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Passive objective measures in the assessment of problematic smartphone use: A systematic review[☆]

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ABSTRACT

Research focussing on problematic smartphone use has predominantly employed psychometric tests which cannot capture the automatic processes and behaviours associated with problematic use. The present review aimed to identify passive objective measures that have been used or developed to assess problematic smartphone use. A systematic search was conducted using Web of Science, Scopus, PsychInfo and PubMed databases to identify passive objective measures that have been employed to assess problematic smartphone use, resulting in 18 studies meeting the inclusion criteria. Objective data that were monitored predominantly focussed on general screen usage time and checking patterns. Findings demonstrate that passive monitoring can enable smartphone usage patterns to be inferred within a relatively short timeframe and provide ecologically valid data on smartphone behaviour. Challenges and recommendations of employing passive objective measures in smartphone-based research are discussed.

1. Introduction

Technological advances within the last decade have led to a significant increase in mobile technologies. The use of smartphones in particular has grown exponentially owing to the portability and connectivity that they allow, enabling access to information and entertainment content almost anywhere without the constraints of physical proximity or spatial immobility (Billieux, 2012; Geser, 2004; Jeong, Kim, Yum, & Hwang, 2016). However, despite the positive affordances that smartphones can enable, prevalence studies have estimated rates of problematic smartphone use to range between 0% to more than 35% (Yen et al., 2009; Lopez-Fernandez, Honrubia-Serrano, Freixa-Blanxart, & Gibson, 2014). Research has indicated that the excessive use of smartphones can lead to negative outcomes in terms of psychopathology (Elhai, Dvorak, Levine, & Hall, 2017), academic settings (Samaha & Hawi, 2016), poor sleep quality (Demirci, Akgönül, & Akpinar, 2015; Chung et al., 2018) and physical health (Kim, Kim, & Jee, 2015), subsequently leading to increasing concern surrounding the addiction of smartphones. Yet, despite the increase of research in regards to smartphone addiction, it is not classified within the DSM-5 or draft of the ICD-11 (Panova & Carbonell, 2018).

As a result, there is no definitive definition or conceptualisation of smartphone addiction, and with notably few papers aiming to clarify nosological questions regarding smartphone addiction, there is an increasing tendency to utilise non-pathological terminology (Bae, 2017). Studies that support the existence of smartphone addictions tend to do so on the belief that smartphone addiction and smartphone usage time are tightly coupled (Shin & Lee, 2017), or if they fit within the component model of addictive behaviours as posited by Griffiths (2005), including the criteria salience, mood modification, tolerance, withdrawal symptoms, conflict and relapse. Subsequently, terms including 'excessive' or 'overuse' of smartphone and 'problematic' smartphone use have been adopted in addition to, or instead of, smartphone addiction to describe the manifestations of problematic usage and maladaptive behaviours associated with the term (Panova & Carbonell, 2018; Tossell, Kortum, Shepard, Rahmati, & Zhong, 2015), whilst problematic habitual use of smartphones (i.e., unconscious automatic urges to check smartphones) has also been employed to explain problematic smartphone behaviour (Oulasvirta, Rattenbury, Ma, & Raita, 2012; Van Deursen, Bolle, Hegner, & Kommers, 2015). To further complicate conceptualisation, internet-based applications such as messenger, social media and online gaming are becoming continuously more synonymous with smartphone usage (Giunchiglia, Zeni, Gobbi, Bignotti, & Bison, 2018; Liu, Lin, Pan, & Lin, 2016), with the portability of smartphones enabling constant connectivity and accessibility to online functions. In particular, research has shown both mobile gaming and higher levels of

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social media to be predictors of smartphone addiction (Salehan & Negahban, 2013; Liu et al., 2016), highlighting the role of online-based applications in the risk of problematic smartphone behaviour.

Nonetheless, the lack of consensus within the field surrounding the conceptualisation of smartphone addiction is problematic as it can influence and potentially misguide research, assessment and treatment of the issue. Whilst there is no other accepted term for a behaviour that manifests the presentation of features such as lack of self-control and increased use, extending the term 'addiction' to conditions that may be better described as problematic or maladaptive may undermine both the integrity and the severity of disorders that genuinely warrant it (Panova & Carbonell, 2018), and suggests that utilising non-pathological terminology is beneficial until smartphone addiction as a disorder entity is clarified. With this is mind, the current review therefore employs the term 'problematic smartphone use' to encompass the behaviours associated with the phenomenon (Pivetta, Harkin, Billieux, Kanjo, & Kuss, 2019). It is important to note that although research often indicates that excessive smartphone use can lead to problems for the user (Ellis, 2019), there are a number of benefits that are also afforded, such as increased social connectedness and information accessibility (Kang, Ha, & Hambrick, 2015; Stawarz, Preist, & Coyle, 2019). Therefore it is likely that outcomes of smartphone usage are proportional to exposure of the device, with too little usage depriving users of social information, and too much usage leading to the negative conclusions often reported (Pryzbylski & Weinstein, 2017). Nevertheless, the detrimental results of smartphone usage have led to greater impact on public opinion, with the World Health Organisation (WHO, 2015) considering excessive mobile phone use as a public health concern. This highlights the importance of establishing an operationalised definition to ensure consistency within research and to allow for a more comprehensive understanding surrounding its aetiology (Kuss et al., 2018).

In terms of assessing problematic smartphone use, much research has predominantly focused on correlational research involving psychometric tests, quantifying experiences with technology, as opposed to assessing actual problematic smartphone behaviour (Ellis, 2019). Self-report instruments assessing smartphone addiction often adopt proxy measures of usage (e.g., the Smartphone Addiction Scale; SAS; Kwon et al., 2013), using high-scores to correlate smartphone usage with negative outcomes (e.g., Boumosleh & Jaalouk, 2017; Jasso-Medrano & Lopez-Rosales, 2018) to provide evidence of behavioural addiction (Ellis, Davidson, Shaw, & Geyer, 2019). However, self-report measures are not always suitable when assessing unconscious behaviours, in addition to dynamically and naturally occurring changes in behaviours, making it difficult to advance in the conceptual understanding of problematic activities (Bentley, Kleiman, Elliott, Huffman, & Nock, 2019; Ellis, Kaye, Wilcockson, & Ryding, 2018). A recent review by Ellis (2019) highlighted that current self-report measures of smartphone addiction do not correlate or predict simple objectively measured behaviours, and although some self-report assessments and duration estimates may correlate with objectively measured time spent on smartphones, this relationship is still rudimentary when operationalizing smartphone use (Boase & Ling, 2013). Since self-report assessments predominantly evaluate conscious measures, it is likely that that the cognitive and automatic processes that are related to problematic smartphone use (e.g., compulsivity) cannot be captured via these tools. In particular, frequent short smartphone use is hard to estimate retrospectively, and may result in distorted time perception by the user (Lin, Lin, Lee, Lin, Lin, Chang, & Tseng, 2015), indicating that self-reports are likely more beneficial in investigating the expectancies associated with smartphone behaviour (Ellis et al., 2018), as opposed to capturing these behaviours retrospectively.

Smartphone-based assessments, which allow data to be collected directly through smartphone devices, can enable the monitoring of participant behaviour in real time. This objective monitoring of behaviours is increasingly employed within research in an attempt to overcome the aforementioned methodological problems, enabling the ability to gather precise, sustained and ecologically valid data on smartphone behaviours and experiences (Miller, 2012). Perhaps the most widely used real-time monitoring is ambulatory assessment (AA), which encompasses an *active* form of monitoring, for example, ecological momentary assessment (EMA) and experience sampling, which involve momentary self-reports through electronic diaries, in addition to pen and paper diaries and beepers, respectively (Trull & Ebner-Priemer, 2014). These methods can deliver near real time assessment by providing information on behaviours of interest as they naturally occur, subsequently minimising retrospective and heuristic biases that may distort recollections of experiences and behaviour (Trull & Ebner-Priemer, 2014; Bentley et al., 2019). However, although AA methods have been found somewhat beneficial in assessing smartphone usage (Deng et al., 2019; Esmaeili Rad & Ahmadi, 2018), self-report EMA still predominantly relies on explicit respondent input, which does not eliminate biases, such as social desirability. Furthermore, it has been shown that EMA compliance rates erode significantly across two weeks of data collection (Stone, Shiffman, Schwartz, Broderick, & Hufford, 2002), indicating that if applied for too long, the response burden may negatively affect the validity of response rates and measurements (Asselbergs et al., 2016).

Passive objective monitoring on the other hand is the collection of data unobtrusively, without active data entry by the participant, allowing for continuous data collection over longer periods of time (Asselbergs et al., 2016; Bentley et al., 2019). Data involving smartphone usage patterns, such as screen time, social media activity and application (app) usage can be collected, which can be beneficial in monitoring proxies of mental health, such as behavioural patterns and contextual triggers (Asselbergs et al., 2016). Indeed, recent research utilising passive monitoring has demonstrated that it is possible to predict users' affective states through smartphone notifications (Kanjo, Kuss, & Ang, 2017), highlighting the influence smartphone technology can have on mood and wellbeing. More generally, recent reviews evaluating passive monitoring have demonstrated how real-time measurement can facilitate assessment of dependent variables more accurately and in a less intrusive manner in comparison to self-report measures (Bentley et al., 2019; Cornet & Holden, 2018). Indeed, smartphone recorded parameters have a higher temporal resolution in comparison to self-reports, allowing fluctuations in smartphone behaviour to be detected (Markowetz, Błaszkiewiscz, Montag, Switala, & Schlaepfer, 2014). The implementation of passive monitoring may therefore not only contribute to the debates surrounding problematic smartphone use conceptualisation, but also provide further validation of existing self-report scales to establish behavioural correlates of diagnostic criteria (Ellis et al., 2018). At present however, there has been no review that evaluates passive objective measures in the context of problematic smartphone use, which is a gap in knowledge that this paper aims to fill.

The present review aims to identify objective measures that have been used and/or developed to assess problematic smartphone usage, with a focus on passive monitoring as opposed to active monitoring. Since active monitoring can largely rely on respondent input, the usage patterns that passive data can provide may deliver more comprehensive information on behavioural patterns when compared across studies, which may, in turn, highlight similarities and differences in terms of problematic smartphone behaviours and the conceptualisations of the phenomenon. Therefore, the present paper aims to (i) identify objective measures that assess problematic smartphone usage, and (ii) summarise the characteristics, strengths and limitations of objective measures for assessing problematic smartphone use.

2. Method

The review process was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analysis statement (PRISMA; Moher, Liberati, Tezlaff & Altman, 2009). To identify papers for review, an extensive search was performed using Web of Science, Scopus, PsychInfo and PubMed databases. These databases were searched using the following search terms: (smartphone OR mobile) AND (addict*OR compuls* OR excess*) AND passive AND (measure* OR track* OR assess*OR app*); (smartphone OR mobile) AND (addict*OR compulsive OR excessive) AND (objective OR real-time OR app*); (smartphone OR mobile OR social network* OR social media) AND (addict*OR compulsive OR excessive) AND behavi* AND passive AND (measure* OR tracking OR assess* OR app*) and (smartphone OR mobile OR social network*) AND screentime* AND (measure* OR tracking OR assess* OR app*). References of collected articles were also scanned for additional studies. Studies were included if they were i) published in English, (ii) published in a peer-reviewed journal, (iii) included *passive* smartphone-based assessment (i.e., the collection of data without active data entry by the user, such as the measurement of either length of time spent on device and/or number of times device is picked up), and (iv) included problematic smartphone use as a variable within the study. Papers were excluded if (i) objective measures used were a form of *active* smartphone-based assessment (e.g., ecological momentary assessment [EMA], experience sampling methodology [ESM] or ambulatory assessment [AA]), as these approaches typically rely on self-reported accounts of behaviour, facilitated through prompts and initiating responses to questions into a mobile device; (ii) used psychometric tests without conjunction of a passive objective measure and (iii) did not make reference to problematic smartphone usage (e.g., used objective assessment in the context of other addictive behaviours, such as alcohol or drugs, in addition to healthcare, i.e., if apps described are based on interventions as opposed to assessment. Although objective in nature, these do not capture behavioural markers/ patterns in the context of smartphone addiction. The title and abstract of each study were screened for eligibility. Full texts of potentially relevant studies were consequently retrieved and examined for eligibility. The search strategy is detailed in Fig. 1.

