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Time distortion associated with smartphone addiction: Identifying smartphone addiction via a mobile application (App)

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A B S T R A C T

Background: Global smartphone penetration has brought about unprecedented addictive behaviors.
Aims: We report a proposed diagnostic criteria and the designing of a mobile application (App) to identify smartphone addiction.
Method: We used a novel empirical mode decomposition (EMD) to delineate the trend in smartphone use over one month.
Results: The daily use count and the trend of this frequency are associated with smartphone addiction. We quantify excessive use by daily use duration and frequency, as well as the relationship between the tolerance symptoms and the trend for the median duration of a use epoch. The psychiatrists' assisted self-reporting use time is significant lower than and the recorded total smartphone use time via the App and the degree of underestimation was positively correlated with actual smartphone use.
Conclusions: Our study suggests the identification of smartphone addiction by diagnostic interview and via the App-generated parameters with EMD analysis.

1. Introduction

The excessive use of smartphones has emerged as a significant worldwide social issue as smartphone penetration has increased. Smartphone addiction consists of four components, tolerance, withdrawal, compulsive symptoms, and functional impairment in our previous factor analysis of Smartphone Addiction Inventory (Lin et al., 2014), which are all variants on aspects of Internet addiction (Block, 2008); this is because a main characteristic of the smartphone is the use of Internet-based applications. However, the portability of the smartphone distinguishes smartphone use from “traditional” Internet use via a computer and this results in different symptoms for smartphone addiction and internet addiction (Lin et al., 2014). It is accepted that a significant degree of time distortion is one of the addictive properties of internet use (Greenfield, 1999) and based on this, side information of an individual's smartphone use is necessary when carrying out a clinical assessment. However, frequent short-period smartphone use is very hard to estimate according to the reports of others. Thus a mobile application (App) that automatically detects smartphone use is likely to improve the accuracy of any assessment of smartphone addiction. On the other hand, two core symptoms of addiction, compulsion and tolerance, which are manifest as an increase in smartphone use, are based on the use time estimation. However, fluctuations in smartphone use usually consist of

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multiple periodic components, and may increase in a non-stationary and/or non-linearly manner. Empirical mode decomposition (EMD) analysis using the Hilbert Huang Transformation provides an adaptive algorithm that is able to decompose a complex time series of smartphone use into a set of intrinsic oscillations, which are called intrinsic mode functions (IMFs); these oscillate at different time scales and are orthogonal to each other (Huang et al., 1998; Wu et al., 2007). The aims of this study are: firstly, to develop and validate proposed diagnostic criteria for smartphone addiction based on interviews by psychiatrists; second, to examine the relationship between smartphone addiction and the parameters generated by the App using novel EMD analysis, as well as two other criteria relevant to time estimation, excessive use and tolerance; and thirdly, to test the differences between actual and self-aware smartphone use time. We hypothesize that time distortion, which has been explored with online game players (Rau et al., 2006), will play an important role, not only in the underestimation of smartphone use, but also will affect reliability and validity when identifying smartphone addiction.

2. Methods

2.1. Participants

In total, 79 young adults were recruited from the Department of Electrical Engineering and Department of Computer and Communication Engineering of two universities in Northern Taiwan between December 2013 and May 2014. The recruitment strategy was based on the potential higher penetration rate of smartphone use among these students. Of these, 57 were male and 22 were female, with a mean age of 22.4 ± 2.3 years. All participants in this study used a smartphone with an Android operation system. They installed a novel App on their smartphones that recorded their smartphone use for at least three weeks. After the researchers had checked the App data, the participants were interviewed by the psychiatrist. The study was approved by the Institutional Review Board of National Taiwan University Hospital. The investigation was carried out in accordance with the latest version of the Declaration of Helsinki.

