen in Figure 3.

Sleep quality is analysed as a three-label nominal variable (bad, medium, good) (see Table I again). Even if the categorisation is somewhat coarse with only three categories, it enables finding differences in the *measured circadian cycle* types and sleep quality. Figure 5(a) shows that **people having good sleep quality tend to assess themselves as moderate morning type whereas the majority of people having bad sleep quality belong to moderate evening type by their self-assessment.**

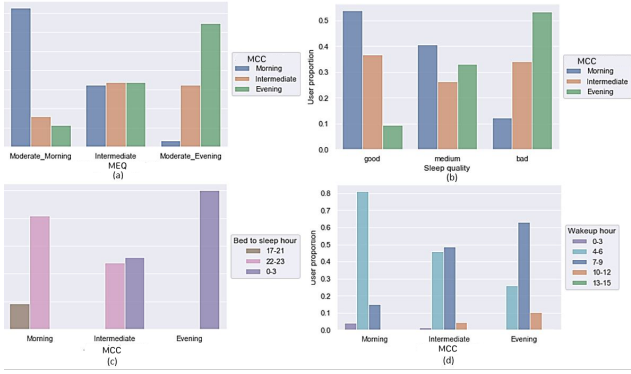


Fig. 4. Measured circadian cycle (MCC) associated with MEQ (a), sleep quality (b), bed to sleep hour (c), and wake-up hour (d).

Statistically speaking, our data agree with previous studies that MEQ results and sleep quality have significant dependency on each other ( $X^2 = 64.86$ ,  $p\text{-value} < 0.001$ ).

Similarly, sleep quality and circadian cycle have significant dependencies on each other ( $X^2 = 93.32$ ,  $p\text{-value} < 0.001$ ). Figure 4(b) shows that people who have bad sleep quality typically have the circadian cycle of evening type. The majority of the participant proportion who have good sleep quality belong to morning type as per their measured circadian cycle, and moderate morning type as per their MEQ results. Sleep quality degrades towards evening types, as well as improves towards morning types (Figure 4(b)). To summarise, our data is in-line with psychology research [4], [5], [31] that **the morning people typically has better overall sleep quality than others, and the evening type has the worst.**

Next, we dive deeper into the different metrics that contribute to the sleep quality for different types of circadian cycles. We use the Chi-square test of independence (with FDR correction) to determine the dependencies between the parameters. The results are listed in Table II. We can see, for example, that the circadian cycle has a significant dependency on the bed to sleep hour, i.e. time spent in bed awake ( $X^2 = 734.14$ ,  $p\text{-value} < 0.001$ ). The highest proportion of people having morning type of circadian cycle goes to bed till fall asleep between hour 22-23pm and considerably many already at 17-21pm, whereas, evening type of people go to bed till fall asleep between hour 0-3am (Figure 4(c)). Also, the dependency between the circadian cycle and wake-up hour is significant ( $X^2 = 158.0$ ,  $p\text{-value} < 0.001$ ). The majority of evening people wake up between hours 7-9am, which is moderately early [31]. Similarly, we can see a proportion of evening people waking up between 10-12am (Figure 4(d)).

Majority of user-proportion who assess themselves as moderate morning people go to bed till fall asleep between hour 22-23pm, whereas majority who consider themselves as moderate evening people go to bed till fall asleep between hour 0-3am (Figure 5(b)). Comparably, the Chi-square test (see Table II) shows that there is a significant dependency between self-reported MEQ and when people go to bed till fall asleep ( $X^2 = 109.24$ ,  $p\text{-value} < 0.001$ ). Like the circadian cycle,

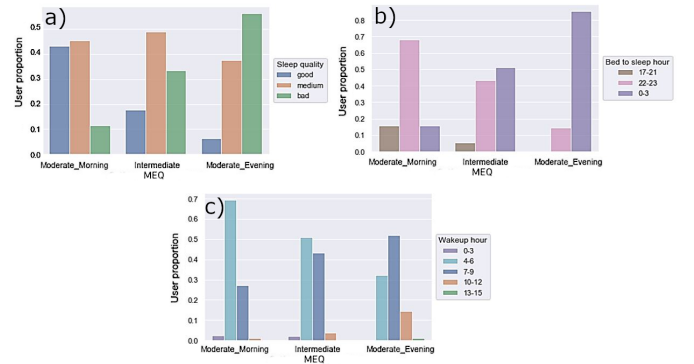


Fig. 5. MEQ associated with measured circadian cycle (MCC) (a), bed to sleep hour (b), and wake-up hour (c).