3. Results

A total of 5390 studies (Web of Science $n = 863$; Scopus $n = 979$; PsychInfo $n = 3185$; PubMed $n = 363$) were initially identified. Identified duplicates were removed ($n = 3026$), leaving 2364 studies for evaluation. The title and abstracts of these papers were screened, resulting in the exclusion of 1862 that were of no relevance, and a total of 502 studies which were eligible for further review. A further 489 papers were consequently excluded as they did not conceptualise smartphone use ($n = 104$), did not contain an objective measure ($n = 48$), only implemented psychometric tests ($n = 310$), the objective measure used was *active*-based assessment ($n = 9$), or they were review papers ($n = 15$). Two relevant studies were also identified through reference lists. Information extracted from each study focussed primarily on (i) sample characteristics (e.g., study size, age, sex and geographical location), (ii) methodology used, including measures implemented (e.g., psychometric measures or interviews used in conjunction with objective measures), and (iii) the application used or developed to measure behaviour objectively, in addition to how the application measured behaviour (e.g., through screen-time, and length of app use). A total of 18 studies were subsequently identified as relevant from the literature. These studies are presented in Table 1.

The results section will outline the following: firstly, the methodology of studies including the demographics of the samples included, in addition to the time period of data collection. Following this, an overview of the applications that were employed within the studies and the smartphone functions that they were able to monitor, such as usage time and frequency of use, will be addressed. Lastly, the manner in which these features assess components of problematic smartphone usage will be discussed.

3.1. Methodology of studies

3.1.1. Demographics

The majority of the included studies consisted of samples recruited from academic settings, predominantly undergraduate university students (e.g., Felisoni & Godoi, 2018; Wilcockson, Ellis, & Shaw, 2018), whilst two studies recruited participants through a polling company and Android market place respectively (Choi et al., 2017; Shin & Dey, 2013). Sample sizes ranged between 27 and 238 participants (Ellis et al., 2019; Wilcockson et al., 2018), whilst the age of participants ranged between 18 and 31 years old (Shin & Lee, 2017; Ellis et al., 2019). Samples were predominantly mixed, consisting of both males and females.

3.1.2. Time period of data collection

In terms of length of time used to assess smartphone use, time periods ranged between seven days (Elhai et al., 2018; Prasad et al., 2018; Rozgonjuk, Levine, Hall, & Elhai, 2018) to a year (Tossell et al., 2015) to collect objective data. It was suggested by Giunchiglia et al. (2018) that the two weeks used to assess behavioural data were a relatively small time-frame in comparison to other studies in computational social sciences, whilst Lin et al. (2015) indicated that data collection for one month may not be sufficient enough to detect trends in some app generated parameters. In contrast, whilst findings by Shin and Dey (2013) demonstrated that smartphone usage observed was indicative of users' routine across an average of 3.5 weeks, it was suggested by the authors that longer term data collection would be more insightful in terms of changes in smartphone usage regarding contextual changes (e.g., differences/changes in users' schedule).

Arguably, alternative findings suggested that a minimum of five days is sufficient to reflect weekly smartphone usage, whilst habitual checking behaviours can be reliably inferred within 48 h (Wilcockson et al., 2018). In addition, Pan, Lin, Chiu, Lin, and Lin (2019) assessed smartphone use for a longer time frame and found that a two week smartphone use duration was a sufficient fundamental time unit to infer a two month period of use. These findings indicate that whilst data collection using passive monitoring over a longer time frame can be beneficial in providing richer information (Shin & Dey, 2013), a longer time period of objective data collection may not be necessary, dependent on the smartphone functionalities that are observed and the behaviour assessed.

3.2. Objective measures of smartphone usage

The objective measures employed collected similar data across all studies. All applications had the functionality to monitor the usage time spent on smartphones generally, in minutes or hours or via screen on/ off (Shin & Lee, 2017; Elhai et al., 2018; Ellis et al., 2019; Felisoni & Godoi, 2018; Lee, Han, & Pak, 2018; Prasad et al., 2018; Rozgonjuk et al., 2018). Applications that were employed and the functions that they monitored are detailed in Table 2.

Applications which were readily available via Apple and Android app stores (detailed below) were predominantly usage management applications, designed to assist smartphone users in understanding and regaining control of their smartphone usage. More specifically, applications such as 'Callistics' and 'Moment' also include features such as organisation of call minutes or messages and enabling phone-free time as part of their functionality. These features however, were not focussed within studies; rather, features that focused on mobile usage behaviours (such as incoming and outgoing calls, or time spent on apps) were assessed. This excluded any explicit input by the user, ensuring that data collection remained as passive monitoring. Likewise, of the applications constructed, these were developed to measure smartphone usage in terms of usage patterns deduced by monitoring features such as app launches and screen on/ off frequency (e.g. Lee et al., 2015; Montag et al., 2015). None of the bespoke applications were specifically

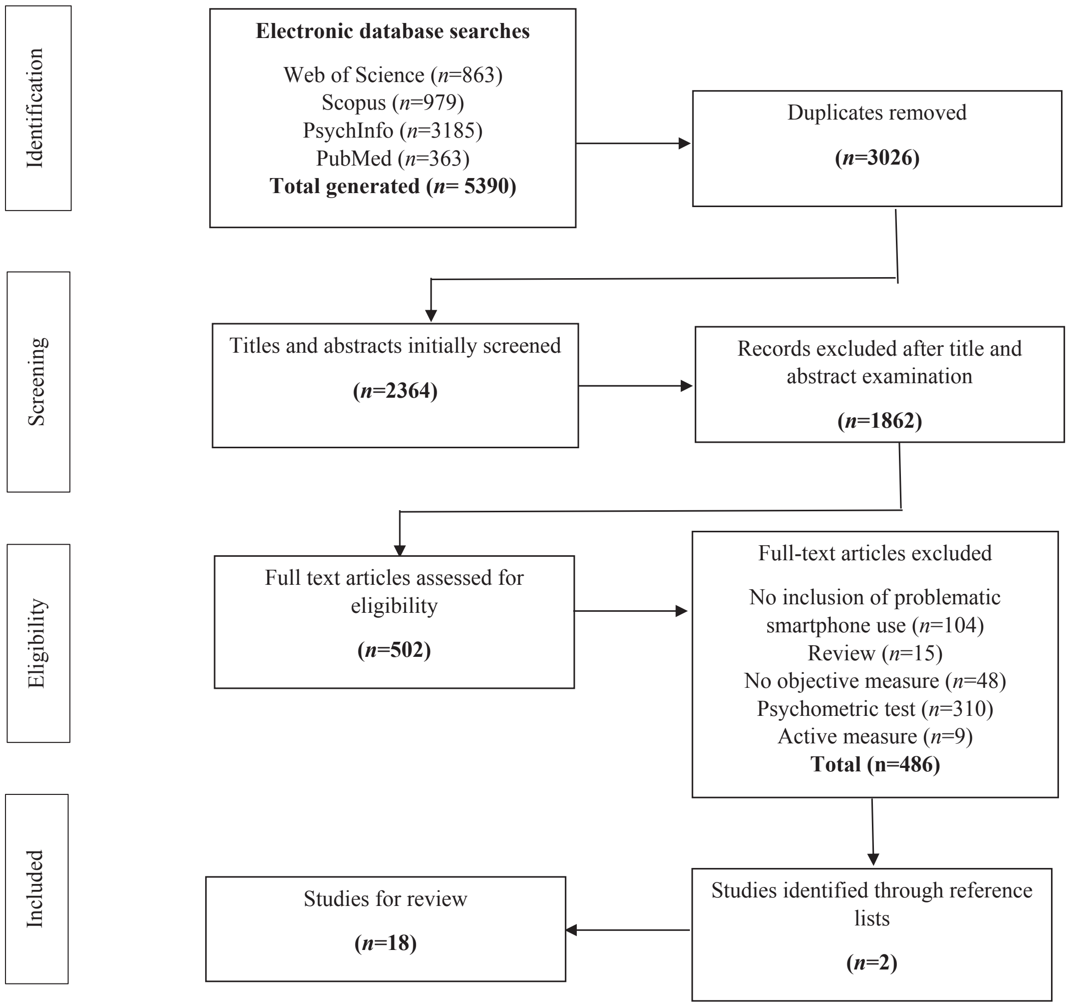

Fig. 1. Search strategy.

developed to measure problematic smartphone use, but rather to assess usage and patterns of smartphone behaviour. All applications that were employed within the present studies were identified as passive objective measures, as they ensured unobtrusive data collection, without explicit data entry by the participants.

Eleven studies developed custom applications to measure behavioural smartphone usage (Choi et al., 2017; Giunchiglia et al., 2018; Lee et al., 2014; Lee, Ahn, Nguyen, Choi, & Kim, 2017; Lin et al., 2015; Lin, Lin, Chiang et al., 2017; Montag et al., 2015; Pan et al., 2019; Shin & Dey, 2013; Tossell et al., 2015; Wilcockson et al., 2018). The remaining seven studies implemented applications that were either a feature already available on the smartphone or downloadable from the Android or Apple app stores. These applications included the 'Moment' app (Apple iOS; Elhai et al., 2018; Rozgonjuk et al., 2018), 'App Usage tracker' (Android; Felisoni & Godoi, 2018; Shin & Lee, 2017), 'Callistics', 'Instant' (Android; Prasad et al., 2018), 'How Often Do You Use' (Lee et al., 2018) and Apple's 'Screen Time' feature on the iOS system (Ellis et al., 2019). For the 'Moment' and 'App Usage Tracker' applications, usage time spent on the smartphone was the only functionality that was monitored, computed when the smartphone is locked and unlocked (Elhai et al., 2018; Felisoni & Godoi, 2018; Prasad et al., 2018; Rozgonjuk et al., 2018; Shin & Lee, 2017). To utilise additional functionalities, 'Callistics' and 'Instant' were also employed by Prasad et al. (2018), which monitor the number and duration of calls made and received from the smartphone, in addition to keeping track of the duration spent on all apps, and the number of locks/unlocks on the smartphone, respectively. The 'Screen Time' feature and 'How Often Do You Use' applications on the other hand contained multiple functionalities to monitor different aspects of smartphone usage in addition to usage time. These included the number of notifications received, the number of times the device was picked up, the number of times the app was launched and data on the most frequently used apps (Ellis et al., 2019; Lee et al., 2018).