2.2. Procedures

First, we propose diagnostic criteria for smartphone addiction. The psychiatrists' diagnostic interview validated each candidate criterion of smartphone addiction by their clinical global impression (CGI). The sensitivity, specificity, and diagnostic accuracy of candidate diagnostic criteria were evaluated between the CGI-positive and CGI-negative groups. The diagnostic accuracy indicated the percentage of all correct decisions, which is the result of dividing the number of true positives and true negatives by the number of all decisions. The candidate diagnostic criteria with low diagnostic accuracy were excluded from further analyses. The cutoff point of the diagnostic criteria to differentiate the smartphone-addictive subjects with non-addictive ones was then determined by the best diagnostic accuracy and the receiver operating characteristic curve (ROC). Finally, the diagnostic criteria for smartphone addiction were constructed. Thus, the participants were classified as smartphone addicts or non-addicts based on the criteria.

Next, we examined the relationship between smartphone addiction and the App-generated parameters. The "smartphone addiction" determined by the criteria was a binary variable, whereas the App-generated parameters were continuous variables. We used the ROC analysis to identify which App-generated parameters can predict the smartphone addiction. Similarly, we examined which App-generated parameters can predict two criteria relevant to time estimation, tolerance (criterion 3) and excessive use (criterion 7). We demonstrated the differences between actual and self-aware smartphone use time in order to interpret the role of underestimation in the diagnosis of smartphone addiction.

2.3. Diagnostic criteria for smartphone addiction

We developed twelve candidate diagnostic criteria to identify the characteristic symptoms of smartphone addiction based on the Diagnostic Criteria of Internet Addiction for College Students (DC-IA-C) (Ko et al., 2005, 2009) and on the research diagnostic criteria of Internet gaming disorder in Diagnostic and Statistical Manual of Mental Disorders (DSM-5) (American Psychiatric Association, 2013). Three qualified psychiatrists, Lin YH, Lin PH and Chang LR, experienced in substance-related disorder and Internet addiction made a CGI with respect to the existence of smartphone addiction according to their clinical experiences and the concepts of addiction proposed by West (2001). The inter-rater reliability was evaluated by the Fleiss-kappa approach. Next, the sensitivity, specificity, and diagnostic accuracy of the twelve candidate diagnostic criteria for smartphone addiction were evaluated between the CGI-positive and CGI-negative groups.

2.4. Designing the mobile application (App) for recording smartphone use

A smartphone addiction App was designed and implemented for the Android operating system and after this App is implemented on a smartphone it operates in the background without interrupting normal smartphone communication. The App records all smartphone behaviors such as power on, call in, call out, program on, clock alarm, screen on/off notification, etc. The App saves all recorded behavior data in a log file. Using the MATLAB program the log file data was analyzed and debugged and only the screen-on and screen-off behavior data was saved after the MATLAB operation. An epoch starts from screen on and ends at screen off. The daily use count (frequency) and the total daily time spent on the smartphone (duration) are obtained from the data. We then calculated the median of the duration per epoch, rather than the mean of the duration per epoch every day; this is because the duration of the epoch does not present as a normal distribution (Fig. 1). The deployment of the App lasted for at least three weeks and we validated the fact that the App did not have a significant impact on the battery life of the participant phones. All the participants were blinded to the locally stored records in order to decrease the effects of "biofeedback", which might result in self-recognition and control. Instead, the usage records were archived at the server database. The three psychiatrists were also blinded to the App records to avoid confounding the clinical global impression.

2.5. Empirical mode decomposition (EMD) and the trend in smartphone use

A powerful data analysis method for nonlinear and non-stationary data has been developed by Huang et al. (1998). This technique, known as the Hilbert–Huang Transform (HHT), is based on empirical mode decomposition (EMD) and the Hilbert Transformation. Unlike Fourier-based time series analysis, EMD holds no a priori assumption as to the underlying structures of the time series and is therefore suitable for analyzing time series that consist of multiple periodic components. The decomposition is based on the simple assumption that any data consist of a finite number of

