



# Development of a mobile application (App) to delineate “digital chronotype” and the effects of delayed chronotype by bedtime smartphone use



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## ABSTRACT

The widespread use and deep reach of smartphones motivate the use of mobile applications to continuously monitor the relationship between circadian system, individual sleep patterns, and environmental effects. We selected 61 adults with 14-day data from the “Know Addiction” database. We developed an algorithm to identify the “sleep time” based on the smartphone behaviors. The total daily smartphone use duration and smartphone use duration prior to sleep onset were identified respectively. We applied mediation analysis to investigate the effects of total daily smartphone use on sleep through pre-sleep use (PS). The results showed participants’ averaged pre-sleep episodes within 1 h prior to sleep are 2.58. The duration of three pre-sleep uses (PS<sub>1–3</sub>) maybe a more representative index for smartphone use before sleep. Both total daily duration and the duration of the last three uses prior to sleep of smartphone use significantly delayed sleep onset, midpoint of sleep and reduced total sleep time. One hour of increased smartphone use daily, delays the circadian rhythm by 3.5 min, and reduced 5.5 min of total sleep time (TST). One hour of increased pre-sleep smartphone use delayed circadian rhythm by 1.7 min, and reduced 39 s of TST. The mediation effects of PS<sub>1–3</sub> significantly impacted on these three sleep indicators. PS<sub>1–3</sub> accounted for 14.3% of total daily duration, but the proportion mediated of delayed circadian rhythm was 44.0%. We presented “digital chronotype” with an automatic system that can collect high temporal resolution data from naturalistic settings with high ecological validity. Smartphone screen time, mainly mediated by pre-sleep use, delayed the circadian rhythm and reduced the total sleep time.

## 1. Introduction

The widespread use and deep reach of smartphones in modern life motivate the use of smartphones to measure mental state and behaviors in an affordable, reliable, and unobtrusive way. Digital footprint, referring to data rising from day-to-day interactions with newer technologies such as smartphones (Bidargaddi et al., 2017), can provide real time data on individual's environment, that when linked with mental state data, may contribute toward our understanding of the etiology of

mental illness (Onnela and Rauch, 2016). When gathered and analyzed appropriately, this data can be considered as an extended phenotype — digital phenotype (Insel, 2017; Jain et al., 2015). Digital phenotyping is being tested in several areas where psychiatry needs better measurement of behavior (Insel, 2017). In addition, many other scientists regard digital phenotyping as part of a new discipline called Psycho-Informatics (Markowitz et al., 2014; Montag et al., 2016; Yarkoni, 2012).

Chronotype refers to the behavioral manifestation of underlying circadian rhythms of multiple physical processes. The differences in

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circadian rhythms suggested an individual's preferences to sleep at a particular time during a 24-h period and optimally perform mentally and physically in the morning or evening hours (Paine et al., 2006). “Evening persons”, tend to go to sleep and get up at a later time, significantly preferred electronic media, whereas “morning persons” preferred traditional media (Nimrod, 2015). Electronic media, such as smartphones and personal computers might shift morning chronotype to evening chronotype (Eugenia et al., 2014). The close human-machine interaction not only resulted in a long-term social jetlag (Jankowski, 2017; Wittmann et al., 2006) or “technology jetlag” (Touitou, 2013) but also provided opportunities to delineate a person's chronotype by digital footprint. “Digital chronotype” is a concept that combines “chronotype” and “digital phenotype”. More specifically, modern people might swipe their smartphone at eye opening and use their smartphone prior to sleep. Nowadays, to delineate a human's chronotypes, typically based on their behaviors would be identical to delineate their “digital chronotype” based on their digital footprints.

Chronotype is a characteristic that results from genetic factors interacting with a person's environment. Estimates from twin studies suggest that chronotype is approximately 50% heritable (Koskenvuo et al., 2007). Light is the most potent environmental signal that impacts the human circadian rhythm and may therefore play a role in delayed chronotype and perpetuating sleep deficiency (Czeisler, 2013). Exposure to light in the evening and early part of the night, even at low intensity, suppresses the release of the sleep-facilitating hormone melatonin (Brainard et al., 1988; Mcintyre et al., 1989; Zeitzer et al., 2000) and delays circadian rhythm (Khalsa et al., 2003; Zeitzer et al., 2000), both of which make it more difficult to fall asleep. Using a light-emitting device in the hours before bedtime is especially a critical timing of the total daily smartphone use to increase the risk of delayed sleep-phase disorder and sleep onset insomnia (Dijk, 2013). Total daily smartphone use, one of the predominant sources light exposure, would delay sleep onset and circadian rhythm (Hale and Guan, 2015). Pre-sleep smartphone use, which was most relevant to sleep time (Cajochen et al., 2011; Chang et al., 2015), would not only be proportioned to total daily smartphone use, but also played the role of mediator in the total effects of daily smartphone use.