In terms of the applications that were developed, these were similar to the pre-existing applications available in regards to their functionality and the measures of behavioural data collection. Out of the eleven apps developed, six monitored smartphone usage time, in addition to functions such as when the smartphone was switched on or off, application data (e.g., internet/game monitoring), smartphone pickups/checks, notifications, screen status information and most used social media apps (Choi et al., 2017; Giunchiglia et al., 2018; Lee et al., 2014, 2017; Shin & Dey, 2013; Wilcockson et al., 2018). Screen on and off episodes were measured in three studies to assess usage patterns (Lin et al., 2015; Lin, Lin, Chiang et al., 2017; Pan et al., 2019). In these three studies, screen on to successive screen off were defined as one epoch or episode of use, the average count of which was then calculated to provide the frequency of use (Lin et al., 2015; Lin, Lin, Chiang et al., 2017; Pan et al., 2019). Time-stamps during monitoring was also used in three studies (Montag et al., 2015; Tossell et al., 2015; Wilcockson et al., 2018); when application launches occurred on the smartphone (Tossell et al., 2015), when the phone became active and inactive (Wilcockson et al., 2018), in addition to all events being monitored (e.g., calls, screen lock/unlock and length of app use; Montag et al., 2015).

Table 1
Overview of included studies.

Authors	Design and Sample	Aims	Method	App used/developed Objective measurement of behaviour	Findings	Strengths/limitations
Choi et al. (2017)	41, 683 logs of 48 smartphone users collected from March 8, 2015 – January 8, 2018. For each participant, log data were collected for an average of 15.8 days. 48 participants from South Korea recruited by polling company Hankook Research, Inc. (aged between 20 and 39 years, *mean age and SD not reported;* 60.42% male) 25 participants were in their 20 s (control group = 11 and addiction group = 14), 23 participants were in their 30 s (control group = 12 and addiction group = 11). There were 29 males (control group = 17 and addiction group = 12) and 19 females (control group = 6 and addiction group = 13).	To derive usage patterns that were directly correlated with smartphone dependence from usage data, including apps and timeslots. Also to predict smartphone dependence through data-driven prediction algorithm.	Analysis procedure consisted of: 1. Collection of smartphone usage log data 2. Derivation of smartphone usage patterns via tensor factorisation (a reduction method to derive meaningful concepts from high dimensional data) 3. Prediction of smartphone dependence based on the patterns Data collected over period of ten months (March 2015- January 2016). Korean Smartphone Addiction Proneness Scale for Adults (S-Scale) and interview with psychiatrist and psychologist (using Korean version of Mini International Neuropsychiatric Interview (MINI) also implemented- used to classify control group and addicted group.	"Smartphone Overdependence Management System" (Developed) Supports only Android phones. Monitoring achieved through 4 main 'sessions'. – For collection of mobile device usage data this was done in the 'Sensoring & Monitoring Session'; Mobile data usage collected included general phone usage, e.g., when phone is turned on/off and general app data (internet, SNS and game monitoring) - exact usage time and period logs monitored through background app.	Usage patterns and membership vectors are effective tools for the assessment and prediction of smartphone dependence.	Limitations: The 6 indicators that were developed and used to assess smartphone overdependence were only developed for internet dependence. App used was only available for Android phones. Strengths: Tensor factorisation can obtain meaningful patterns from large-scale data.
Felisoni and Godoi (2018)	43undergraduate students from Business Administration of Fundação Getúlio Vargas in São Paulo, Brazil (*mean age and SD not reported;* 46.5% male)	To investigate whether increasing smartphone usage among college students has a significant impact on their academic performance.	Both survey (personal information, self-efficacy while learning and usage perception) and objective data (through apps) collected. Questionnaire also included Self-Efficacy for Self-Regulated Learning (SE:SRL scale) to assess student ability to self-regulate in learning related activities. Academic performance for the college entry exam for each student was obtained through Undergraduate's Office used as a predictor for academic performance in college Objective data collected across 14 days.	"Moment" (iPhone) and "App Usage Tracker" (Android) Usage time is only computed when cell phones are unlocked, therefore does not include time checking time/notifications. Data collected contained total minutes on phone each day for two week period. Average usage time subsequently calculated.	Significant negative relationship between total time spent using smartphones on academic performance. Average usage time for men = 217.7 min per day Average usage time for women = 240.7 min per day	Direct measurement of usage as opposed to relying on self-report data; allows observation of students' natural behaviour during the day and to collect data unrelated to own bias. Allows automatic extraction of information from students' regular routine with least intervention possible.
Lee et al. (2017)	35 college students enrolled at a public University in the Metropolitan region of northeast Asia (mean age 22.3, *SD* = 2.4, 68.57% male)	To examine the similarity and variance in smartphone usage patterns between measured and self-reported data.	Both survey (demographic information, smartphone addiction scale short version (SAS-SV) and smartphone usage patterns) and objective measure implemented. Objective data collected over 6 weeks.	'Smartphone Addiction Management System' (SAMS). (Custom app) Android phones. SAMS software runs in the background and measures which application, website or document is used. (Usage time, pattern and most used application types.)	Unconscious users underestimate their usage time. Findings show that there are significant cognitive biases in actual usage patterns in self-report of smartphone addictions.	Limitations: IT usage trends change rapidly, therefore continual and successive studies should be taken in a systematic way regularly. Ambiguity in time periods measured; definition of time period, e.g., evening/night can depend on personal life and culture. This should be clarified when considering life patterns of participants

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Table 1 (*continued*)

Authors	Design and Sample	Aims	Method	App used/developed Objective measurement of behaviour	Findings	Strengths/limitations
						Strength: The app implemented demonstrated that there is significant cognitive bias in actual usage pattern and self-report of smartphone addictions; participants reported favourite app and usage time did not match with their most used ones. (It is proposed by the authors that underestimate of real usage time may suggest the development of tolerance)
Lee et al. (2018)	125 students; most of which attended computer classes (49% male) *Age (mean and SD) and location not reported.* 64 participants agreed to participate in objective data collection. These data were combined with results of addiction on Smartphone Addiction Scale (SAS) with the final dataset.	To analyse smartphone addiction by considering the differences between smartphone usage patterns as well as cognition.	A standardised smartphone addiction self-diagnosis scale was used as the smartphone addiction self-diagnosis scale (based on SAS). Objective data collected over a period of a month, twice a week.	'How often do you use' Android system. Data was collected from the following items: total usage time, usage time by day, data usage, number of screen turns, usage time by app, number of executions by app and frequently used apps.	Average smartphone usage based on results is more than 6hr a day. There is significant cognitive bias between self-reports and behavioural data. The higher the 'recurrence' item, the higher the addiction. The number of times screen was turned on and/cognitive time use had the greatest influence in higher risk users.	Combination of self-report and smartphone data can improve the accuracy of data and ensuring data reliability from respondents. Smartphone usage data is beneficial to be mined for useful correlations. Only 64 participants agreed to participate in objective measures from the original 125 respondents.
Lin, Lin, Lin, et al. (2017)	79 young adults recruited form the Department of Electrical Engineering and Department of Computer and Communication Engineering of two Universities in northern Taiwan (mean age = 22.4 years, *SD = 2.3;* 72.15% male).	1. To develop parameter needed to assess use/non-use reciprocity (i.e., screen off to screen on, which indicates impaired control for smartphone use). 2. To examine the predictive ability of smartphone use, non-use and use/non-use parameters when making a problematic smartphone diagnosis.	Predominantly based on App developed. Data recorded across at least 3 weeks. Psychiatrists also determined whether individual participants were smartphone addicts or non-addicts using criteria consisting of three parts: Criterion A: eight characteristic symptoms of smartphone use Criterion B: functional impairment caused by smartphone use, or that causes distress Criterion C: excluded addictive behaviours that accounted for obsessive compulsive disorder or bipolar I disorders.	App developed by authors, to support data collection on Android phones. Smartphone use parameters: screen on to successive screen off was defined as one epoch of use; the app calculated the average daily epoch count for one month as the use frequency parameter. Smartphone non-use parameters: event from screen off to screen on was defined as one epoch of non-use. Defined as maximal non-use epoch between 21:00 h and 12:00 h. Use/non-use reciprocity: two parameters introduced to assess the reciprocity between use and non-use patters- Roots Mean Square of the Successive Differences (RMSSD) and Similarity Index.	App-generated parameters were more associated with the App-assisted diagnosis than with psychiatric interviews alone. Frequency of use and non-use demonstrated identical prediction in relation to problematic smartphone use diagnosis.	Strengths: The high predictive natures of RMSSD and the Similarity Index imply that use/non-use reciprocity is validated with respect to the compulsive symptoms of problematic smartphone use. Limitations: Any smartphone use epoch is recorded as screen on to screen off by the app- however the app is unable to distinguish between proactive and reactive use, which may have resulted in non-use parameters being more accurate when predicting problematic smartphone use that the use parameters. Smartphone use and non-use were defined as screen on and screen off; this cannot wholly represent the status of smartphone use
Lin, Chang et al. (2015)	79 young adults recruited form the Department of Electrical Engineering and Department of Computer and Communication	To develop and validate proposed diagnostic criteria for smartphone addiction based on interviews with	App recorded phone data across three weeks. Psychiatrist interviews also	App developed by authors to support data collection on Android phones. App operates in background to	Daily use count and frequency are associated with smartphone addiction (rather than duration). Self-reported time use was	Limitations: Further information such as how many and what kinds of apps are used were not looked at.

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Table 1 (*continued*)

Authors	Design and Sample	Aims	Method	App used/developed Objective measurement of behaviour	Findings	Strengths/limitations
	Engineering of two Universities in northern Taiwan (mean age = 22.4, *SD* = *2.3;* 72.15% male).	psychiatrists. To examine the relationship between smartphone addiction and the parameters generated by the app using EMD and criteria to excessive use, tolerance and time estimation. To test the differences between actual and self-aware usage time.	undertaken with participants, based on criteria of the Diagnostic Criteria of Internet Addiction for College Students (DC-IA-C) and Internet gaming disorder in DSM-5.	record smartphone behaviours e.g. power on, program on, calls in/out, alarm clock, screen on/off, notifications.	significantly lower than the recorded use via the app. Frequent short-period smartphone use may result in subjective distress or functional impairment. Excessive use- both frequency and duration - are part of smartphone addiction.	Data collection of one month may not be enough to allow for the detection of trends in some significant app-generated parameters. Strengths: Empirical mode decomposition (EMD) analysis was used, allowing for the ability of decomposing a complex series of smartphone use into a set of intrinsic mode functions.
Montag et al. (2015)	58 participants recruited through psychology and computer sciences classes (mean age = 24.22, *SD* = 5.02; 56.9% males)	To further support studies that indicate actual smartphone behaviour constitutes a better predictor for addictive tendencies that self-reported variables. To also investigate excessive mobile phone and smartphone behaviour.	App recorded phone data across five weeks. Participant also provided self-report of average mobile phone behaviour for a week, prior installing app, for comparison against actual usage and self-report – Mobile Phone Problem Use Scale (MPPUS)	Self-developed app 'Menthal'- (non-private version, which presents no feedback to the user). Records behaviour such as incoming/outgoing calls, screen lock/unlocked and length of app use. Also recorded call and SMS related variables and computed means for average use of variable on a weekly basis. All events were associated with a user-ID and timestamp.	Weekly phone usage in hours was overestimated, while call and text message variables were underestimate. Associations between actual usage and addiction to mobile phones could be derived from recorded behaviour, but not through self-report variables.	Strengths: Overall patterns and correlations between recorded and self-reported variable and mobile phone addiction scores demonstrate recorded behaviour is more strongly associated with addictive tendencies-potential benefits in diagnostic process by direct tracking of behaviours. Limitations: Did not monitor activities in social networking sites that may have been more strongly associated with smartphone addiction compared to the present variables. First week of data discarded due to possibility results may have been influenced by being observed
Pan et al. (2019)	33 adult participants (mean age = 29.48, *SD* = 10.44; 84.84% male).	To illustrate the time periods or span of weeks required to reliably infer patterns of long term smartphone use. To investigate how long could a smartphone use cycle perpetuate by assessing maximum time intervals (i.e., weeks) between two smartphone use periods. To validate smartphone use and use/non-use reciprocity parameters.	Self-report; The 5 item Smartphone Addiction Inventory (SPAI = 5). To assess smartphone addiction. Objective measure data collection across two months.	The 'Know Addiction' database. (Custom app) Measured smartphone use patterns; predominantly frequency and use duration. Parameters developed; root mean square of successive differences (RMSSD), control index (CI) and similarity index (SI) to indicate impaired control and compulsive behaviours. Episode of smartphone use defined as a time period from screen on to the successive screen off. App calculated daily episode count as total use frequency, and total daily episode lengths were calculated as total use duration.	Two week (bi-weekly) smartphone use is an adequate fundamental time unit to infer a two-month period of use. Significant correlation found between proactive use duration in two months and smartphone addiction; suggesting that self-reported smartphone addiction may correlate with long term duration than with short term use as indicated in previous studies. However this may be due to the adaptation of more app generated parameters within the current study.	Smartphone use episode was recorded as screen-on to screen off, providing an opportunity to distinguish between proactive and reactive use. The use/non-use parameters (RMSSD, SI and CI) allow the assessment of reciprocal patterns of smartphone use and may represent control ability of individuals; CI demonstrated better temporal stability than SI and RMSSD. Smartphone uses were defined as screen on/off, which cannot completely represent the status of smartphone use. Used a selective sample with excessive smartphone use; limited