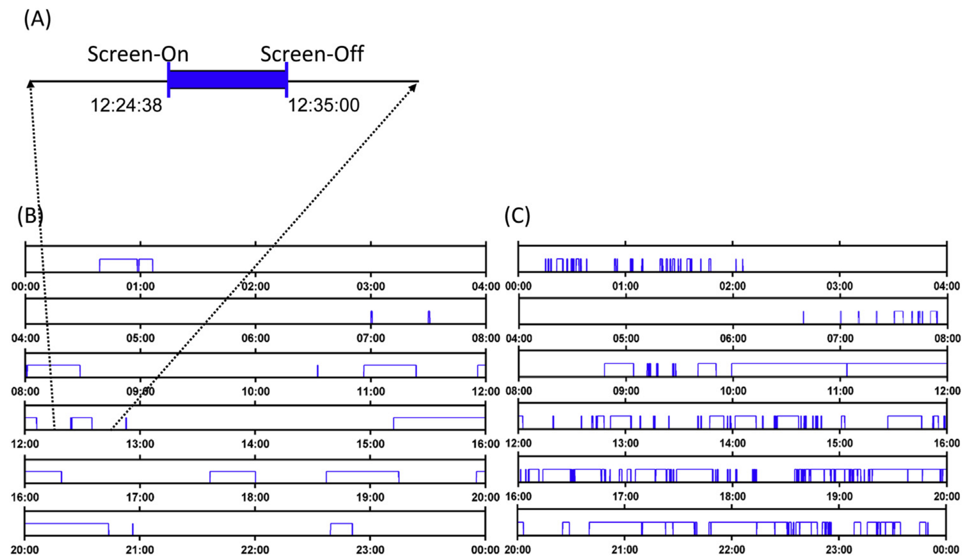

Fig. 1. The raw data of smartphone use for one day. (A) An epoch starts with the screen-on (from 12:24:38) and ends with the screen-off (12:35:00). The duration of this epoch is 622 s. (B) One-day raw data in a non-addictive subject identified by the psychiatrist: there are 19 epochs in this day (frequency = 19) and the total duration of the 19 epochs is 25,121 s. Among the 19 epochs, the epoch with the median duration is magnified into (A), that is, the median duration is 622 s (C) an addictive subject with the frequency: 211, duration: 26,562 s and the median: 283 s.

intrinsic components or oscillations. Each oscillation component, termed an intrinsic mode function (IMF), is sequentially decomposed from the original time series by a sifting process (Huang et al., 1998; Wu et al., 2007).

Briefly, the sifting process is comprised of the following steps: (1) connecting local maxima or minima of a targeted signal to form the upper and lower envelopes by natural cubic spline lines, respectively; (2) extracting the first prototype IMF by estimating the difference between the targeted signal and the mean of the upper and lower envelopes; and (3) repeating the above procedures to produce a set of IMFs that are represented by a certain frequency-amplitude modulation at a characteristic time scale. The decomposition process is completed when no more IMFs can be extracted, and the residual component (not an IMF) is treated as the overall trend of the raw data. Although IMFs are empirically determined, they remain orthogonal to one another and should therefore have independent physical meanings that are relevant to other parameters.

In the present study, the intrinsic trends of three basic App-generated parameters were calculated via EMD, these were frequency (F-trend), duration (D-trend) and median (M-trend). Fig. 2 shows the decomposition of smartphone use by the EMD method, using daily median use duration as the example. The decomposition of the raw data yielded a total of three IMFs and a residual (overall trend). A publicly available EMD algorithm based on Matlab software (version 2007; The MathWorks, Natick, Massachusetts, U.S.A) was used in this study.

2.6. The association between the self-reporting and App recorded smartphone use

The psychiatrists asked participants how many hours did they spend on their smartphone on average during a weekday, and then asked if there was any difference between their weekday and weekend use; this was then used to estimate the total duration of the participants' smartphone use. If the participants thought their use pattern was too frequent to estimate the total duration, the psychiatrists would help the participants to recall what were the majority of Apps they had used, that is social networking, etc. If the participants still could not estimate their smartphone use, they were coded as "frequent usage, very hard to estimate".