While research has successfully used a number of techniques for assessing circadian rhythms over the decades to untangle the biological basis of circadian rhythms, most studies are done either in the artificial settings of a laboratory (e.g. polysomnography) with small sample size (Chang et al., 2015) or through subjective self-report (e.g. Composite Scale for Morningness, Munich ChronoType Questionnaire) in large scale epidemiological studies (Lin and Gau, 2013; Roenneberg et al., 2003, 2007). Understandably, the methods used in laboratory studies are not scalable for administration to a large population. On the other hand, the value of subjective reports and surveys, while more broadly deployable, was reduced by biases. It is now feasible to install a mobile application which runs in the background collecting data. Collecting data passively from a person's smartphone (App) may be more informative than self-reports. This data collection method can provide continuously monitoring over longitudinal periods and has potential to capture subtle details and instantaneous changes regarding the relationship between the circadian system (Behar et al., 2013; Chen et al., 2013; Hao et al., 2013), individual sleep patterns, and environmental effects. However, analysis of data generated by the smartphone usage patterns also posed several challenges. An individual's digital footprint is characterized with more data points over time than conventional epidemiological or experimental approaches. This requires correcting inter-individual variances in the statistical analysis. At an individual level, the time-varying environmental exposures and behavior changes may contribute to investigation of complicated causal mechanisms in naturalistic setting. For example, although the impact of daily screen time and pre-sleep smartphone use on sleep have been well-studied (Carter et al., 2016; Hale and Guan, 2015) the accurate proportion of pre-sleep use could only be estimated by these time-varying data in

naturalistic setting. The approach for analyzing this type of data should involve mediation analysis model (Lin et al., 2017a; Lin et al., 2017b; VanderWeele and Tchetgen Tchetgen, 2017; Zheng and van der Laan, 2017).

The specific aims of this study are (1) to delineate “digital chronotype” combining automated recording smartphone use behaviors by an App along with newly developed algorithm, and (2) to examine the impacts of daily smartphone screen time and the mediation effects of using smartphone before bedtime on sleep and circadian timing in naturalistic settings. We hypothesize that pre-sleep use of smartphone may delay sleep onset, circadian rhythm and reduced total sleep time.

## 2. Methods

### 2.1. Participants

We selected sixty-one adult participants (47 men, mean age:  $26.7 \pm 9.4$ , range: 20–56) from the “Know Addiction” database (From: March to August 2017; <http://www.pokepsych.com/>), which is owned by National Health Research Institutes. All participants are volunteers who are interested in excessive smartphone use and concerned about their smartphone use patterns. All of them used a smartphone with an Android operation system, and downloaded the App from Google Play voluntarily and consented to allow data to be collected electronically. This App is only available in Taiwan. A newly developed App “Know Addiction” created by our team (Lin et al., 2015, 2017c, 2017d) was installed on their smartphones to record their smartphone use for at least 4 weeks. Data collected on the first day and the last day was excluded due to the incomplete nature of data on those dates. We selected 14-day data from each participant based on a two-step procedure. First, we identified an excessive 14-day sleep time data recorded by Know Addiction from each participant. Next, we ensured if all App-recorded and self-reported sleep time for each participant were within typical bed times (i.e. 22:00 ~ next 10:00) to exclude shift workers. The 14-day data consisted of 9–10 days weekday data and 4–5 days weekend data. The study was approved by the Institutional Review Board of National Health Research Institutes, who waived the need for written informed consent from the participants, since the data was analyzed anonymously. All clinical investigations were conducted according to the principles expressed in the Declaration of Helsinki.