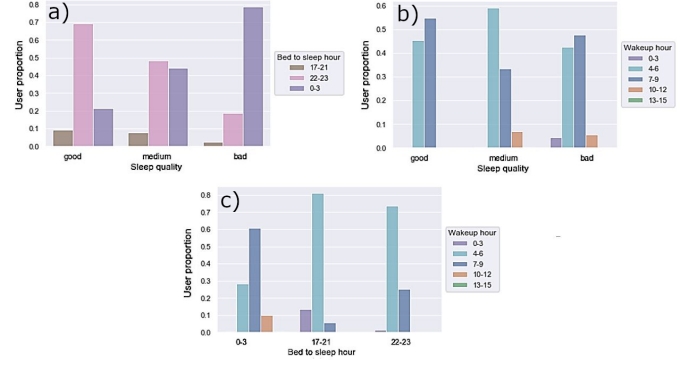


Fig. 6. Associations among sleep quality, bed to sleep and wake-up hours.

self-reported MEQ result also has a significant dependency on the wake-up hour ( $X^2 = 51.16$ ;  $p\text{-value} < 0.001$ ). We can see that a good proportion of people who go to bed till fall asleep between hour 0-3am under moderate evening type (Figure 5(b)), which is very low within the moderate morning and also considerably lower within the intermediate type of people.

Finally, we can **conclude that the sleep quality has significant dependency with people's bed to sleep hour and when people wake-up** ( $X^2$  (bed to sleep hour) = 112.68,  $p\text{-value} < 0.001$ ;  $X^2$  (wake-up hour) = 45.47,  $p\text{-value} < 0.001$ ). Sleep quality of people degrades towards late time bed to sleep hour but improves towards the early bed to sleep time (Figure 6(a)). We can see late-rising people (hour 10-12am) under bad sleep quality, whereas good sleep quality people do not wake up after 9m (Figure 6(b)). People's wake-up hour is also associated with when people go to bed till they fall asleep. From Figure 6(c), we can see the majority of people who wake up between 7-9am, go to bed till fall asleep between 0-3am; who wake up between 4-6am, go to bed till fall asleep between 17-21pm. People who go to bed and fall asleep between 22-23pm tend to wake up between 4-6am (Chi-square significance:  $X^2 = 191.61$ ,  $p < 0.001$ ). This identified phenomenon is critical when considering the applications of our research. Potentially, tracking bed to sleep and wake up hours could provide enough insights into recommendations to improve sleep quality.

The dependencies between different sleep metrics we discussed above have very high significance ( $p\text{-value} < 0.001$ ).

TABLE II  
CHI-SQUARE TEST OF INDEPENDENCE RESULT (FDR-CORRECTED) FOR  
PAIRS OF SLEEP METRICS (P-VALUE\* < 0.05, P-VALUE\*\*\* < 0.001).

Metric pairs	p-value	Reference
MCC ↔ MEQ	1.01e-27***	[Figure 4(a)]
MCC ↔ Sleep quality	2.60e-19***	[Figure 4(b)]
MCC ↔ Bed to sleep hour	3.14e-15***	[Figure 4(c)]
MCC ↔ Wake-up hour	1.34e-27***	[Figure 4(d)]
MEQ ↔ Sleep quality	2.76e-13***	[Figure 5(a)]
MEQ ↔ Bed to sleep hour	2.09e-19***	[Figure 5(b)]
MEQ ↔ Wake-up hour	8.70e-20***	[Figure 5(c)]
Sleep quality ↔ Bed to sleep hour	4.18e-20***	[Figure 6(a)]
Sleep quality ↔ Wake-up hour	8.53e-06***	[Figure 6(b)]
Bed to sleep hour ↔ Wake-up hour	1.75e-34***	[Figure 6(c)]
App interaction level ↔ MEQ	0.036*	
App interaction level ↔ Bed to sleep hour	0.049*	
App interaction level ↔ MCC	0.048*	
App interaction level ↔ Wake-up hour	0.207	
App interaction level ↔ Sleep quality	0.991	

TABLE III  
PREDICTION ACCURACY (HIGHER IS BETTER).