We investigated the association between the psychiatrists' assisted self-reporting (D_{self}) and the App recorded total smartphone use time (D_{App}) by Pearson's correlation and examined the differences by paired t-test. We further calculated the differences

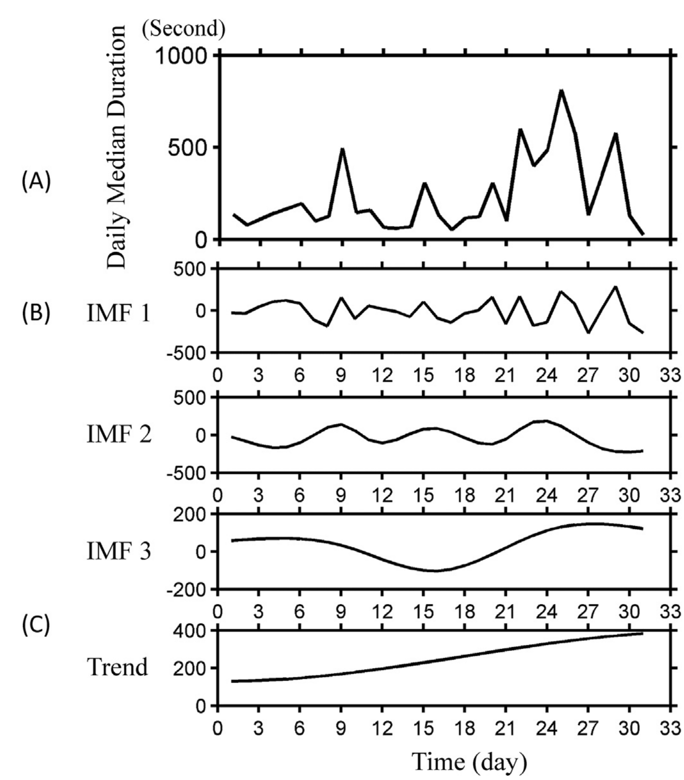

Fig. 2. Example of decomposition using the empirical mode decomposition method: (A) Time series of daily median smartphone use duration over 33 days (B) The input is raw data and it is outputted as intrinsic mode functions (IMF1-3) (C) Residual component (overall trend).

(ΔD) between the self-reporting (D_{self}) and the App recorded (D_{App}) total smartphone use duration, i.e. $\Delta D = (D_{App} - D_{self})/D_{App}$. The correlation between ΔD and D_{App} was also examined.

2.7. Smartphone addiction and the relevant App-generated parameters

We used the definition of smartphone addiction by the proposed criteria as the gold standard to examine the potentially relevant six App-generated parameters, frequency, duration, median, and their trends (F-trend, D-trend and M-trend) via EMD. To investigate the two time-relevant criteria and their associated App-generated parameters, "tolerance" (criterion 3) and "excessive use" (criterion 7) were used as the gold standard. In order to avoid the type I error, we only tested frequency and duration for "excessive use" and the trend for duration and median for "tolerance" according to the definition of criteria. Statistically, the "smartphone addiction", "tolerance" (criterion 3) and "excessive use" were binary variables. The App-generated parameters were continuous variables. We presented the area under the curve (AUC) of ROC with 95% confidence interval (CI). A C-statistics for the AUC of the parameters higher than 0.5 indicated that the App-generated parameter had potential diagnostic ability. We defined the significant prediction if the 95% CI of the AUC did not cross the 0.5, that is, the p-value was less than 0.05.

3. Results

3.1. Development of the proposed diagnostic criteria of smartphone addiction

The inter-rater reliability as evaluated by the mean of the Fleiss-kappa for twelve candidate diagnostic criteria ranged from 0.809 (criteria 3, "tolerance") to 0.952 (criteria 7, "excessive use"), while that for the interviewers' CGI was 0.864. As defined by the psychiatrists' CGI, 28 participants were classified as members of the CGI-positive group, while 51 participants were classified as members of the CGI-negative group. According to the psychiatrists' CGI as the gold standard, the specificity, sensitivity, and diagnostic accuracy for the twelve candidate diagnostic criteria for smartphone addiction are shown in Table 1. The diagnostic accuracy for the twelve candidate diagnostic criteria ranged from 64.6% to 83.5% (Table 1). The diagnostic accuracies of criterion 8 (68.4%), criterion 10 (68.4%), criterion 11 (64.6%), and criterion 12 (68.4%) were relatively low compared to the diagnostic accuracy of the other eight criteria, which ranged from 69.6% to 83.5%. Therefore, the four diagnostic criteria with the lowest diagnostic accuracies were excluded from the study at this point.