### 2.2. The App-generated parameters

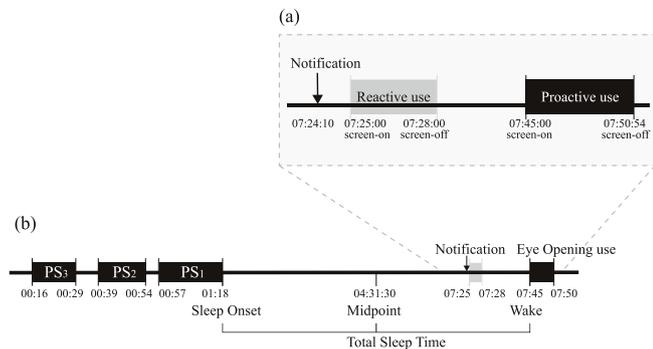
The App “Know Addiction” automatically recorded smartphone behaviors, mainly the notifications, screen-on and screen-off timing. This App collects data in the background without interrupting smartphone operation or impacting battery life (less than 1%) (Lin et al., 2015, 2017c, 2017d). The App saves all recorded behavior data in a log file and uploaded data to the database server every midnight.

#### 2.2.1. Total duration and frequency of daily smartphone use

Smartphone use from screen-on to the successive screen-off was defined as one episode of use. This App calculated the daily epoch count as the daily frequency parameter. Similarly, the daily total duration of episode was calculated as the total daily duration parameter.

#### 2.2.2. Sleep indicators

We developed an algorithm to identify the “sleep time” based on the smartphone behaviors and excluded the reactive screen-on from notifications. First, each smartphone use episode was classified into proactive use or reactive use according to the chronological order of screen-on and notification. The reactive use episode was defined as whether there was any notification within 1 min prior to the screen-on. In contrast, the proactive use episode was defined as no notifications within 1 min prior to the screen-on. All reactive use episodes would be excluded in the sleep indicators calculation. Secondly, we defined non-



**Fig. 1. The algorithm to calculate sleep time.** The measure of smartphone use from screen-on to the successive screen-off was defined as one episode.

(a) **Proactive and reactive use episodes.** The solid bar indicates a proactive use episode, which starts with the screen-on (07:45:00) and ends with the screen-off (07:50:54). The duration of this proactive use episode is 354 s. The bar with diagonal stripes is defined as a reactive use episode because there is a notification at 07:24:10, 50 s prior to the screen-on (07:25:00). All reactive use episodes, with any notification within 1 min prior to the screen-on, would be excluded in the sleep indicators calculation.

(b) **Sleep indicators.** The maximal duration of the non-use episode between 22:00 and 10:00 the following day is the non-use episode starting with the screen-off of the last proactive use episode (01:18:00) to the screen-on of the next proactive use episode (07:45:00). The App-generated sleep onset (SO<sub>App</sub>) is identical to the screen-off of the last proactive use episode (01:18:00), and the App-generated wake time (WT<sub>App</sub>) is identical to the screen-on of the eye opening proactive use episode (07:45:00). The App-generated total sleep time (TST<sub>App</sub>) is 6 h and 27 min, or 6.45 h. The midpoint of sleep (MoS<sub>App</sub>) is 04:31:30.

(c) **Pre-sleep use parameters.** The last pre-sleep episode (PS<sub>1</sub>) starts with the screen-on (00:57:00) and ends with the screen-off (01:18:00). The duration of this proactive use episode is 21 min. Similarly, the durations of PS<sub>2</sub> and PS<sub>3</sub> are 15 min and 13 min respectively. Therefore, PS<sub>1-3</sub> = PS<sub>1</sub> + PS<sub>2</sub> + PS<sub>3</sub> is 49 min.

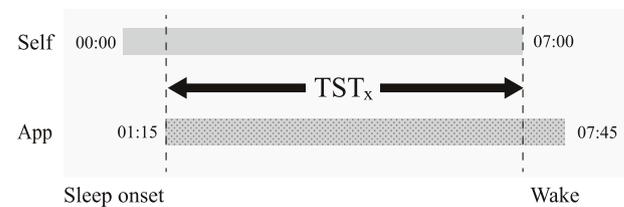
use episode as event from screen-off to screen-on. The maximal non-use episode between 22:00 and next 10:00 is defined as “sleep time”. Finally, App-generated sleep onset (SO<sub>App</sub>), App-generated wake time (WT<sub>App</sub>), App-generated midpoint of sleep time (MoS<sub>App</sub>), and App-generated total sleep time (TST<sub>App</sub>) could be identified (Fig. 1). Because App-recorded “sleep onset” would refer to the time going to bed, or “lights off time” rather than physiological sleep onset, the midpoint of sleep time includes the effects of prolonged sleep latency, which is more suitable to represent delayed circadian rhythm (De Souza and Hidalgo, 2014; Naismith et al., 2014). Therefore, MoS<sub>App</sub> was considered as an indicator of circadian rhythm.