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Table 1 (*continued*)

Authors	Design and Sample	Aims	Method	App used/developed Objective measurement of behaviour	Findings	Strengths/limitations
				Proactive use defined as one use episode without any notification within one minute before the screen on. Subsequently the proactive use frequency and proactive use duration were calculated.		generalisability. Different smartphone use patterns may generate identical values on the temporal stability on use/non-use parameters. E.g. frequent, .long use periods spread out in short intervals may generate similar CI with sparse use period with sporadic checking.
Prasad et al. (2018)	140 undergraduate and postgraduate students from a tertiary care hospital were recruited in India (mean age = 22.89, *SD* = 2.79; 50% male)	To evaluate psychological correlates and predictors of excessive smartphone use with a telemetric (objective) approach.	Both psychometric tests (including the Smartphone Addiction Scale) and objective measures (three apps). Objective data collected across seven days.	'Callistics'; 'App Usage Tracker'; 'Instant' Android phone only. Callistics'; tracks number and duration of calls made and received from device. 'App Usage Tracker'; tracks duration of minutes spent on all apps by the user- recorded in minutes and seconds. 'Instant'; keeps track of duration in minutes spent on all apps by the user-recorded in min. It also provides the number lock/unlock cycle an individual has performed on the phone over a certain time-frame.	SAS score significantly predicted time spent on a smartphone in a seven day period. Psychological factors predict overall smartphone usage as well as usage on individual apps. Predictors for time spent on social networking sites were ego resiliency, conscientiousness, neuroticism and openness.	Limitations: Unwillingness of participants to install apps to track usage and reset WhatsApp usage statistics. Exclusion of iOS/Windows users.
Rozgonjuk et al. (2018)	101 college students recruited from a Midwestern, U.S. public university. (mean age = 19.53, *SD* = 4.31, 76.2% female)	To investigate how self-reported levels of PSU, depression, anxiety and daily depressive mood relate to objectively measured smartphone use over one week	Implementation of both psychometric test (SAS) and objective measure. Objective data collected over period of one week.	'Moment'; Support iOS system only. Tracks usage of screen time (time phone screen is active and unlocked) and number of screen unlocks (unlocking phone).	Self-reported PSU was positively associated with the average minutes of screen time over a week, and that it positively predicted the minutes of screen time over a week in growth curve analysis. Phone screen locks could not be predicted from PSU scores. Self-reported PSU was not significantly related to the number of phone screen unlocks over a week.	Different types of smartphone usage measures e.g. screen time and screen unlocks could provide insight into PSU and negative mood from different perspectives. Time lag between web survey completion and participating in the week-long phone observation study, which may have influenced findings. Participants aware of smartphone usage being monitored, which may have increased self-criticism and self-monitoring in those with depression/anxiety monitoring, potentially influencing them to adjust smartphone usage downwardly over the study period.
Shin and Lee (2017)	195 undergraduate and graduate students from a university in Korea (age range 18–30 years, *mean age and SD not reported;* 63.59% males).	To discover the relationship between smartphone addiction diagnostic scale and smartphone usage patterns. To characterise smartphone addiction in terms of	Participant to install app and send average smartphone usage patterns to research. Also filled out modified version of	'Smartphone Usage Tracker' Android system only. Collects usage patterns; monitors the usage time of each individuals	Smartphone addiction is highly correlated with communication but not entertainment. Solely measuring total usage time is not enough to predict whether a smartphone user is addicted.	While smartphone usage is more accurate, it is limited in representing the multifaced nature of smartphone addiction. Usage time does not capture

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Table 1 (*continued*)

Authors	Design and Sample	Aims	Method	App used/developed Objective measurement of behaviour	Findings	Strengths/limitations
		categorial usage patterns of smartphone, and to discriminate smartphone addicts from non-addicts.	the smartphone addiction self-diagnosis scale (S scale).	app and averages them to get the total usage time per day		psychopathological symptoms, such as compulsive smartphone usage and interpersonal conflict, implying that measuring smartphone usage alone is not sufficient enough to predict smartphone addiction.
Tossell et al. (2015)	34 students from both a community college and university in Houston Texas. (*mean age and SD not reported;* 55.88% male)	To examine smartphone user behaviours and their relation to self-reported smartphone addiction through the use of both survey and telemetric data.	Quasi-experimental approach. Use of both survey (Smartphone Addiction Measurement Instrument (SAMI) and Internet Addiction Test and objective measure. Objective data collected over one year.	'LiveLAb' (Custom developed) Data captured every night. Data that was collected included all application launches, the duration of application launches, and when the application launches occurred (i.e. date/time stamps). Further information such as how many texts were sent/received and URL's visited on Safari, was also collected.	Addicted users demonstrated differentiated smartphone use as compared to users who did not indicate addiction. Addicted used spent twice as much time on their phone and launched application almost twice as often compared to the non-addicted user; mail, messaging, Facebook and the Web drove this use. Addictive users showed significantly lower time-per-interaction than non-addicts for the above apps.	The telemetric use data provides more depth and precision than typical survey = based research and helps to mitigate small sample sizes.
Wilcockson et al. (2018)	27 students and staff from the University of Lincoln (mean age = 22.52, *SD not reported;* 62.96% female)	To examine how much time should be spent measuring mobile phone operation to reliably infer general patterns of usage and repetitive checking behaviours, and whether self-report measures of problematic smartphone use is associated with real-time patterns of use.	Both psychometric test (Mobile Phone Problem Use Scale; MPPUS) and objective measure implemented. Objective data collected across 14 days.	Custom developed app through Funf in a Box framework. Android only. Provided timestamp when the phone became active, and a second when the activity stopped and phone became inactive-primarily that involved screen use, but also included processor intensive activities, e.g., calls and playing music. Two behavioural measures were generated by the end of the day: total hours of usage and the frequency of use. (Total hours of usage determined by the amount of time the phone was active, whilst frequency of use was measured by the number of smartphone checks.)	Smartphone usage collected for a minimum of five days will reflect typical weekly usage in hours, but habitual checking behaviours can be reliably inferred within two days. Objective measures did not reliably correlate with self-reported measure.	Relatively little data is required to quantify typical usage for longer periods of time. The first day of data collection was removed due to participant time differences when the app was installed, which may have implicated the inference of typical behaviour.
Ellis et al. (2019)	238 participants recruited from Lancaster, Bath and Lincoln universities and via Prolific Academic (mean age = 31.88, *SD* = 11.19, 52.10% female).	To compare the accuracy of ten smartphone usage scales and single estimates against objective measures of smartphone behaviour.	Self-report estimate on number of hours/minutes spent on smartphone daily, in addition to number of notification received daily and how many times they pick up their device each day. Psychometric tests (Mobile Phone Problem Use Scale; MPPUS, Nomophobia Questionnaire; NMP-Q, Possession Incorporation in the Extended Self, Attachment Scale, Smartphone Addiction	Apple's Screen Time App. iOS system only. Measure of number of hours and minutes spent on phone, number of notifications received and number of times device picked up.	Correlations between psychometric scales and objective behaviour are generally poor. Single estimates and measures that attempt to frame technology use as habitual as opposed to addictive correlate more favourably with subsequent smartphone behaviour.	Behavioural measures utilised were limited; use of daily tracking as opposed to finer temporal measurements based on hourly patterns of usage. System used allows participants to view their own data in real, which may have implicated correlation between self-report data and objective measure.

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Table 1 (*continued*)

Authors	Design and Sample	Aims	Method	App used/developed Objective measurement of behaviour	Findings	Strengths/limitations
			Scale; SAS, Smartphone Application-Based Addiction Scale; SABAS, Problematic Mobile Phone Use Questionnaire; PMPUQ, Media and Technology Usage and Attitudes Scale; MTUAS, Smartphone Use Questionnaires (SUQ-G&A). Objective measure implemented; data collected from a period of one week.			
Elhai et al. (2018)	68 college students from a Midwestern, U.S. university (mean age = 19.75, *SD* = 2.03, 64.70% female).	To examine smartphone use over the course of one week by employing a repeated measures design that allowed for direct tests of associations between depression severity and emotion regulation, in addition to the correlates involved in increased and problematic smartphone use.	Both objective measure and survey implemented: (self-report on frequency of smartphone features, Smartphone Addiction Scale-Short Version; SAS-SV, Patient Health Questionnaire-9; PHQ-9, Emotion Regulation Questionnaire; ERQ). Objective measure collected across one week.	'Moment'; Support iOS system only. Measures screen time actively used daily (time that phone is locked is not included)	Lower depression severity predicted increased smartphone use over a period of one week. Greater use of expressive suppression as an emotion regulation strategy predicted more baseline smartphone use, but less smartphone use during the week.	Strengths: Moment app ran in the background, therefore it is possible that that participants did not think/forgot that their smartphone use was being monitored, subsequently maintaining their regular use over the course of the week without bias or influence. Limitations: Similarly, participants were aware that their smartphone usage was being monitored, which may have implicated their smartphone use behaviour. Due to limitations on Moment app, data on specific types of smartphone features used over the week were not acquired.
Giunchiglia et al. (2018)	72 undergraduate students from the University of Trento, Italy (*mean age and SD not reported;* 61.1% male).	To define new metrics in representing social media use and using smartphones to both track app usage and to administer time diaries. To employ both time diaries and smartphone data to establish the correlation between social media usage and academic performance.	Objective data collection and time diaries through application used. Academic performance assessed with two measures: Grade Point Average (GPA)- the average grade of point student obtained during the semester. Represents qualitative dimension of academic performance. Credito Formativo Universitario (CFU) - course credits obtained by students for each exam taken. Represents quantitative dimension of academic performance. Data collection across two weeks.	'iLog' (Custom developed) Both data collection from multiple sensors (hardware- GPS, accelerometer, gyroscope) and software (in/out calls, apps running on device) and time diaries, consisting of three-sub questions on activities, location and social relations of students every 30 mins. Data included social media app usage (most used), screen status information (collection of data of apps that are running at the time at which they are running) and academic performance.	Social media app usage during academic activities (in terms of session and duration) is negatively associated with student academic performance.	Limitations: small time frame of two weeks. However in regards to time diaries this is more than usual (one week) allowing a bigger window to extract patterns from through this data Strengths: three different parameters defined (social media, usage and academic performance) - distinction allows capturing different types of usage patterns.
Lee, Lee, Ko, Lee, Kim,		To identify the usage patterns related to smartphone overuse	Survey (Smartphone Addiction Proneness Scale for Adults) and	'SmartLogger' Custom app. Android only.	Compared to non-risk group, risk group has longer usage time per day	Fine-grained usage features such as session time distribution exhibited