The remaining eight criteria formed the diagnostic criteria for smartphone addiction. The number of characteristic symptoms within criteria A needed to make a diagnosis of smartphone addiction was further analyzed using diagnostic accuracy and ROC analysis (Table 2). The results reveal that a cutoff point of either three or four criteria showed the best diagnostic accuracy (87.3%). When functional impairment (Criterion B) is added, a cutoff point of three demonstrated a higher diagnostic accuracy (91.1%) than a cutoff point of four (88.6%). In addition, the sensitivity increased to 92.9% and the specificity increased to 90.2% when the cutoff point was three. The proposed diagnostic criteria for smartphone addiction are listed in Table 3.

Criterion A consists of the eight characteristic symptoms of smartphone addiction and Criterion B describes the functional impairment that is secondary to smartphone use and subjective distress this causes (Table 3). According to the proposed diagnostic criteria for smartphone addiction, 31 participants were diagnosed as having smartphone addiction (the addictive group), and 48 were found not to have smartphone addiction (the non-addictive group).

3.2. An examination of time distortion among smartphone users

The 79 participants who had installed the App were monitored for 29.9 ± 4.6 days. In total, 66 (83.5%) participants estimated how many hours they had spent on their smartphone per week with the psychiatrists' assistance during the diagnostic interview. Their daily use count (frequency) was 73.1 ± 43.8 times they switched the smartphone on, that is, the weekly use frequency was 511.7 ± 306.6 times. Their daily use time (duration) was 4.20 ± 2.06, that is, the weekly use duration was 29.39 ± 14.45 h. The other 13 individuals fell into the choice "frequent usage, very hard to estimate". The "frequent" users' daily use count (frequency) was found to be 63.1 ± 28.1 and their weekly use time was found to be 27.84 ± 15.55 h. No significant differences are present for frequency and duration between these two groups for these values ($p = 0.301$ and 0.745 respectively).

The estimation of time spent on a smartphone contributes to the diagnosis of smartphone addiction and therefore we investigated the association between the psychiatrists' assisted self-reporting (D_{self}) and App recorded total smartphone use time (D_{App}) among the 66 participants. The D_{self} (20.11 ± 12.40 h/week) is significantly lower than D_{App} (29.39 ± 14.45 h/week) ($p < 0.001$). There is a moderate positive correlation between D_{self} and D_{App} ($r = 0.456$, $p < 0.001$). ΔD is positively correlated to D_{App} ($r = 0.352$, $p = 0.004$), that is, as the participants use their smartphone more, the greater is the underestimation.

3.3. Smartphone addiction and the relevant App-generated parameters

We examined whether the App-generated parameters could predict the smartphone addiction by psychiatrists interview. The smartphone addiction is a binary variable, there are 31 participants in the smartphone addictive group, and 48 in the non-addictive group. Table 4 shows that among the six App-generated parameters, frequency and F-trend via EMD were significant associated with smartphone addiction with the AUC greater than 0.5, i.e. the p value less than 0.05. Similarly, we further examined the relationship between the App-generated parameters and the two criteria related to use estimation, namely "Excessive use (criterion 7)" and "tolerance (criterion 3)". These criteria respectively suggested the actual frequency, duration and the trend, but present with high and low inter-rater reliability and validity (diagnostic accuracy to psychiatrists' CGI) (Table 1).