### 2.2.3. Pre-sleep smartphone use

Fig. 1 showed the parameters of pre-sleep smartphone use. The last pre-sleep episode (PS<sub>1</sub>) ends with the screen-off identical to the sleep onset. The duration of the last pre-sleep episode (PS<sub>1</sub>) and the last three pre-sleep episodes (PS<sub>1-3</sub> = PS<sub>1</sub> + PS<sub>2</sub> + PS<sub>3</sub>) were calculated respectively.

### 2.3. Validation of the App-recorded sleep time

We used two items to assess the participants’ sleep onset time and wake time during weekdays and weekends one month after Know Addiction installed (e.g. “What time do you go to sleep on weekdays and weekends in the last month?“, “What time do you wake up on weekdays and weekends in the last month?“). We validated the App-recorded sleep time by comparing the overlap between self-reported and App-recorded sleep time. Considering the sleep patterns significantly differed from weeknights and weekend nights (Lin and Gau, 2013), the validation of App-recorded sleep time was carried out according to self-reported weeknights and weekend nights sleep time



**Fig. 2. Validation of the app-recorded sleep time.**

The overlap ratio is applied to indicate the consistency between self-reported and App-recorded sleep time. A representative process is shown as an example. The self-reported sleep time starts from 00:00 (self-reported sleep onset, SO<sub>self</sub>) to 07:00 (self-reported wake time, WT<sub>self</sub>) with a total sleep time (TST<sub>self</sub>) of 7 h. The App-recorded sleep time starts from 01:15 (App-generated sleep onset, SO<sub>App</sub>) to 07:45 (App-generated wake time, WT<sub>App</sub>) with a total sleep time (TST<sub>App</sub>) of 6.5 h. The overlapping sleep time starts from 01:15 (SO<sub>App</sub>) to 07:00 (WT<sub>self</sub>) with overlapping total sleep time (TST<sub>x</sub>) of 5.75 h. The overlap ratio is 85.2%.

$$\text{Overlap Ratio} = \frac{\text{Overlap}(TST_x)}{TST_{App} + TST_{self}} = \frac{07:00 - 01:15}{6.5 + 7} = 85.2\%$$

respectively. Fig. 2 illustrated the calculation of overlapping ratio between TST<sub>App</sub> and self-reported total sleep time (TST<sub>self</sub>).

$$\text{Overlap Ratio} = \frac{\text{Overlap}(TST_x)}{TST_{App} + TST_{self}}$$

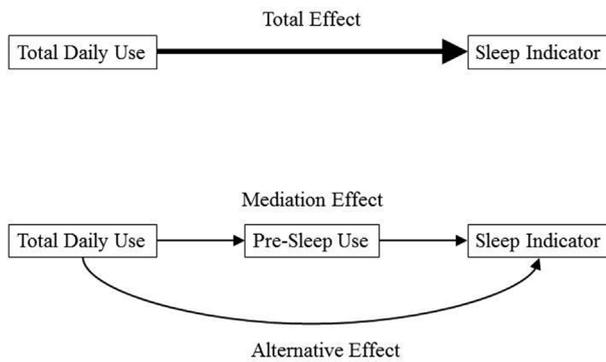
### 2.4. Statistical analysis

We herein applied product method for mediation analysis to investigate the effects of total daily smartphone use on sleep through pre-sleep use. Here pre-sleep use is viewed as a particular independent pattern of smartphone use before sleep from and affected by daily smartphone use. According to a previous study, smartphone use duration represents the distortion of time perception for an individual (Lin et al., 2015). A participant with longer duration of daily smartphone use had severer time distortion compared with the actual use duration. Therefore, the daily duration can be viewed as the severity of time distortion and loss of control for time management in the daytime. In contrast, pre-sleep time indicates a time in which people are more relax. Similarly, the pre-sleep smartphone use represents a similar measurement before sleep. We here hypothesize the loss of control in daytime will affect the loss of control in pre-sleep time, which construct the first causal relationship between the exposure and mediator shown in Fig. 3. Consider a setting with an exposure (A), mediator (M), and outcome (Y) measured at a single time. Total duration of daily smartphone use is the exposure and pre-sleep use is the mediator in this study. PS<sub>1</sub> and PS<sub>1-3</sub> represented different extent of pre-sleep smartphone use, and we examined these two parameters as parallel mediators. Three sleep indicators recorded by App – SO<sub>App</sub>, WT<sub>App</sub> and TST<sub>App</sub> – are the outcome variables. Through mediation analysis, the total effect of daily smartphone use on sleep was decomposed into the mediation effect (the effect through the pre-sleep smartphone use) and the alternative effect (the effect not through the pre-sleep smartphone use). Because the pre-sleep smartphone use is most directly relevant to TST<sub>App</sub> in time series, and the pre-sleep smartphone use is the critical part of total daily smartphone use. Therefore, pre-sleep smartphone use plays the role of mediator in the impacts of total daily smartphone use on sleep indicators and its effect is the mediation effect or direct effect. In contrast, the effect not through the pre-sleep smartphone use is the alternative effect or indirect effect.