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Table 1 (*continued*)

Authors	Design and Sample	Aims	Method	App used/developed Objective measurement of behaviour	Findings	Strengths/limitations
Yang et al. (2014)	95 college students from university in Korea (mean age = 20.6, *SD* = 1.7, 70.5%)	and to provide several guidelines to facilitate the design of intervention software.	interview implemented in addition to objective measure. Data collected across an average of 27 days.	Logs active/inactive apps, touch and text input events, web browsing URLs and notifications, power on/off, screen on/off, calls and SMS.	and different diurnal usage patterns. Risk group more susceptible to push notification and tend to consume more online content. Usage time and frequency correlated to smartphone overuse.	consistent patterns across datasets. Allowed for unobtrusive monitoring that has minimal impacts on user behaviour.
Shin and Dey (2013)	48 participants recruited through local university community and Android market place (mean age = 26.7, *SD not reported;* 70.83% male).	To explore and automated, objective and repeatable approach for assessing problematic smartphone usage.	Psychometric assessments of addiction based on Mobile Phone Problematic Use Scale (MPPUS). Individual interviews. Objective measure. Objective data collected over a period of 25.1 days	Custom app. Android only. Collected sensory data, including apps that were installed and in use, battery usage, events and notifications and screen status data. Also extracted usage features of smartphones such as battery usage, network data usage, session usage (interval between screen turning on/off (a session indicates a unit of usage that involves app and event usage), app usage, touch inputs and push event usage (events sent form apps, e.g., new incoming SMS or email, upcoming events from calendar).	The number of apps used per day, ratio of SMSs to calls, event-initiated sessions, number of apps used event initiated session and length of non-event initiated sessions are useful in detecting problematic smartphone usage.	Strengths: Since the detection approach for problematic usage implemented is objected and automated, it can be repeated as frequently as desired. Also low inconvenience for the user and can detect problematic use after behaviour is exhibited. Limitations: Limited to Android users. Observation deemed relatively short (3.5 weeks average) - long term data may be more insightful in terms of changes in usage depending on context.

Table 2
Applications employed and features monitored.

		Times device picked up	Hours/mins on phone	Screen on/ off	Calls in/ out	SMS sent/ received	Web URL's	App launches	Most used apps	Length of app use	Notifications	Timestamps
Available through app store	Moment			✓								
	Callistics				✓					✓		
	App Usage Tracker			✓					✓	✓	✓	
	Instant			✓						✓		
	Smartphone Usage Tracker									✓		
	How Often Do You Use		✓	✓				✓	✓	✓		
	Apple Screen Time	✓	✓								✓	
Bespoke app	Smartphone Overdependence Management System			✓				✓		✓		
	Smartphone Addiction Management System		✓						✓	✓		
	Menthal			✓	✓	✓				✓		✓
	Know Addiction			✓							✓	
	LiveLab					✓	✓	✓		✓		✓
	Smartlogger			✓	✓	✓				✓	✓	
	iLog				✓			✓		✓		
	Unnamed (Shin & Dey, 2013)		✓	✓	✓	✓		✓	✓		✓	
	Know Addiction (Prototype) (Lin et al., 2015)			✓	✓						✓	
	Know Addiction (Prototype) (Lin, Lin, Chiang et al., 2017)			✓								
	Unnamed (Wilcockson et al., 2018)			✓	✓							✓

Consistent with the features of passive objective assessment, all applications employed within the present studies allowed for the collection of data without extra user input by the participants involved. Data collection was unobtrusive in nature, enabling a variety of smartphone interaction and behaviours to be assessed through functionalities such as screen time and screen locks/unlocks. A handful of studies also included the measurement of notifications received by the user (e.g. Lee et al., 2014; Lin et al., 2015) which although can be objectively monitored, are not a direct measure of behaviour. Yet, in the context of problematic smartphone use here, notifications were viewed as a cue for triggering problematic smartphone behaviour, and were subsequently monitored to predict user behaviour through assessing how notifications act as a request for user attention and observing how users respond (Ellis et al., 2019; Kanjo et al., 2017; Lee et al., 2014).

3.3. Objective assessment of problematic smartphone use

3.3.1. Usage time

All passive objective measures had the ability to monitor usage time spent on smartphones. Smartphone usage was assessed by the total usage time in minutes and hours (e.g., Shin & Dey, 2013; Montag et al., 2015; Shin & Lee, 2017; Elhai et al., 2018, 2019; Felisoni & Godoi, 2018; Lee et al., 2018; Prasad et al., 2018; Wilcockson et al., 2018), albeit there were differences in terms of the parameters being measured to assess usage within these studies. For three studies, usage was monitored via screen time, tracked when the phone was unlocked and the phone screen was active (Elhai et al., 2018; Felisoni & Godoi, 2018; Rozgonjuk et al., 2018). In these, the average usage was then calculated for screen time per day (Felisoni & Godoi, 2018), per week (Rozgonjuk et al., 2018) and both weekdays and weekends (Elhai et al., 2018). Findings demonstrated that males spent an average of 217.7 min per day on their smartphones, whilst women spent an average of 240.7 min per day (Felisoni & Godoi, 2018). Furthermore, this study also focussed on the impact of excessive smartphone use on academic performance, in which academic performance was assessed through the Self-Efficacy for Self-Regulated Learning scale (SE: SRL; Zimmerman, Bandura, & Martinez-Pons, 1992), in addition to performance on students' entrance exam. A significant negative relationship was found between the total time spent on smartphones on academic performance (Felisoni & Godoi, 2018). On the other hand, Elhai et al. (2018) indicated that increased smartphone use over a week was predicted by lower baseline depression severity, whilst findings by Rozgonjuk et al. (2018) found that self-reported problematic smartphone use was also positively associated with the average minutes of screen time across one week.

In addition to length of smartphone usage, three studies also included additional functions during data collection and analysis (Lee et al., 2018; Montag et al., 2015; Prasad et al., 2018). These included data usage and number of screen turn ons (Lee et al., 2018), session usage and app usage (Shin & Dey, 2013), in addition to incoming and outgoing calls, screen lock and unlock and app usage (Montag et al., 2015; Prasad et al., 2018). Findings by Shin and Dey (2013) demonstrated that individuals spent an average of three hours a day on their smartphone, and executed applications 147.7 times per day. It was observed that the average number of usage sessions per day across all users was 89.9, whilst users who were assessed as having greater problematic smartphone use also used more apps and increased interaction sessions (Shin & Dey, 2013). On the other hand, Lee et al. (2018) suggested that individuals at high risk of problematic use were those that turned their screen on more than 110 times per day and spent more than 72.5 h per week on their smartphone. It was also indicated that the higher number of screen turn ons was the greatest influence within those at high risk, with higher number of screen turn ons leading to greater differences between the actual usage time and perceived usage time, suggesting that high risk users were unable to identify their actual usage time (Lee et al., 2018). Similarly, findings by Montag et al. (2015) demonstrated that aggregated weekly mobile phone usage was overestimated by users, whilst more specific behaviours (e.g., outgoing calls) were underestimated. In contrast, findings by Prasad et al. (2018) demonstrated that individuals with problematic usage (as indicated by the SAS) spent significantly more time on their smartphone and performed more lock-unlock cycles. More specifically, females also spent longer durations on calls, photo gallery and camera, whilst males predominantly used video streaming applications and smartphone-based academic apps (Prasad et al., 2018). This suggests that although general usage time was the most monitored function across studies, more specific functions such as applications executed may be more informative in terms of pinpointing certain smartphone features that are associated with problematic smartphone usage and its consequences.

3.3.2. Frequency of use and checking behaviours

Studies observing checking behaviour patterns or habitual problematic usage analysed different functionalities in terms of the objective measures used. To assess habitual checking behaviours, Ellis et al. (2019) focused on the number of pickups and notifications on the phone, in addition to hours of use. Although it was highlighted that the number of notifications received is not a measure of behaviour, it was used within this study as a predictive measure on the number of times the user may pick-up or check their smartphone. In contrast, Wilcockson et al. (2018) implemented timestamps to monitor when the phone became active and inactive, generating frequency of use (i.e., phone checks, defined as any usage lasting < 15 s) in addition to total hours of usage. It was observed that smartphone behaviours across all users were highly predictive of total smartphone usage and checks, whilst usage was also similar during weekdays and weekends, and it was further indicated by the authors that multiple checks could signal absent-minded smartphone use, subsequently suggesting more habitual behaviour that is automatic. Tossell et al. (2015) used a similar method in terms of implementing timestamps to monitor when applications were launched, in addition to data on the duration of application launches, how many texts were sent and received and URLs visited online. Time per Interaction (TPIs) rates were calculated, where lower TPIs reflect app usage that is short in duration and more frequently launched, and higher TPIs reflect longer duration usage, but with less frequent app launches. It was observed that lower TPI rates were exhibited by individuals addicted to their smartphones, suggesting that shorter and more fragmented interactions are more likely to lead to habitual usage patterns.

Bespoke applications implemented in two studies also calculated the average daily epoch (defined as smartphone use from screen on to successive screen off). Empirical mode decomposition (EMD) was employed, whereby the underlying structures of the time series can be deduced to analyse the app generated parameters. In particular, trends of frequency, duration and median use were calculated, with frequency and duration testing the criterion of "excessive use", and duration and median for "tolerance" (defined as a marked increase in the duration of smartphone use to achieve satisfaction) (Lin et al., 2015). Findings illustrated excessive frequency of use as > 68.4 counts per day, and a cut-off point of 4.6 h per day for duration (Lin et al., 2015; Lin, Lin, Chiang et al., 2017), suggesting that short periods of frequent use may result in subjective distress or functional impairment (Lin et al., 2015). The assessment of the mean trend was also significant in identifying tolerance, demonstrating the use of EMD analysis is beneficial in evaluating parameters associated with problematic smartphone use, and indicating that excessive usage, including both frequency and duration, contribute to problematic smartphone use. Following this, a further app prototype calculated the reciprocity between smartphone use and non-use epochs (Lin, Lin, Chiang et al., 2017) to evaluate compulsive smartphone behaviour. It was found that use frequency, duration and median, in addition to non-use frequency, predicted problematic smartphone use, whilst non-use duration and non-use median parameters predicted non-problematic smartphone use. These patterns subsequently indicated the extent of impaired control of smartphone use, corresponding to that of compulsive symptoms presented in problematic behaviour (Lin, Lin, Chiang et al., 2017), demonstrating the assessment of use and non-use reciprocity advantageous in identifying the nuances of problematic smartphone usage.

Similarly, Pan et al. (2019) defined an episode of smartphone use as screen on to successive screen off. In this study, usage was distinguished between “proactive” and “reactive”, where proactive use was defined as one episode without a notification within one minute before screen on. Proactive usage was described as more reflective of compulsive smartphone behaviour, as it reveals more information on the intention of usage, such as checking for notifications or messages, which can contribute to the assessment of reciprocal usage patterns that reflect the control ability of individuals (Pan et al., 2019), suggesting that shorter interactions and checking behaviours are likely to play an important part in driving smartphone behaviour, and may be a potential source in the development of problematic usage.