Features (input)	Labels (output)	RF (%)	KNN (%)	SVM (%)
App categories	Sleep quality	37%	45%	49%
App categories	MEQ	67%	65%	67%
App categories	MCC	32%	36%	35%

Comparatively, the dependency significance associated with interaction levels to different sleep metrics is not highly significant but passes the general test of significance ( $p < 0.05$ ) in three cases. Dependency significance between app interaction level and bed to sleep hour is marginally significant ( $X^2 = 17.00$ ,  $p\text{-value} < 0.05$ ), so as with *measured circadian cycle* ( $X^2 = 12.70$ ,  $p\text{-value} < 0.05$ ) and MEQ results ( $X^2 = 13.45$ ,  $p\text{-value} < 0.05$ ). However, even if not passing the  $p < 0.05$  test, wake-up hour and sleep quality in general gain somewhat small p-values, showing they might have, at some level, some influence from or to overall smartphone usage.

## VI. PREDICTION ANALYSIS

The goal of the prediction analysis is to understand if general and category-wise app usage in bed can indicate changes in sleep quality and circadian cycles. It is noteworthy to remember that these indications do not implicate causality; higher smartphone or app interaction can be either a reason or result of worsened sleep or disordered circadian cycle. For prediction features, i.e. the input of the model, we consider the amount of interaction count in each app category during the time in bed (before falling asleep). We use three widely used machine learning methods as the prediction models: Random Forest (RF), Keras Neural Network (Keras NN), and Support Vector Machine (SVM). For categorical output metrics (sleep quality, *measured circadian cycle*, and MEQ), we apply the classifier version to the models and regression versions for the numerical sleep metrics correspondingly.

Sleep quality can be predicted with an accuracy of 37%-49% based on their application category usage while awake in bed (see Table III). This slightly outperforms a random guess, which with three output labels would be around 33% if each label is considered equally likely and the dataset is

TABLE IV  
IMPORTANT FEATURES, THREE MOST IMPORTANT ARE HIGHLIGHTED.

Importance metric	Sleep metrics	Other	Communication	Tools	Entertainment	Social	Productivity	Media and Video	Sports	Lifestyle
MDI (RF)	Sleep quality	<b>1</b>	<b>2</b>	<b>3</b>	4	5	6	7	8	9
	MEQ	<b>1</b>	<b>2</b>	6	8	<b>3</b>	7	4	5	
	Circadian cycle	<b>1</b>				<b>2</b>		<b>3</b>		
PFI (KNN)	Sleep quality	<b>1</b>		4		<b>3</b>			<b>2</b>	
	MEQ	<b>1</b>	<b>2</b>							
	Circadian cycle	<b>1</b>	<b>3</b>		<b>2</b>					
FWC (SVM)	Sleep quality	7	<b>3</b>	<b>2</b>		5	4	6	<b>1</b>	
	MEQ	<b>1</b>	<b>2</b>	6		<b>3</b>	7	4	5	
	Circadian cycle	5	7	4	<b>2</b>			6	<b>1</b>	<b>3</b>

balanced. When sleep quality is concerned, addictive usage of mobile phones is an indicator of degrading sleep quality as per the study of Sahin et al. [32]. Even if our study does not directly consider addictive behaviour but the frequency of usage, we can confirm these previous findings that the amount of interaction is linked to sleep quality.

The model accuracy in predicting MEQ results is 65%-67%. The prediction is good compared to sleep quality and outperforms the random guess substantially. We have already seen that app interaction level and MEQ results have significant dependency on each other (Table II). The result of 65%-67% predictive accuracy shows that app interaction as a whole is a good indicator of how people assess their morningness-eveningness type, whether considered as app interaction level or individual app category usage count. However, *measured circadian cycle* can be predicted only with an accuracy of 32%-35% that is much lower compared to MEQ results and does not outperform a random guess. This is a negative result we see necessary to report as well as the more positive outcomes.