Three regression models were built and fitted for mediation analysis, as follows:

$$Y = \theta_0 + \theta_1 A + \varepsilon_Y$$

$$Y = \beta_0 + \beta_1 A + \beta_2 M + \varepsilon_Y$$



**Fig. 3.** Causal relationship among total duration of daily smartphone use, pre-sleep use, and sleep. The causal relationship among total duration of daily smartphone use, pre-sleep use, and sleep is hypothesized. Sleep is the outcome of interest, indicated by three measurements – App-generated sleep onset (SO<sub>App</sub>), App-generated midpoint of sleep (MoS<sub>App</sub>) and App-generated total sleep time (TST<sub>App</sub>). Pre-sleep use is viewed as an particular independent pattern of smartphone use before sleep from and affected by daily smartphone use. Through mediation analysis, the total effect of daily smartphone use on sleep was decomposed into the mediation effect (the effect through the pre-sleep smartphone use) and the alternative effect (the effect not through the pre-sleep smartphone use).

$$M = \alpha_0 + \alpha_1 A + \epsilon_M$$

Where  $\alpha_1$ ,  $\beta_1$ ,  $\beta_2$ , and  $\theta_1$  are coefficients in these regression models. The unstructured variance-covariance matrices of residuals ( $\epsilon_Y$  and  $\epsilon_M$ ) were assumed in order to adjust the correlation among repeated measurements of the same individual. We calculated the total effect, mediation effect, and proportion mediated as following formula:

$$\text{Total Effect (TE)} = \theta_1$$

$$\text{Mediation Effect (ME)} = \alpha_1 \times \beta_2$$

$$\text{Proportion Mediated} = \text{ME/TE (100 \%)}$$

Individuals’ sleep time, pre-sleep use and total duration of daily smartphone use continuously undergo changes. In the present study, these daily variables were repeatedly generated by the App “Know Addiction”, therefore it is not possible to treat such measurements as fully independent of the participants. In other words, there will be auto-correlative association between every App-generated parameter obtained from a given participant, and such App-generated parameters need to be treated as a “random effect” within the same participant. In this model, the coefficients for the association between the sleep indicators and pre-sleep use or daily smartphone use were treated as “fixed effects.” Compared with Conventional regression analysis in which there is an assumption that all observed data are mutually independent of each other, the linear mixed model is more reasonable when analyzing such data and is powerful enough to deal with both the

repeated measurements obtained from individuals and the fixed/random effects contained within them.

The procedure PROC MIXED in SAS 9.4 was used to implement the mixed model. A *p* value < 0.05 was considered statistical significant.

### 3. Results

The average total daily smartphone use duration of the participants was 5.73 ± 3.42 h with 61.3 ± 43.18 episodes per day.

Participants average 2.58 ± 2.49 pre-sleep episodes within 1 h prior to sleep, which accounts for 4.2% of total daily duration. The duration of the last three pre-sleep episodes (PS<sub>1–3</sub>) is 49.1 ± 58.2 min, which accounts for 14.3% of total daily duration (5.73 h). The duration of the last pre-sleep episode (PS<sub>1</sub>) is 21.8 ± 37.6 min, which accounts for 6.3% of total daily duration.

The average App-recorded sleep onset starts at 01:18 and ends at 07:45 with the midpoint of sleep at 04:32 and total sleep time 6.45 h. The overlap ratio is 83.0 ± 14.3% between self-reported and App-recorded sleep time.