3.3.3. Rewards

In terms of rewards, whereby individuals use their smartphones to gain instant gratifications, Lee et al. (2014) monitored functions such as active/ inactive applications, web browsing URLs, notifications and screen locks/unlocks. Subsequently, aggregated usage, session-level usage and temporal usage patterns were analysed to identify usage patterns within problematic risk individuals and non-risk individuals. Findings demonstrated that usage time and frequency were related with smartphone overuse, suggesting that repeated usage for mood adjustment purposes may depend mainly on function as opposed to usage amount, and that this may subsequently lead to the formation of habitual usage and addictive behaviours (Lee et al., 2014).

In addition, it was demonstrated in two studies that users seek out specific content to satisfy certain needs, which influenced the development of problematic smartphone use (Elhai et al., 2018; Tossell et al., 2015). As aforementioned, Tossell et al. (2015) monitored data in regards to application launches, text messaging and URLs visited online, followed by the calculation of TPIs. Findings also showed that problematic users spent more time on Mail, Facebook, Entertainment and Safari applications as opposed to non-problematic users, and it was indicated that phone checking satisfied an uncontrollable urge, which was demonstrated across all users considered smartphone addicts, indicating that rather than being addicted to the smartphone itself, it is the content to which the phone provides access that can lead to addictive behaviours (Tossell et al., 2015). Conversely, although findings illustrate problematic users spending more time on entertainment than non-problematic users, it was highlighted that there were no differences between users in terms of smartphone gaming (Tossell et al., 2015). Similar results were reflected by Shin and Lee (2017), whereby online gaming was not associated with problematic smartphone use. However, one study found gaming to be significantly associated with problematic usage (Choi et al., 2017), suggesting that nuances regarding smartphone users and their personal affordances should be taken into account when assessing for problematic smartphone use.

In contrast, Elhai et al. (2018) focused on the daily averages of smartphone usage to observe smartphone gratifications in the context of psychopathology. Here, it was found that whilst lower depression severity was associated with decreased smartphone use, increased smartphone use was observed for individuals who used expressive suppression as a maladaptive emotion regulation strategy, and it was suggested that expressive suppression may be gratified by an increase in smartphone use as a specific medium (Elhai et al., 2018). This suggests that distinguishing between general smartphone usage and the affordances that they provide is important when assessing for problematic usage, as it can allow further understanding into problematic use to smartphones as a medium, and how different the affordances available can also lead to problematic use.

3.4. Additional assessments of problematic smartphone use employed in conjunction with objective monitoring

In addition to objective monitoring, 15 studies included a self-report measure to assess smartphone usage and addiction. These included variations of the Smartphone Addiction Scale (Elhai et al., 2018; Ellis et al., 2019; Lee et al., 2017; Prasad et al., 2018; Rozgonjuk et al., 2018), variations of the Smartphone Addiction Proneness Scale (SAPS; Kim, Lee, Lee, Nam, & Chung, 2014; Lee et al., 2014; Choi et al., 2017), the Mobile Phone Problematic Use Scale (MPPUS; Bianchi & Phillips, 2005; Shin & Dey, 2013; Montag et al., 2015; Ellis et al., 2019; Wilcockson et al., 2018) and the five item Smartphone Addiction Inventory (SPAI-5; Lin et al., 2014; Pan et al., 2019).

Of these, ten studies implemented psychometric tests to assess the association between self-reported smartphone usage and behaviour in comparison to actual usage (e.g., Prasad et al., 2018; Ellis et al., 2019), whilst four used psychometric tests to classify into addicted or not addicted groups (e.g., Lee et al., 2014; Shin & Lee, 2017) using cut-off scores of 30 for the SAS-SV (Lee et al., 2017), ≥ 40 for the SAPS and ≥ 29 for the Smartphone Addiction Self-Diagnosis Scale (S-scale; Shin & Lee, 2017) to be indicative of addictive smartphone use. The SAPS, SPAI-5 and MPPUS were found to be positively associated with smartphone behaviour (Lee et al., 2014; Pan et al., 2019; Shin & Dey, 2013). Findings by Ellis et al. (2019) however, indicated that the MPPUS did not reliably correlate with the objective measures; scores were unable to predict the number of smartphone checks or total use across the period of objective data collection, indicating that such scales perhaps struggle to capture problematic behaviour that is atypical and habitual in nature. The SAS on the other hand resulted in significant positive correlations when analysed against general smartphone use objective measures (e.g., Prasad et al., 2018; Rozgonjuk et al., 2018).

In addition, three studies employed interviews to assess problematic smartphone use, of which all were found to predict problematic behaviours (Choi et al., 2017; Lin et al., 2015; Lin, Lin, Chiang et al., 2017). These were conducted using the Diagnostic Criteria of Internet Addiction for College Students (DC-IA-C; Ko, Yen, Chen, Chen, & Yen, 2005; Lin et al., 2015) and the Mini International Neuropsychiatric Interview (MINI; Sheehan et al., 1998; Choi et al., 2017). In addition, one study based the interview on criteria consisting of (i) characteristic symptoms of problematic smartphone use (e.g., persistent desire and/or unsuccessful attempts to cut down or reduce smartphone use), (ii) functional impairment caused by smartphone use (e.g., jeopardized or lost a significant relationship, job or educational/career opportunity due to smartphone use), and (iii) excluded addictive behaviour that accounted for obsessive compulsive disorders or bipolar I disorders (Lin, Lin, Chiang et al., 2017). These results indicate that interviews used to assess for problematic usage may be more beneficial than psychometric tests to predict and capture problematic behaviours, particularly in regards to smartphone checks and total smartphone use time, supporting previous research that has found increased accuracy when combining both psychiatric interview and objective smartphone data (Lin, Lin, Chiang et al., 2017). However, employing objective assessments in conjunction with psychometric measures may be useful in highlighting the more nuanced behaviours associated with problematic smartphone use, and may provide further clarification into how these behaviours align with potential diagnostic criteria and psychological constructs (Ellis et al., 2018).

4. Discussion

The present review aimed to identify passive objective measures that are available and employed to assess problematic smartphone use. A total of 18 smartphone-based assessments that were used to monitor smartphone behaviour were reviewed. A number of functionalities were demonstrated, with general screen time use and smartphone checks being among the most monitored. The extent to which these functionalities capture problematic behaviour and smartphone use are discussed.

4.1. Assessment of problematic usage

Usage time, in particular overuse of smartphones, is often the most utilised variable when assessing problematic smartphone behaviours (Ellis et al., 2018), and was the most predominant function observed across all of the present studies, monitored through screen time (calculated either via screen locks/unlocks or screen time in hours or minutes). In particular, five of the reviewed studies indicated that an individual is considered a problematic user if their usage time exceeds a predefined usage amount (Lee et al., 2014; Lin et al., 2015; Lin, Lin, Chiang et al., 2017; Felisoni & Godoi, 2018; Lee et al., 2018), which can be beneficial in terms of modelling further understanding of problematic smartphone usage when considered as a variable within research (Gökçearslan, Mumcu, Haşlaman, & Çevik, 2016). However, the cut-off times across these studies ranged between four to eight hours per day, the variability of which limits comparisons within findings and may further warrant issues when trying to establish the conceptualisation of problematic usage and the potential development of diagnostic criteria. This emphasises that a standardised baseline needs to be implemented to allow for comprehensive comparison and distinguishing between problematic and non-problematic use, if utilising a pre-defined usage cut-off is to be considered as a measure within research and especially if it were to extend into clinical assessment.

In addition, an excess of smartphone usage time does not necessarily indicate problematic behaviour (Andrews, Ellis, Shaw, & Piwek, 2015). Smartphone developments and increased internet access via these devices have meant that individuals are increasingly using their smartphones for a variety of things and for some, smartphones have become a substitute for the computer (Aljomaa, Al.Qudah, Albursan, Bakhiet, & Abduljabbar, 2016), which can undermine methods of employing a cut-off time to distinguish between problematic and non-problematic usage if they are increasingly being used for work or informational purposes (LaRose, Lin, & Eastin, 2003). However, one functionality that was employed within the present objective measures was the monitoring of specific applications, including when they were launched and the length of time being spent on these applications (e.g., Choi et al., 2017; Lee et al., 2018). These measures can deduce what the user is engaged in whilst on their smartphone and can be highly beneficial in distinguishing between 'problematic' and 'required' usage (Ryding & Kaye, 2018). For instance, it has been shown that problematic users tend to spend more time on social networking or communication sites, as opposed to educational purposes (Kormas, Critselis, Janikian, Kafetzis, & Tsitsika, 2011; Pivetta et al., 2019; Wu, Cheung, Ku, & Hung, 2013); findings which were consistent within the present review, demonstrating Facebook as one app most frequently engaged with by problematic users (Tossell et al., 2015). However, findings also illustrated there to be no differences between problematic users and non-problematic users in regards to gaming (Shin & Lee, 2017; Tossell et al., 2015). This is contrary to previous research indicating gaming is a predictor of problematic usage (Liu et al., 2016), albeit this may be due to the genre of game in the present studies. Specifically, it has been demonstrated that the genre of gaming is platform-specific, with smartphone gaming more ephemeral in comparison to online games via PC (Jin, Chee, & Kim, 2013), which is likely to lead to less immersive gaming interactions and subsequently lesser association with problematic smartphone use, which may reflect the results of the present review. This highlights that nuances surrounding gaming on smartphones need to be specified, so that affordances are clearly explored and understood as an entity in the conceptualisation of problematic smartphone use, particularly since internet-mediated gaming through smartphone may be classified under the remit of Gaming Disorder (GD) (Ryding & Kaye, 2018). Nevertheless, the findings of the present review highlight the importance of distinguishing between affordances available via smartphones, to further understand users' problematic usage of smartphones as a medium, in addition to how differential content types can lead to problematic smartphone use.

The notion of habitual smartphone use is often employed to explain problematic smartphone behaviour (Anshari et al., 2016; Lee, Kim, & Choi, 2017; Van Deursen et al., 2015), whereby habitual use is strongly influenced by frequency of behaviour, such as checking the smartphone (Neal, Wood, Labrecque, & Lally, 2012). A number of studies within the present review utilised various functions to monitor checking behaviour patterns and frequency of use, including timestamps, screen on and off counts (e.g., Tossell et al., 2015; Lin, Lin, Chiang et al., 2017), and notifications (Ellis et al., 2019). Although notifications are not an assessment of behaviour, they can be used as a predictive measure in checking behaviour and are a more ecologically valid means of assessment in comparison to traditional methods, which cannot provide continual monitoring of usage patterns (Kanjo et al., 2017). Moreover, lower Time per Interaction rates (calculated as duration in seconds/number of launches) were exhibited by individuals with problematic smartphone use, indicating that shorter and more fragmented interactions are more likely to lead to habitual usage patterns (Tossell et al., 2015), whilst use and non-use reciprocity patterns provided the ability to observe compulsive behaviours associated with problematic usage (Lin, Lin, Chiang et al., 2017). Monitoring such variables can therefore provide a better measure of preoccupation with smartphones, whereby multiple checks are indicative of absent-minded, habitual usage (Wilcockson et al., 2018). It should be noted however, that habitual smartphone usage is not necessarily negative in nature; it can have a positive social feature by characterising an individual and predicting one's action, in addition to enabling multitasking in certain situations (Wood & Neal, 2007). Rather, maladaptive habits can cause unintended behaviour that is activated by internal or external cues, for instance, when a user experiences urges, such as unintended smartphone checking for notifications (Van Deursen et al., 2015). Research has demonstrated that behaviour is controlled less by intentions when habit increases strength (Danner, Aarts, & de Vries, 2008), indicating that problematic smartphone usage is better described as a struggle to maintain effective self-regulation over maladaptive habit driven behaviour, in which habit and problematic usage, through loss of self-control, are part of the same continuum (Oulasvirta et al., 2012). This signifies that checking habits constitute an important part in the behaviour driving smartphone use, making them a potential source of problematic behaviours (Oulasvirta et al., 2012), which should not be overlooked in future research that aims to further understand problematic smartphone use.