**Important features.** Table IV shows the ranks of important features, i.e., app categories (from 1 to 9, 1 being the most important feature) calculated by three feature importance indicators: Mean Decrease Impurity (MDI) for RF model, permutation feature importance for Keras NN, and feature weight by the coefficient for SVM. As these indicators are not the same unit and, as mentioned, different models require different metrics, the comparison is made by ranks only. The most highly ranked app categories are related to the basic functioning of the phone, including *Other* and *Tools*. Also somewhat "classically" purposeful app categories *Communication* and *Productivity* are present. In addition to these, leisure and pastime-related categories are highlighted, including categories *Entertainment*, *Social*, *Media and Video*, *Sports*, and *Lifestyle*. There are more than 50 categories in Google Play; only these emerge as the most important categories – an issue that can be caused by them being both popular in terms of apps they contain and how many basic smartphone functionalities they include. However, such a bias is present in every smartphone study based on crowdsourced, real-life data [33]. In contrary to the previous literature that highlights the role of games as a bed-time activity



TABLE V  
NRMSE COMPARISON (SMALLER ERROR RATE IS BETTER).

Features (input)	Labels (output)	RF (%)	Keras NN (%)	SVR (%)
App categories	light	19%	21%	18%
App categories	rem	20%	20%	21%
App categories	deep	20%	18%	20%
App categories	total	18%	19%	17%
App categories	onset_latency	12%	36%	10%
App categories	rmssd	19%	25%	20%
App categories	bed_hour	45%	44%	54%
App categories	sleep_hour	46%	46%	50%
App categories	wakeup_hour	16%	20%	15%
App categories	efficiency	20%	18%	20%
App categories	hr_average	17%	20%	22%
App categories	restfulness	18%	24%	19%

[11], we cannot see game-related categories in the top results. Whether it is, they do not affect that much on sleep anymore, ten years later, or their popularity among our participants is simply scarce.

TABLE VI  
IMPORTANT FEATURES, THREE MOST IMPORTANT ARE HIGHLIGHTED.

Importance metric	Sleep metrics	Other	Communication	Tools	Entertainment	Social	Productivity	Media& Video	Sports	Lifestyle
MDI (RF)	light	1	4	6		5	7	3	2	
	rem	1	3	5		4		3		
	deep	2	1	5		4	6	3	7	
	total	1	4	3				2		
	onset_latency	1	4	5		2		3		
	rmssd	2	4	3		7	6	1	5	
	bed_hour	3	6	5		2	7	4	1	
	sleep_hour	1	4	2		3		5		
	wakeup_hour	1	2			3				
	efficiency	1	2	5		4		3		
	hr_average	1	2	4		3	6	5		
PFI (KNN)	light			1						
	rem			1						
	deep		4	2	1	5		3		
	total			1				2		
	onset_latency	1	2			3		4		
	rmssd						2			
	bed_hour			2	3			1	5	4
	sleep_hour	1	7	2	6	3	9	4	5	8
	wakeup_hour	1	2	5	6		3	4	7	
	efficiency	1	4	2	7	3	5	1	6	
	hr_average	1	3	2	4			5	6	
FWC (SVR)	light	1	3	4	8	5	7	2	6	9
	rem	1	5	3	6	9	2	8	4	7
	deep	1	5	4	6	3	7	2	9	8
	total	1	2	5	7	4	6	3	8	
	onset_latency	3		2	5	4	7	1	6	
	rmssd	8	4	2	6	9	5	1	3	7
	bed_hour	9	4	8	2	3	5	7	1	6
	sleep_hour	7	1	5	6	3		2	4	
	wakeup_hour	9	6	7	2	5	1	8	4	3
	efficiency	8	6	3	4	9	2	1	7	5
	hr_average	5	8	6	3	7	1	4	2	

Table V shows the comparison among normalised root-mean-square error (NRMSE) of the models for each numerical predicting metrics, again, category-wise app usage as a predictor or input value and sleep parameters as output values. The amount of light sleep, deep sleep, rapid eye movement (REM), and total sleep (REM + light sleep + deep sleep) can be predicted with 18%-20% error from app categories. In terms of "accuracy",

in comparison to the classifiers is wished to be made, it means 80%-82% of goodness. As per earlier studies [34], smartphone usage in bed can lead to reduced sleep duration and sleep quality. In our study, the error rate of predicting light sleep, rem, and the total amount of sleep agree that the mobile interaction is a good predictor of these metrics.