Table 1 shows the total effects of total daily smartphone use, the mediation effects of pre-sleep use and its proportion mediation to sleep indicators. Total daily duration of smartphone use was significantly correlated with delayed sleep onset (estimate: 0.0808, 95% confidence interval [CI]: 0.0434 ~ 0.1182), midpoint of sleep (estimate: 0.0578, 95% CI: 0.0264 ~ 0.0891) and reduced total sleep time (estimate: -0.0912, 95% CI: (-0.1272 ~ -0.0553)). The mediation effects of the last three pre-sleep episodes duration (PS<sub>1–3</sub>) also significantly impacted on these three sleep indicators. Whereas, only the mediation effects of the last pre-sleep episodes duration (PS<sub>1</sub>) significantly delayed midpoint of sleep. The proportion mediated by PS<sub>1</sub> and PS<sub>1–3</sub> accounted for 6.3% and 14.3% of total daily duration, but the proportion mediated of delayed circadian rhythm (midpoint of sleep) were 14.1% and 44.0%.

### 4. Discussion

To our knowledge, this is the first study to propose a sophisticated approach to demonstrate the impacts of smartphone screen time and the mediation effects of bed-time use on sleep. We found that smartphone use before bedtime delayed the sleep onset, circadian rhythm, and decreased total sleep time, and these findings were consistent with results in previous experimental studies (Cajochen et al., 2011; Chang et al., 2015) and meta-analysis (Carter et al., 2016). Furthermore, our research in naturalistic settings offers a way to characterize the longitudinal variability of circadian rhythm and light exposure of smartphone, and our methods compensate the critical shortcoming in previous experimental studies. For example, the bias of self-reports might resulted from distorted time perception (Lin et al., 2015). Therefore, this paper introduces digital chronotype, data generated passively from day to day interaction with smartphone, as a means to facilitate large-

**Table 1**

Total effects of total daily duration and mediation effects of pre-sleep use and its proportion mediated to sleep indicators.

| Model<br>Exposure → Mediator → Outcome      | Mediation Effect |                      | Total Effect |                      | Proportion Mediated |
|---|------------------|----------------------|--------------|----------------------|---------------------|
|   | Estimate         | (95% CI)             | Estimate     | (95% CI)             |                     |
| TD → PS <sub>1</sub> → SO <sub>App</sub>    | 0.0074           | (-0.0004 ~ 0.0152)   | 0.0808       | (0.0434 ~ 0.1182)*   | 9.2%                |
| TD → PS <sub>1–3</sub> → SO <sub>App</sub>  | 0.0287           | (0.0176 ~ 0.0398)*   | 0.0808       | (0.0434 ~ 0.1182)*   | 35.5%               |
| TD → PS <sub>1</sub> → MoS <sub>App</sub>   | 0.0081           | (0.0013 ~ 0.0149)*   | 0.0578       | (0.0264 ~ 0.0891)*   | 14.0%               |
| TD → PS <sub>1–3</sub> → MoS <sub>App</sub> | 0.0254           | (0.0157 ~ 0.0351)*   | 0.0578       | (0.0264 ~ 0.0891)*   | 44.0%               |
| TD → PS <sub>1</sub> → TST <sub>App</sub>   | -0.0057          | (-0.0135 ~ 0.0021)   | -0.0912      | (-0.1272 ~ -0.0553)* | 6.2%                |
| TD → PS <sub>1–3</sub> → TST <sub>App</sub> | -0.0109          | (-0.0214 ~ -0.0004)* | -0.0912      | (-0.1272 ~ -0.0553)* | 11.9%               |

\**p* < 0.05 indicate a significant effect on outcomes (sleep indicators). Abbreviations: TD, total duration of daily smartphone use; 95% CI, 95% confidence interval; PS<sub>1</sub>, the duration of last pre-sleep use; PS<sub>1–3</sub>, the duration of three pre-sleep uses; SO<sub>App</sub>, App-generated sleep onset; MoS<sub>App</sub>, App-generated midpoint of sleep; TST<sub>App</sub>, App-generated total sleep time.

scale epidemiological research. In this study, barring demographics and self-reported sleep time used to validate App-recorded sleep indicators, all App-generated parameters were objective, passive, and continuously recorded. However, it is noteworthy that we did not directly manipulate participants' screen-time to examine these impacts on sleep indicators. Neither did we controlled potentially influencing variables, such as day-time activities, environment illumination and light exposure other than smartphone. Instead, we only assessed their smartphone activity and sleep/inactivity with mediation analysis in naturalistic setting.