When we examined the frequency and duration against the gold standard of "Excessive use (criterion 7)", 32 participants were found to be positive and 47 were found to be negative for this criterion. The AUC of ROC is 0.660 (95% CI: 0.538–0.783, $p = 0.016$) for frequency and the AUC of ROC is 0.616 (95% CI: 0.489–0.742, $p = 0.082$) for duration. The cutoff point for frequency of 68.35 shows the maximal sensitivity (65.6%) + specificity (66.0%) and the cutoff point for duration of 4.62 h daily shows maximal sensitivity (53.1%) + specificity (72.3%) for the "Excessive use (criterion 7)". In the same way, we examined the M-trend and D-trend against the gold standard of "tolerance (criterion 3)". A total of 27 participants were found to be positive and 52 were found to be negative for this criterion. The AUC of ROC is 0.654 (95% CI: 0.533–0.775, $p = 0.025$) for M-trend. The AUC of ROC is 0.616 (95% CI: 0.488–0.745, $p = 0.092$) for D-trend. The cutoff point for M-trend of −0.019 shows maximal sensitivity (77.8%) + specificity (57.7%) and cutoff point for D-trend of 0.072 shows the maximal sensitivity (77.8%) + specificity (57.7%) for the "tolerance (criterion 3)".

Table 1
Profile of the candidate diagnostic criteria for smartphone addiction.

Criterion		CGI-positive (N = 28)	CGI-negative (N = 51)	Sensitivity	Specificity	Diagnostic accuracy
A1	Preoccupation with smartphone use, and hence keeping smartphone available all day					
	Yes (22.8%)	11	7	39.3%	86.3%	69.6%
	No	17	44			
A2	Recurrent failure to resist the impulse to use the smartphone					
	Yes (29.1%)	19	4	67.9%	92.2%	83.5%
	No	9	47			
A3	Tolerance: a marked increase in the duration of smartphone use is needed to achieve satisfaction					
	Yes (34.2%)	16	11	57.1%	78.4%	70.9%
	No	12	40			
A4	Withdrawal: manifested as a dysphoric mood, anxiety and irritability after a period without smartphone use					
	Yes (31.6%)	16	9	57.1%	82.4%	73.4%
	No	12	42			
A5	Smartphone use for a period longer than intended					
	Yes (35.4%)	18	10	64.3%	80.4%	74.7%
	No	10	41			
A6	Persistent desire and/or unsuccessful attempts to cut down or reduce smartphone use					
	Yes (20.3%)	10	6	35.7%	88.2%	69.6%
	No	18	45			
A7	Excessive smartphone use and/or time spent on leaving the use					
	Yes (40.5%)	23	9	82.1%	82.4%	82.3%
	No	5	42			
A8	Excessive effort spent on smartphone use as much as he/she can do					
	Yes (49.4%)	21	18	75.0%	64.7%	68.4%
	No	7	33			
A9	Continued excessive smartphone use despite knowledge of having a persistent or recurrent physical or psychological problem caused by smartphone use					
	Yes (27.8%)	15	7	53.6%	86.3%	74.7%
	No	13	44			
A10	Use of the smartphone to escape or relieve a dysphoric mood (e.g. helpless, guilt, anxiety)					
	Yes (19.0%)	9	6	32.1%	88.2%	68.4%
	No	19	45			
A11	Loss of previous interests, hobbies and entertainment as a result of, and with the exception of smartphone use					
	Yes (17.7%)	7	7	25.0%	86.3%	64.6%
	No	21	44			
A12	Has deceived family members, therapists, or others regarding the time spent on smartphone use					
	Yes (8.9%)	5	2	17.9%	96.1%	68.4%
	No	23	49			
B1	Functional impairment					
	Yes (49.4%)	27	12	96.4%	76.5%	83.5%
	No	1	39			
B2	Excessive smartphone use causes significant subjective distress, or is time-consuming					
	Yes (28.8%)	15	3	53.6%	94.1%	79.7%
	No	13	48			

CGI: clinical global impression.

4. Discussion

To our knowledge, these are the first proposed diagnostic criteria for smartphone addiction. Since the Rosenhan experiment, there has been strong criticism of psychiatric diagnoses that largely rely on patients' reported experiences only (Rosenhan, 1973) and as a result more and more biomarkers for mental illness and its diagnosis have evolved over the past decades (American Psychiatric Association, 2013). This is also the first study to use a mobile App to identify the relevant App-generated parameters related to smartphone addiction using a novel EMD analysis approach. Our findings indicated the smartphone addiction was significantly associated with the trend of frequency via EMD.