As discussed above, immediate usage of a mobile phone prior to sleep interrupts falling asleep. Onset\_latency is the time between bed-time to first five minutes of persistent sleep. The NRMSE of predicting onset\_latency by our model is 10%-12% (accuracy 88%-90%) by RF and SVR, 36% (accuracy 64%) by Keras NN considering category-wise app usage as the predictor. The sleep efficiency and restful sleep can be predicted with the 18%-24% level of NRMSE, which in terms of the accuracy would be 76%-88%. The heart rate related sleep metrics – average heart rate and rmssd (average heart rate variability calculated by rMSSD method) – can be predicted with NRMSE of 17%-25%. Unlike the high prediction accuracy of other sleep parameters mentioned above, the error rate is high (44%-54%) for predicting bed and sleep hours.

**Important features.** Table VI shows the most important app categories that predict different sleep metrics discussed above. Among the most common app categories which have high importance as predictors, are *Other*, *Sports*, *Media and Video*, *Communication*, *Tools*, and *Social*. These app categories are also common to the classifiers for predicting MEQ (see Figure IV). Among the other app categories, *Lifestyle* and *Entertainment* are among the important features for Keras NN and SVR models but, are not for RF. Similarly interestingly, certain app categories, such as *Media and Video*, seem to predict well some of the sleep metrics (ranks 1 to 3) but less the others (ranks 7 to 9).

## VII. DISCUSSION AND CONCLUSIONS

In this paper, we concluded by analysing the circadian cycle of people from different sleep-related metrics collected by a wearable ring and their smartphone usage before falling asleep. Our results show that people's self-assessment about their circadian type matches with measured circadian cycles measured with a wearable device. We have assessed statistical relationships between in-bed smartphone interaction before falling asleep and different sleep metrics. Our results show that smartphone interaction plays some role in worsened sleep quality. However, it is important to note that our results merely indicate a relationship without any specific direction, not causality between factors.

Intensive smartphone usage has been seen to be affecting sleep quality [35]. Longer screen times during time spent in bed can be associated with poorer sleep quality [36] and high usage of any media devices, including TV, tablets, and smartphones, can weaken the sleep quality [37]. However, these studies mention the causation being problematic in their findings, and results can also be reflected on other biological and cultural factors, or the "vice versa" effect: people who suffer from sleep problems spend more time on screens just to pass time [38]. It is unclear also in psychological research,

which behavioural factor is driving the trend of worsened sleep quality or disordered circadian cycles, and which existing sleep problems merely cause behavioural patterns. However, with long-term studies and suitable causality analysis metrics, these questions could be considered.

We are aware of the limitations in our work. Any crowd-sourced study is reliant on mobile, and wearable sensing exhibits some data loss, which is unfortunate but often unavoidable. Even with recruiting 100 participants, only data of 61 people could be utilised for this study after data loss and preprocessing steps, yet larger samples sizes could produce more verifiable results. This study did not focus on sociological aspects widely reported in psychological research, including daytime occupations requiring an early wake-up hour or shift work causing irregular sleeping patterns. The regularity of the sleep and the circadian cycle is, indeed, an interesting question to be studied further.

#### ACKNOWLEDGEMENTS

This work is supported by the GenZ strategic profiling project (Academy of Finland grant 318930), CRITICAL (335729), and 6Genesis Flagship (318927). Part of the work was carried out with the support of Biocenter Oulu, spearhead project ICON.