We examined both “sleep onset” (i.e.  $SO_{App}$ ) and “midpoint of sleep” (i.e.  $MoS_{App}$ ) as the sleep indicators because we were not only aware of the limitations of sleep time recorded by smartphone in this naturalistic setting, but also broadened these indicators to delineate individual's circadian rhythm since the revolutionary data type with temporal resolutions differed from data collection in conventional research. The  $MoS_{App}$  not only represented “deep sleep time” but also the time point with most inactive online-behaviors. Both implications contribute to delineate an individual's circadian rhythm and chronotype. The last pre-sleep smartphone use duration significantly delayed the midpoint of sleep but not sleep onset. The  $SO_{App}$  should refer to the time going to bed, or “lights off time” rather than physiological sleep onset. The physiological sleep onset is the lights off time plus sleep latency, which can only be accurately measured by polysomnography. However, light-emitting electronic devices use before bedtime is well-known to prolong the sleep latency (Chang et al., 2015), with the effect size of eszopiclone treatment on sleep latency in patients with primary insomnia (Krystal et al., 2012). Therefore, the  $SO_{App}$  was not significantly delayed by the last pre-sleep smartphone use, but the midpoint of sleep, which included the effects of prolonged sleep latency and more suitable to represent the circadian rhythm was significantly delayed.

There are several implications regarding the finding of the last three pre-sleep use episodes ( $PS_{1-3}$ ) delaying  $SO_{App}$  and reducing  $TST_{App}$  more significantly than the last pre-sleep use episode alone ( $PS_1$ ). First, the frequent and short duration use of smartphones made the single episode not representative of pre-sleep use. Similarly, we delineated the compulsive smartphone use parameters by one non-use episode corresponded to three successive use episodes (Lin et al., 2017d). In our previous study, this use/non-use parameter was the most consistent parameter with psychiatrists' clinical diagnosis. Second, participants averaged  $2.58 \pm 2.49$  pre-sleep episodes within 1 h prior to sleep onset, and the average duration of  $PS_{1-3}$  were 49.1 min. These results supported the last three episodes being representative of pre-sleep use. Third,  $PS_1$  and  $PS_{1-3}$  accounted for 6.3% and 14.3% of total daily duration, but the proportion mediated of delayed circadian rhythm ( $MoS_{App}$ ) were 14.1% and 44.0% respectively. This is the first study to estimate the proportion mediated of pre-sleep smartphone use to delay circadian rhythm despite mounting evidence from countries around the world showing total daily screen time (Hale and Guan, 2015) and pre-sleep electronic device use delayed circadian rhythm (Carter et al., 2016). The duration of pre-sleep use longer than the average duration of daily use episode resulted from the fact that individuals felt more relaxed to use their smartphone before bedtime. However, this pre-sleep light exposure negatively affected sleep and circadian timing, and this impact accounted for nearly half (45%) of the impact of total daily screen time.

Chronic circadian dysregulation has recently been implicated in the increased risk of breast, colorectal, and advanced prostate cancer associated with night-shift work (Costa et al., 2010), and has now been classified as a probable carcinogen by the World Health Organization (Erren, 2010; Straif et al., 2007). Circadian disruption has also been associated with some psychiatric disorders, such as bipolar disorder, major depression, and schizophrenia. For example, the onset of relapse for patients with bipolar disorder has been linked to circadian disturbance (Benedetti et al., 2008; Frank et al., 2000). Also, circadian rhythm disruption has become one of the most common symptoms

reported by patients with schizophrenia (Peirson and Foster, 2015). Although there were a significant number of studies, it may be difficult for patients with psychiatric disorders to record their daily sleep patterns in clinical practice. Digital chronotype, generated from the passive data collected by this App with a validated sleep pattern estimation in this study, could assist patients and clinicians in detecting the changes of circadian rhythm more easily and detect the relapse or onset of mental illness earlier. However, our algorithm to determine sleep time could not deal with sleep interruption with proactive smartphone use nor poor sleep quality. Future studies should adjust and validate this algorithm for patients with sleep disturbances. Therefore, the concept of digital chronotype in the present study was adopted from the Munich ChronoType Questionnaire (MCTQ) (Roenneberg et al., 2003), which estimates chronotype as the midpoint of sleep time. However, there are also other methods can assess chronotype, such as using the Morningness-Eveningness Questionnaire (MEQ) (Horne and Ostberg, 1976), which evaluates psychological preference for behavior. Although the previous studies found chronotype estimated by the MCTQ and the MEQ have reasonable convergence (Kantermann et al., 2015; Zavada et al., 2005), future studies should integrate and evaluate different elements of chronotype (e.g. midpoint of sleep time, diurnal preference, etc.).