4.2. Methodological challenges of objective passive monitoring

Although there are advantages of utilising objective passive monitoring within smartphone use research, there are also numerous challenges associated with this type of assessment.

Firstly, the time period of objective data collection varied considerably across studies, ranging from one week to one year (Tossell et al., 2015; Elhai et al., 2018). Generally, longer periods of data collection are considered more advantageous, allowing for the potential to produce richer information concerning patterns that may not be prominent in shorter studies (Tossell et al., 2015). However, it is crucial with real-time monitoring that participant compliance rates are considered. Although passive smartphone-based assessments are unobtrusive in nature and less burdensome than active monitoring, these types of assessment can have a noticeable impact on battery life on the device, which can lead to a decrease in user motivation and increased potential of participant dropout (Bentley et al., 2019; Boonstra et al., 2018). However, it was highlighted in the present findings that a minimum of five days was enough to reflect weekly smartphone usage, while habitual behaviours can be reliably inferred within 48 h (Wilcockson et al., 2018). Similarly, findings by Pan et al. (2019)

demonstrated that assessing smartphone use duration across a two week period was sufficient to infer a two month period of smartphone usage, indicating that it may not be necessary to collect smartphone data across a long time frame. Nevertheless, it is likely that the time-period of data collection for smartphone usage patterns is dependent on the functionalities and variables being assessed, and should be considered carefully in future research to ensure optimisation of passive data monitoring, particularly when utilised within longer studies.

Secondly, participant privacy must be considered at all times, especially if data collection is perceived as personal, such as recording the content of messages or phone calls (Bentley et al., 2019). Collecting such data can adversely impact user engagement and behaviour, particularly if their privacy is not guaranteed (Tossell et al., 2015). It has been indicated that individuals are more reserved when commercial interests are concerned (Bietz et al., 2015), which may be attributed to lack of trust in technology ensuring data that is collected is kept confidential or scepticism that the information gained from passive monitoring is accurate and beneficial (Dennison, Morrison, Conway, & Yardley, 2013; Torous & Roberts, 2017). Whilst ethical considerations were reported in several studies within the present review (e.g., Lee et al., 2017; Felisoni & Godoi, 2018), this highlights that privacy constraints are ensured within future studies. For example, the rationale of the study and the anonymisation process must be detailed prior the commencement of the study so that participants are aware of how their data are used, whilst researchers should implement methods, such as encryption to retain important data without collecting sensitive data (Cornet & Holden, 2018; Tossell et al., 2015).

Furthermore, analysing real-time behavioural monitoring is also complex in comparison to self-report assessments (Ellis et al., 2018). Particularly when data are collected continuously as with passive monitoring, data sets can become extremely large, with previous research demonstrating that a total of up to 9000 data points can be collected across a period of four weeks for each participant, dependent on the functionalities monitored (Boonstra et al., 2018). In addition, it is also difficult to map passive objective data onto specific variables of interest during research (Bentley et al., 2019). However, although the large volume of data may make data interpretation more cumbersome, developments in the area of experience sampling may help to improve the complexities of passive data collection interpretation, facilitating adoption within smartphone-based research, whilst pre-built applications such as the Screen Time feature on iOS can provide access to simpler behavioural metrics (Ellis et al., 2019; Thai & Page-Gould, 2017).

5. Recommendations for future research

Considering the findings of the present review, six functionalities are recommended for researchers when assessing problematic smartphone usage: general usage time in (i) hours or minutes or (ii) screen on/off, (iii) most used applications, (iv) application launches and (v) length of app use and (vi) notifications.

Firstly, although general time spent on smartphones, either through hours or minutes, or screen on/off, can lack specificity in terms of patterns of usage, overuse of time spent on smartphones can model problematic smartphone use and provide a basis for discovering influential factors contributing to problematic usage (Shin & Dey, 2013). However, consideration of contextual factors must be made, particularly if a pre-defined cut-off time to establish problematic use is implemented. Ideally, functionalities such as most used applications, app launches, and length of app use should be employed in conjunction with general usage time to enable insight into what the user is engaged in on the smartphone, and can be beneficial in distinguishing between 'problematic' and 'required' usage (Ryding & Kaye, 2018). In addition, frequency of use can be calculated via these functions to indicate habitual usage patterns, whilst notifications can indirectly predict checking behaviour, which can be indicative of absent-minded smartphone use.

It is also emphasised that future research addresses privacy more explicitly. Whilst passive monitoring can be beneficial in defining the behaviours associated with problematic smartphone use, future studies must comprehensively assess the acceptance and long term implementation of passive monitoring, as well as any adverse consequences that may arise through these means of data collection (Holden & Karsh, 2010; Cornet & Holden, 2018).

6. Avenues for intervention in problematic smartphone use

Objective monitoring of smartphone behaviour can provide further directions in developing appropriate digital interventions in the field of problematic smartphone use. Although a number of applications have been developed to help users regulate their smartphone use, these applications lack psychological underpinning and are often not adaptable or tailored to address the specific needs of different people (Van Velthoven, Powell, & Powell, 2018). Having the ability to assess the nuances of user behaviour via real-time monitoring can help towards identifying, understanding and challenging the underlying motivations in individual users, and allow for these behaviours to be targeted in detail within smartphone regulation apps (Van Velthoven et al., 2018).

7. Limitations

The present review is not without its limitations. Active smartphone-based assessments, such as EMA, were not included as they fell outside the scope of the review. In addition, due to the focus on smartphone functionalities, the review did not incorporate broader literature on specific psychological constructs (Griffiths, 2005), which may implicate conclusions drawn regarding the extent passive objective data can operationalize specific constructs associated with problematic smartphone usage.

8. Conclusion

Overall, passive objective monitoring has vast potential in the domain of problematic smartphone usage, enabling the ability to gather both precise and ecologically valid data on real-time smartphone behaviour. As presented within the present review, applications within smartphones provide numerous functionalities, which can run in the background to capture both checking and usage behaviours and patterns across time. Despite the challenges associated with passive monitoring, when employed appropriately, these can drive both theoretical and practical developments surrounding the assessment and conceptualisation of problematic smartphone use and contribute to providing valuable insight within technology use research.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.abrep.2020.100257.

References

Aljomaa, S. S., Al.Qudah, M. F., Albursan, I. S., Bakhiet, S. F., & Abduljabbar, A. S. (2016). Smartphone addiction among university students in the light of some variables. *Computers in Human Behavior, 61*, 155–164. https://doi.org/10.1016/j.chb.2016.03.041.

Andrews, S., Ellis, D. A., Shaw, H., & Piwek, L. (2015). Beyond self-report: Tools to compare estimated and real-world smartphone use. *PloS One, 10*(10), e0139004.

https://doi.org/10.1371/journal.pone.0139004.

Anshari, M., Alas, Y., Hardaker, G., Jaidin, J. H., Smith, M., & Ahad, A. D. (2016). Smartphone habit and behavior in Brunei: Personalization, gender, and generation gap. *Computers in Human Behavior, 64*, 719–727. https://doi.org/10.1016/j.chb.2016.07.063.

Asselbergs, J., Ruwaard, J., Ejdys, M., Schrader, N., Sijbrandij, M., & Riper, H. (2016). Mobile phone-based unobtrusive ecological momentary assessment of day-to-day mood: An explorative study. *Journal of Medical Internet Research, 18*(3), e72. https://doi.org/10.2196/jmir.5505.

Bae, S. M. (2017). Smartphone addiction of adolescents, not a smart choice. *Journal of Korean Medical Science, 32*(10), 1563–1564. https://doi.org/10.3346/jkms.2017.32.10.1563.

Bentley, K. H., Kleiman, E. M., Elliott, G., Huffman, J. C., & Nock, M. K. (2019). Real-time monitoring technology in single-case experimental design research: Opportunities and challenges. *Behaviour Research and Therapy, 117*, 87–96. https://doi.org/10.1016/j.brat.2018.11.017.

Bianchi, A., & Phillips, J. G. (2005). Psychological predictors of problem mobile phone use. *CyberPsychology & Behavior, 8*(1), 39–51. https://doi.org/10.1089/cpb.2005.8.39.

Bietz, M. J., Bloss, C. S., Calvert, S., Godino, J. G., Gregory, J., Claffey, M. P., ... Patrick, K. (2015). Opportunities and challenges in the use of personal health data for health research. *Journal of the American Medical Informatics Association, 23*(e1), e42–e48. https://doi.org/10.1093/jamia/ocv118.

Billieux, J. (2012). Problematic use of the mobile phone: A literature review and a pathways model. *Current Psychiatry Reviews, 8*(4), 299–307.

Boase, J., & Ling, R. (2013). Measuring mobile phone use: Self-report versus log data. *Journal of Computer-Mediated Communication, 18*(4), 508–519. https://doi.org/10.1111/jcc4.12021.

Boonstra, T. W., Nicholas, J., Wong, Q. J., Shaw, F., Townsend, S., & Christensen, H. (2018). Using mobile phone sensor technology for mental health research: Integrated analysis to identify hidden challenges and potential solutions. *Journal of Medical Internet research, 20*(7), e10131. https://doi.org/10.2196/10131.

Boumosleh, J. M., & Jaalouk, D. (2017). Depression, anxiety, and smartphone addiction in university students-A cross sectional study. *PloS one, 12*(8), e0182239.

Choi, J., Rho, M. J., Kim, Y., Yook, I. H., Yu, H., Kim, D. J., & Choi, I. Y. (2017). Smartphone dependence classification using tensor factorization. *PloS one, 12*(6), e0177629. https://doi.org/10.1371/journal.pone.0177629.

Chung, J. E., Choi, S. A., Kim, K. T., Yee, J., Kim, J. H., Seong, J. W., ... Gwak, H. S. (2018). Smartphone addiction risk and daytime sleepiness in Korean adolescents. *Journal of Paediatrics and Child Health, 54*(7), 800–806. https://doi.org/10.1111/jpc.13901.

Cornet, V. P., & Holden, R. J. (2018). Systematic review of smartphone-based passive sensing for health and wellbeing. *Journal of Biomedical Informatics, 77*, 120–132. https://doi.org/10.1016/j.jbi.2017.12.008.

Danner, U. N., Aarts, H., & de Vries, N. K. (2008). Habit vs. intention in the prediction of future behaviour: The role of frequency, context stability and mental accessibility of past behaviour. *British Journal of Social Psychology, 47*(2), 245–265. https://doi.org/10.1348/014466607X230876.

Demirci, K., Akgönül, M., & Akpinar, A. (2015). Relationship of smartphone use severity with sleep quality, depression, and anxiety in university students. *Journal of Behavioral Addictions, 4*(2), 85–92. https://doi.org/10.1556/2006.4.2015.010.

Deng, T., Kanthawala, S., Meng, J., Peng, W., Kononova, A., Hao, Q., ... David, P. (2019). Measuring smartphone usage and task switching with log tracking and self- reports. *Mobile Media & Communication, 7*(1), 3–23. https://doi.org/10.1177/2050157918761491.

Dennison, L., Morrison, L., Conway, G., & Yardley, L. (2013). Opportunities and challenges for smartphone applications in supporting health behavior change: Qualitative study. *Journal of Medical Internet Research, 15*(4), e86. https://doi.org/10.2196/jmir.2583.