#### REFERENCES

- [1] I. Li, A. K. Dey, and J. Forlizzi, "Understanding my data, myself: supporting self-reflection with ubicomp technologies," in *Int. conf. on Ubiquitous computing*, 2011.
- [2] H. Koskimäki, H. Kinnunen, T. Kurppa, and J. Rönning, "How do we sleep: a case study of sleep duration and quality using data from oura ring," in *Int. Symp. on Perv. and Ubiquitous Comp. and Wear. Comp.*, 2018.
- [3] J. C. Dunlap, J. J. Loros, and P. J. DeCoursey, *Chronobiology: biological timekeeping*. Sinauer Associates, 2004.
- [4] N. L. Barclay, T. C. Eley, D. J. Buysse, S. N. Archer, and A. M. Gregory, "Diurnal preference and sleep quality: same genes? a study of young adult twins," *Chronobiology international*, vol. 27, no. 2, 2010.
- [5] S. Kitamura, A. Hida, M. Watanabe, M. Enomoto, S. Aritake-Okada, Y. Moriguchi, Y. Kamei, and K. Mishima, "Evening preference is related to the incidence of depressive states independent of sleep-wake conditions," *Chronobiology international*, vol. 27, no. 9-10, 2010.
- [6] C. Carney, J. Edinger, B. Meyer, L. Lindman, and T. Istre, "Daily activities and sleep quality in college students," *Chronobiology int.*, vol. 23, no. 3, 2006.
- [7] R. Ravichandran, S. Sien, S. Patel, J. Kientz, and L. Pina, "Making sense of sleep sensors: How sleep sensing technologies support and undermine sleep health," in *CHI Conf. on Human Factors in Comp. Sys.*, 2017.
- [8] J. M. Shneerson, *Sleep medicine: a guide to sleep and its disorders*. John Wiley & Sons, 2009.
- [9] T. I. Morgenthaler, T. Lee-Chiong, C. Alessi, L. Friedman, R. N. Aurora, B. Boehlecke, T. Brown, A. L. Chesson Jr, V. Kapur, R. Maganti *et al.*, "Practice parameters for the clinical evaluation and treatment of circadian rhythm sleep disorders," *Sleep*, vol. 30, no. 11, pp. 1445–1459, 2007.
- [10] G. D. Potter and T. R. Wood, "The future of shift work: Circadian biology meets personalised medicine and behavioural science," *Frontiers in Nutrition*, vol. 7, 2020.
- [11] M. Böhmer, B. Hecht, J. Schöning, A. Krüger, and G. Bauer, "Falling asleep with angry birds, facebook and kindle: a large scale study on mobile application usage," in *13th Int. Conf. on Human-Computer Interaction with Mobile Devices and Services*, 2011, pp. 47–56.
- [12] E. L. Murnane, S. Abdullah, M. Matthews, M. Kay, J. A. Kientz, T. Choudhury, G. Gay, and D. Cosley, "Mobile manifestations of alertness: Connecting biological rhythms with patterns of smartphone app use," in *Int. Conf. on HCI with Mobile Devices and Services*, 2016.
- [13] N. Nowreen and F. Ahad, "Effect of smartphone usage on quality of sleep in medical students," *Nat. J. of Physiology, Pharmacy and Pharmacology*, vol. 8, no. 10, 2018.
- [14] L. Rosen, L. Carrier, A. Miller, J. Røkkum, and A. Ruiz, "Sleeping with technology: cognitive, affective, and technology usage predictors of sleep problems among college students," *Sleep health*, vol. 2, no. 1, 2016.
- [15] P. Randjelović, N. Stojiljković, N. Radulović, I. Ilić, N. Stojanović, and S. Ilić, "The association of smartphone usage with subjective sleep quality and daytime sleepiness among medical students," *Biological Rhythm Research*, vol. 50, no. 6, pp. 857–865, 2019.
- [16] L. Jeon and J. Finkelstein, "Consumer sleep tracking devices: a critical review," *Digital Healthcare Empowering Europeans: Proceedings of MIE2015*, vol. 210, p. 458, 2015.
- [17] S. Bhat, A. Ferraris *et al.*, "Is there a clinical role for smartphone sleep apps? comparison of sleep cycle detection by a smartphone application to polysomnography," *J. of Clinical Sleep Med.*, vol. 11, no. 07, 2015.
- [18] A. A. Ong and M. B. Gillespie, "Overview of smartphone applications for sleep analysis," *World Journal of Otorhinolaryngology-Head and Neck Surgery*, vol. 2, no. 1, pp. 45–49, 2016.
- [19] K. E. Bloch, "Polysomnography: a systematic review," *Technology and health care*, vol. 5, no. 4, pp. 285–305, 1997.