The eight criteria used when constructing the smartphone addiction criteria all originated from DC-IA-C, and five criteria of these criteria, which overlap with the criteria from DSM-5, were retained. The only one criterion underwent major revision from DC-IA-C, while three other criteria that originated from Internet gaming disorder and DSM-5 were excluded in the present study. Smartphone addiction is similar to broad spectrum Internet addiction as defined by DC-IA-C rather than the specific Internet gaming disorder as defined by DSM-5; this is because smartphone use is characterized by the use of multiple Apps.

We have demonstrated the presence of time distortion, which has been explored previously among online game players (Rau et al., 2006). The underestimation of smartphone use can be

Table 2
Cutoff point for criteria A within the diagnostic criteria for smartphone addiction.

Cutoff point for criteria A	Sensitivity	Specificity	Diagnostic accuracy	Positive predictive rate	Negative predictive rate
1	100%	41.2%	62.0%	48.3%	100%
2	100%	64.7%	77.2%	60.9%	100%
3	92.9%	84.3%	87.3%	76.5%	95.6%
4	75.0%	94.1%	87.3%	87.5%	87.3%
5	42.9%	96.1%	77.2%	85.7%	75.4%
6	28.6%	96.1%	72.2%	80.0%	71.0%
7	17.9%	100%	70.9%	100%	68.9%

Table 3
Proposed diagnostic criteria for smartphone addiction.

A. Maladaptive pattern of smartphone use, leading to clinically significant impairment or distress, occurring at any time within the same 3-month period. Three (or more) of the following symptoms having been present:
1. Preoccupation with smartphone use, and hence keeping smartphone available all day
2. Recurrent failure to resist the impulse to use the smartphone
3. Tolerance: a markedly increase in the duration of smartphone use is needed to achieve satisfaction
4. Withdrawal: as manifested by a dysphoric mood, anxiety and/or irritability after a period without smartphone use
5. Smartphone use for a period longer than intended
6. Persistent desire and/or unsuccessful attempts to cut down or reduce smartphone use
7. Excessive smartphone use and/or time spent on leaving the use
8. Continued excessive smartphone use despite knowledge of having a persistent or recurrent physical or psychological problems caused by smartphone use

B. Functional impairment:
- B-1. Functional impairment: one (or more) of the following symptoms have been present
  - (1) Excessive smartphone use resulting in a persistent or recurrent physical or psychological problems
  - (2) Smartphone use in situations in which it is physically hazardous (e.g., smartphone use during driving, or cross the street)
  - (3) Has jeopardized or lost a significant relationship, job or educational/career opportunity because of smartphone use
- B-2. Excessive smartphone use causes significant subjective distress, or is time-consuming

C. Exclusion criteria
The smartphone addictive behavior is not better accounted for by obsessive–compulsive disorder or by bipolar I disorder.

applied to illustrate the low reliability and validity of tolerance as assessed by diagnostic interview. Tolerance is defined as “a marked increase in the duration of smartphone use is needed to achieve satisfaction”. Since the element “duration of use” may be underestimated, it is conceivable that any “increase in the duration” is likely to be quite unreliable without side information.

Our results are consistent with a previous pilot study, which showed smartphone addiction to be more associated with frequency rather than duration (Lee et al., 2014). In contrast, the literature has consistently showed that excessive time spent in terms of (computer) Internet use is an important risk factor or sign of Internet addiction (Ko et al., 2007) and that there is moderate correlation between the addiction score and the time spent on online-gaming (Smahel et al., 2008). Frequent short-period smartphone use may interfere with an individual's normal routine and thus decrease work efficiency (criterion B1-3), and this can occur even in situations that are physically hazardous, which is similar to the criteria for substance related disorder (American Psychiatric Association, 2013) (criterion B1-2). Texting, using the Internet and reaching for your phone all increase the risk of a motor vehicle crash or near-crash (Klauer et al., 2014). Among all substance and behavior addictions, these functional impairment symptoms are unique to smartphone addiction, and, more specifically, to frequent smartphone use.