There are several methodological limitations that should be noted when interpreting our findings. Firstly, the study utilized a sample with excessive smartphone use (average daily smartphone use duration: 5.73 h/day) and eveningness chronotype (average sleep onset at 01:18, midpoint sleep time at 04:32, and total sleep time: 6.45 h), which limits the ability to generalize these findings. Secondly, we only used smartphone screen time to estimate sleep and light exposure. Although smartphone is the most portable screen device near bedtime, our findings may not replicate in individuals who do not use smartphone as the predominant screen device. Thirdly, we did not further identify the purpose of smartphone use. There are thousands of mobile health Apps, including Apps to improve sleep quality or ameliorate insomnia (Anthes, 2016). Fourthly, the basic elements of App-generated parameters, i.e. screen-on, screen-off and notification, could be automatically recorded in Android operation system. Therefore, it may bias the data, if different systems of smartphone users would differ in certain psychological traits. Fifthly, we did not stratify gender and age because the size of subgroup will be too small to verify the model. In addition, we did not have information about participants' socioeconomics composition and health status, which may be important in interpreting our results. Such characteristics should be collected in any future study. Although we collected users'  $SO_{App}$  and  $WT_{App}$  during weeknights and weekend nights, and tried to validate the App-recorded sleep time by comparing the overlap between  $TST_{self}$  and  $TST_{App}$ , the validation of users' sleep time might not still accurate enough. Hence, it may impact our findings. We also consider using polysomnography or actigraph to validate sleep time measurement in our future study. Using smartphone use data combined with a “smartwatch”, which gathers other physiological parameters, may also give broader information about digital chronotype. Furthermore, the data collection was conducted in naturalistic settings, so we did not ask the participants if they used their smartphone as alarm clock in the bedroom (Montag et al., 2015). It might potentially impact the validity of the results. Finally, there may be multiple time-varying exposures responsible for the delayed circadian rhythm besides screen time. More sophisticated causal inference analysis should be addressed to the methodology challenges (Lin et al., 2017a; Lin et al., 2017b; VanderWeele and Tchetgen Tchetgen, 2017; Zheng and van der Laan, 2017). The amount, duration, and intensity of light exposure may impact chronotype predominantly. The future research may combine our technology with physiological measurement (e.g. serum melatonin level, delta power in electroencephalography) to better evaluate the underlying mechanism between different zeitgebers and chronotype. The current study estimates sleep time based on only a very few information about the participants' smartphone use (e.g.

screen-on and screen-off), but this kind of study may still has potential risk to involving information security issues such as misuse. Future studies for tracking this kind of data must be designed with caution.

In conclusion, we presented “digital chronotype” with an automatic system that can collect high temporal resolution data from naturalistic settings with high ecological validity. Smartphone screen time, mainly mediated by bedtime use, delayed the circadian rhythm and reduced the total sleep time. The technology we used in the present study can record sleep time automatically via App. It can avoid recall bias of self-report and provide a more objective, convenient, and time-saving way to record sleep time day by day. With automatically recording, the clinicians could have opportunity to obtain longitudinal data for computing circadian rhythm.

### Author contributions

Yu-Hsuan Lin, M.D., Ph.D.: Contributed to conceptualize and design the study, analysis and interpretation of data, drafting the article, and final approval of the version to be published.

Bo-Yu Wong, B.S.: Contributed to analysis and interpretation of data, drafting the article, and final approval of the version to be published.

Sheng-Hsuan Lin, M.D., Sc.M., Sc.D.: Contributed to analysis and interpretation of data and final approval of the version to be published.

Yu-Chuan Chiu, M.D.: Contributed to revising the article critically for important intellectual content, and final approval of the version to be published.

Yuan-Chien Pan, M.S.: Contributed to analysis and interpretation of data, drafting the article, and final approval of the version to be published.

Yang-Han Lee, Ph.D.: Contributed to programing support, data collection, and final approval of the version to be published.

### Potential conflicts of interest

The authors declare no conflict of interest.

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### Role of the sponsor

The supporters had no role in the design, analysis, interpretation, or publication of this study.

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