- [20] M. de Zambotti, L. Rosas, I. M. Colrain, and F. C. Baker, "The sleep of the ring: comparison of the oura sleep tracker against polysomnography," *Behavioral sleep medicine*, vol. 17, no. 2, pp. 124–136, 2019.
- [21] M. De Zambotti, J. Godino, F. Baker, J. Cheung, K. Patrick, and I. Colrain, "The boom in wearable technology: cause for alarm or just what is needed to better understand sleep?" *Sleep*, vol. 39, no. 9, 2016.
- [22] J. Horne and O. Östberg, "A self-assessment questionnaire to determine morningness-eveningness in human circadian rhythms," *Int. j. of chronobiology*, 1976.
- [23] D. Ferreira, V. Kostakos, and A. K. Dey, "Aware: mobile context instrumentation framework," *Frontiers in ICT*, vol. 2, p. 6, 2015.
- [24] M. Reardon and M. Malik, "Changes in heart rate variability with age," *Pacing and clinical electrophysiology*, vol. 19, no. 11, 1996.
- [25] K. Danielsson, A. Sakarya, and M. Jansson-Fröjmark, "The reduced morningness-eveningness questionnaire: Psychometric properties and related factors in a young swedish population," *Chronobiology international*, vol. 36, no. 4, pp. 530–540, 2019.
- [26] J. A. Vitale, E. Roveda, A. Montaruli, L. Galasso, A. Weydahl, A. Caumo, and F. Carandente, "Chronotype influences activity circadian rhythm and sleep: differences in sleep quality between weekdays and weekend," *Chronobiology international*, vol. 32, no. 3, pp. 405–415, 2015.
- [27] T. Roenneberg, A. Wirz-Justice, and M. Mrosovsky, "Life between clocks: daily temporal patterns of human chronotypes," *Journal of biological rhythms*, vol. 18, no. 1, pp. 80–90, 2003.
- [28] M. Terman, J. Rifkin, J. Jacobs, and T. White, "Morningness-eveningness questionnaire: Self-assessment version (meq-sa)," *Center for Environmental Therapeutics [Internet]*, pp. 1–7, 2008.
- [29] M. Wright, B. Phillips-Bute, J. Mark, M. Stafford-Smith, K. Grichnik, B. Andregg, and J. Taekman, "Time of day effects on the incidence of anesthetic adverse events," *BMJ Quality & Safety*, vol. 15, no. 4, 2006.
- [30] M. J. Blanca, J. Arnau, D. López-Montiel, R. Bono, and R. Bendayan, "Skewness and kurtosis in real data samples," *Methodology*, 2013.
- [31] A. M. Soehner, K. S. Kennedy, and T. H. Monk, "Circadian preference and sleep-wake regularity: associations with self-report sleep parameters in daytime-working adults," *Chronobiology int.*, vol. 28, no. 9, 2011.
- [32] S. Sahin, K. Ozdemir, A. Unsal, and N. Temiz, "Evaluation of mobile phone addiction level and sleep quality in university students," *Pakistan journal of medical sciences*, vol. 29, no. 4, p. 913, 2013.
- [33] E. Peltonen, E. Lagerspetz, J. Hamberg, A. Mehrotra, M. Musolesi, P. Nurmi, and S. Tarkoma, "The hidden image of mobile apps: geographic, demographic, and cultural factors in mobile usage," in *Int. Conf. on HCI with Mobile Devices and Services*, 2018.
- [34] N. Rod, A. Dissing, A. Clark, and *et al.*, "Overnight smartphone use: A new public health challenge? a novel study design based on high-resolution smartphone data," *PloS one*, vol. 13, no. 10, 2018.
- [35] K. Demirci, M. Akgönül, and A. Akpinar, "Relationship of smartphone use severity with sleep quality, depression, and anxiety in university students," *J. of Behavioral Addictions*, vol. 4, no. 2, pp. 85–92, 2015.
- [36] M. A. Christensen, L. Bettencourt, L. Kaye, and *et al.*, "Direct measurements of smartphone screen-time: relationships with demographics and sleep," *PloS one*, vol. 11, no. 11, 2016.
- [37] E. Kenney and S. Gortmaker, "Us adolescents' television, computer, videogame, smartphone, and tablet use: associations with sugary drinks, sleep, physical activity, and obesity," *J of pediatrics*, vol. 182, 2017.
- [38] K. Katevas, I. Arapakis, and M. Pielot, "Typical phone use habits: Intense use does not predict negative well-being," in *Int. Conf. on HCI with Mobile Devices and Services*, 2018.