Excessive use, including both excessive frequency and excessive duration, are both part of smartphone addiction. The cutoff point of more than 4.62 h daily suggests that the excessive smartphone use involves a lower level of usage than Internet addiction (Leung, 2004; Tao et al., 2010). It is noteworthy that individuals use a smartphone when they are doing something else at the same time, whereas online game player are highly preoccupied with their game. Nevertheless, relatively short periods of frequent use, which is similar to obsessive-compulsive disorder, may result in significant subjective distress or functional impairment.

There are several implications of our findings that the M-trend shows more significance in terms of identifying tolerance than the D-trend. Firstly, the results suggest that smartphone users find it easier to perceive the change in duration of a single epoch (M-trend) than total duration (D-trend) under the current gold standard of self-reported tolerance. Secondly, the cutoff point for the M-trend at highest sensitivity + specificity is around zero. This means that the participants were still able to sense the increase in duration of an epoch (median) over the past month. However, a trend for the other App-generated parameter may need to be detected over a longer record than one month, for example using our definition of an increase over the past three months. Thirdly, similarly, time distortion results in the total duration of smartphone use being underestimated. Nevertheless, we still consider both the M-trend and the D-trend to be valuable when identifying the tolerance symptom. Furthermore, we only tested the trend for total duration and for median duration because the definition of tolerance is “a markedly increase in the duration of smartphone use”. The modified definition “a markedly increase in the daily use count of smartphone use” and the F-trend, which are related to the CGI of smartphone addiction, may be useful way of elevating the diagnostic accuracy of tolerance.

There are several methodological limitations that should be noted when interpreting our findings. Firstly, the sample contained only college students, which limits the generalization of the findings; furthermore, a larger sample size is needed to confirm the proposed diagnostic criteria. Second, the epoch of smartphone use is recoded as the screen on to off by the App and more information, such as how many Apps are used, and what kind of Apps the participants use, should be identified in a future study. Thirdly, the fact that the App records for one month may not be enough to allow detection of trends in some significant App-generated parameters. Finally, psychiatrists did not have the side information available during the interview, which is the gold standard in the present study. The App-generated parameters relevant identified in the preset study related to smartphone addiction will be useful references when identifying smartphone addiction in the future.

In conclusion, our study indicates the time distortion effect resulted in differences in reliability and validity between excessive use and tolerance. These core symptoms, excessive use and an increased use trend can be measured by the App and analyzed by novel EMD analysis making them critical to identify smartphone addiction.

Table 4
Receiver operating characteristic (ROC) analysis of the App-generated parameters using the proposed diagnostic criteria for smartphone addiction.

App-generated parameters	Area under the curve (95% CI)	*p*-value
Frequency	0.633 (0.506–0.760)	0.047
F-trend	0.631 (0.507–0.755)	0.050
Duration	0.607 (0.476–0.738)	0.110
D-trend	0.534 (0.401–0.667)	0.609
Median	0.581 (0.454–0.708)	0.228
M-trend	0.571 (0.444–0.689)	0.287

We applied the empirical mode decomposition (EMD) to delineate the trends in the three basic parameters, frequency (F), duration (D) and median (M) use time. CI = confidence interval.

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None.

Contributors

Y.-H. Lin, S.-H. L., and P.-H. L. designed research; Y.-H. Lin, P.-H. L. and L.-R. C. developed and carried out the diagnostic interview; Y.-H. Lee and H.-W. T. performed research; Y.-C. L., C. C-H. Y. and T. B-J. K. contributed new analytic tools; Y.-H. Lee, H.-W. T. and L.-Y. Y. developed the mobile Application; Y.-H. Lin, Y.-C. L. and S.-H. L. analyzed data; and Y.-H. Lin, C. C-H. Y., and T. B-J. K. wrote the paper.

Conflict of interest

None.

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