Elhai, J. D., Dvorak, R. D., Levine, J. C., & Hall, B. J. (2017). Problematic smartphone use: A conceptual overview and systematic review of relations with anxiety and depression psychopathology. *Journal of Affective Disorders, 207*, 251–259. https://doi.org/10.1016/j.jad.2016.08.030.

Elhai, J. D., Tiamiyu, M. F., Weeks, J. W., Levine, J. C., Picard, K. J., & Hall, B. J. (2018). Depression and emotion regulation predict objective smartphone use measured over one week. *Personality and Individual Differences, 133*, 21–28. https://doi.org/10.1016/j.paid.2017.04.051.

Ellis, D. A. (2019). Are smartphones really that bad? Improving the psychological measurement of technology-related behaviors. *Computers in Human Behavior, 97*, 60–66. https://doi.org/10.1016/j.chb.2019.03.006.

Ellis, D. A., Davidson, B. I., Shaw, H., & Geyer, K. (2019). Do smartphone usage scales predict behavior? *International Journal of Human-Computer Studies, 130*, 86–92. https://doi.org/10.1016/j.ijhcs.2019.05.004.

Ellis, D. A., Kaye, L. K., Wilcockson, T. D., & Ryding, F. C. (2018). Digital traces of behaviour within addiction: Response to Griffiths (2017). *International Journal of Mental Health and Addiction, 16*(1), 240–245. https://doi.org/10.1007/s11469-017-9855-7.

Esmaeili Rad, M., & Ahmadi, F. (2018). A new method to measure and decrease the online social networking addiction. *Asia-Pacific Psychiatry, 10*(4), e12330. https://doi.org/10.1111/appy.12330.

Felisoni, D. D., & Godoi, A. S. (2018). Cell phone usage and academic performance: An experiment. *Computers & Education, 117*, 175–187. https://doi.org/10.1016/j.compedu.2017.10.006.

Geser, H. (2004). Towards a sociological theory of the mobile phone. *Human Technology, 1*(1), 45–57.

Giunchiglia, F., Zeni, M., Gobbi, E., Bignotti, E., & Bison, I. (2018). Mobile social media usage and academic performance. *Computers in Human Behavior, 82*, 177–185. https://doi.org/10.1007/978-3-319-67256-4_1.

Gökçearslan, Ş., Mumcu, F. K., Haşlaman, T., & Çevik, Y. D. (2016). Modelling smartphone addiction: The role of smartphone usage, self-regulation, general self-efficacy and cyberloafing in university students. *Computers in Human Behavior, 63*, 639–649. https://doi.org/10.1016/j.chb.2016.05.091.

Griffiths, M. (2005). A 'components' model of addiction within a biopsychosocial framework. *Journal of Substance use, 10*(4), 191–197 10.108014659890500114359.

Holden, R. J., & Karsh, B.-T. (2010). The technology acceptance model: Its past and its future in health care. *Journal of Biomedical Informatics, 43*(1), 159–172. https://doi.org/10.1016/j.jbi.2017.12.008.

Jasso-Medrano, J. L., & Lopez-Rosales, F. (2018). Measuring the relationship between social media use and addictive behavior and depression and suicide ideation among university students. *Computers in Human Behavior, 87*, 183–191.

Jeong, S. H., Kim, H., Yum, J. Y., & Hwang, Y. (2016). What type of content are smartphone users addicted to?: SNS vs. games. *Computers in Human Behavior, 54*, 10–17. https://doi.org/10.1016/j.chb.2015.07.035.

Jin, D. Y., Chee, F., & Kim, S. (2013). Transformative mobile game culture: A sociocultural analysis of Korean mobile gaming in the era of smartphones. *International Journal of Cultural Studies, 18*(4), 413–429. https://doi.org/10.1177/1367877913507473.

Kang, S. J., Ha, J.-P., & Hambrick, M. E. (2015). A mixed-method approach to exploring the motives of sport-related mobile application among college students. *Journal of Sport Management, 29*, 272–290. https://doi.org/10.1123/jsm.2013-0065.

Kanjo, E., Kuss, D. J., & Ang, C. S. (2017). Notimind: Utilizing responses to smart phone notifications as affective sensors. *IEEE Access, 5*, 22023–22035. https://doi.org/10.1109/ACCESS.2017.2755661.

Kim, S. E., Kim, J. W., & Jee, Y. S. (2015). Relationship between smartphone addiction and physical activity in Chinese international students in Korea. *Journal of Behavioral Addictions, 4*(3), 200–205. https://doi.org/10.1556/2006.4.2015.028.

Kim, D., Lee, Y., Lee, J., Nam, J. K., & Chung, Y. (2014). Development of Korean smartphone addiction proneness scale for youth. *PloS One, 9*(5), e97920. https://doi.org/10.1371/journal.pone.0097920.

Ko, C. H., Yen, J. Y., Chen, C. C., Chen, S. H., & Yen, C. F. (2005). Proposed diagnostic criteria of Internet addiction for adolescents. *The Journal of Nervous and Mental Disease, 193*(11), 728–733. https://doi.org/10.1097/01.nmd.0000185891.13719.54.

Kormas, G., Critselis, E., Janikian, M., Kafetzis, D., & Tsitsika, A. (2011). Risk factors and psychosocial characteristics of potential problematic and problematic internet use among adolescents: A cross-sectional study. *BMC Public Health, 11*(1), 595. https://doi.org/10.1186/1471-2458-11-595.

Kuss, D. J., Kanjo, E., Crook-Rumsey, M., Kibowski, F., Wang, G. Y., & Sumich, A. (2018). Problematic mobile phone use and addiction across generations: The roles of psychopathological symptoms and smartphone use. *Journal of Technology in Behavioral Science, 3*(3), 141–149. https://doi.org/10.1007/s41347-017-0041-3.

Kwon, M., Lee, J. Y., Won, W. Y., Park, J. W., Min, J. A., Hahn, C., ... Kim, D. J. (2013). Development and validation of a smartphone addiction scale (SAS). *PloS one, 8*(2), e56936. https://doi.org/10.1371/journal.pone.0056936.

LaRose, R., Lin, C. A., & Eastin, M. S. (2003). Unregulated Internet usage: Addiction, habit, or deficient self-regulation? *Media Psychology, 5*(3), 225–253. https://doi.org/10.1207/s1532785xmep0503_01.

Lee, H., Ahn, H., Nguyen, T. G., Choi, S. W., & Kim, D. J. (2017). Comparing the self-report and measured smartphone usage of college students: A pilot study. *Psychiatry Investigation, 14*(2), 198. https://doi.org/10.4306/pi.2017.14.2.198.

Lee, M., Han, M., & Pak, J. (2018). Analysis of behavioral characteristics of smartphone addiction using data mining. *Applied Sciences, 8*(7), 1191. https://doi.org/10.3390/app8071191.

Lee, H., Kim, J. W., & Choi, T. Y. (2017). Risk factors for smartphone addiction in Korean adolescents: Smartphone use patterns. *Journal of Korean Medical Science, 32*(10), 1674–1679. https://doi.org/10.3346/jkms.2017.32.10.1674.

Lee, U., Lee, J., Ko, M., Lee, C., Kim, Y., Yang, S., ... Song, J. (2014). Hooked on smartphones: An exploratory study on smartphone overuse among college students. *Proceedings of the 32nd annual ACM conference on Human Factors in Computing Systems* (pp. 2327–2336). . https://doi.org/10.1145/2556288.2557366.

Lin, Y. H., Chang, L. R., Lee, Y. H., Tseng, H. W., Kuo, T. B., & Chen, S. H. (2014). Development and validation of the Smartphone Addiction Inventory (SPAI). *PloS One, 9*(6), e98312. https://doi.org/10.1371/journal.pone.0098312.

Lin, Y. H., Lin, Y. C., Lee, Y. H., Lin, P. H., Lin, S. H., Chang, L. R., Tseng, Yen, L. Y., Yang, C. C., & Kuo, T. B. (2015). Time distortion associated with smartphone addiction: Identifying smartphone addiction via a mobile application (App). *Journal of Psychiatric Research, 65*, 139–145. https://doi.org/10.1016/j.jpsychires.2015.04.003.

Lin, Y. H., Lin, P. H., Chiang, C. L., Lee, Y. H., Yang, C. C. H., Kuo, T. B. J., & Lin, S. H. (2017b). Incorporation of mobile application (app) measures into the diagnosis of smartphone addiction. *The Journal of Clinial Psychiatry, 7*(7), 866–872. https://doi.org/10.4088/JCP.15m10310.

Lin, Y. H., Lin, Y. C., Lin, S. H., Lee, Y. H., Lin, P. H., Chiang, C. L., ... Kuo, T. B. J. (2017a). To use or not to use? Compulsive behavior and its role in smartphone addiction. *Translational Psychiatry, 7*(2), e1030.

Liu, C.-H., Lin, S.-H., Pan, Y.-C., & Lin, Y.-H. (2016). Smartphone gaming and frequent use pattern associated with smartphone addiction. *Medicine, 95*(28), e4068. https://doi.org/10.1097/MD.0000000000004068.

Lopez-Fernandez, O., Honrubia-Serrano, L., Freixa-Blanxart, M., & Gibson, W. (2014). Prevalence of problematic mobile phone use in British adolescents. *CyberPsychology, Behavior, and Social Networking, 17*(2), 91–98. https://doi.org/10.1089/cyber.2012.0260.

Markowetz, A., Błaszkiewiscz, K., Montag, C., Switala, C., & Schlaepfer, T. E. (2014). Psycho-informatics: Big data shaping modern psychometrics. *Medical Hypotheses, 82*(4), 405–411. https://doi.org/10.1016/j.mehy.2013.11.030.

Miller, G. (2012). The smartphone psychology manifesto. *Perspectives on Psychological Science, 7*(3), 221–237. https://doi.org/10.1177/1745691612441215.

Montag, C., Błaszkiewicz, K., Lachmann, B., Sariyska, R., Andone, I., Trendafilov, B., & Markowetz, A. (2015). Recorded behavior as a valuable resource for diagnostics in mobile phone addiction: Evidence from psychoinformatics. *Behavioral Sciences, 5*(4), 434–442. https://doi.org/10.3390/bs5040434.

Neal, D. T., Wood, W., Labrecque, J. S., & Lally, P. (2012). How do habits guide behavior? Perceived and actual triggers of habits in daily life. *Journal of Experimental Social Psychology, 48*(2), 492–498. https://doi.org/10.1016/j.jesp.2011.10.011.

Oulasvirta, A., Rattenbury, T., Ma, L., & Raita, E. (2012). Habits make smartphone use more pervasive. *Personal and Ubiquitous Computing, 16*(1), 105–114. https://doi.org/10.1007/s00779-011-0412-2.

Pan, Y. C., Lin, H. H., Chiu, Y. C., Lin, S. H., & Lin, Y. H. (2019). Temporal stability of smartphone use data: Determining fundamental time unit and independent cycle. *JMIR mHealth and Health, 7*(3), e12171. https://doi.org/10.2196/12171.

Panova, T., & Carbonell, X. (2018). Is smartphone addiction really an addiction? *Journal of Behavioral Addictions, 7*(2), 252–259. https://doi.org/10.1556/2006.7.2018.49.

Pivetta, E., Harkin, L., Billieux, J., Kanjo, E., & Kuss, D. J. (2019). Problematic smartphone use: An empirically validated model. *Computers in Human Behavior*. https://doi.org/10.1016/j.chb.2019.06.013.

Prasad, S., Harshe, D., Kaur, N., Jangannavar, S., Srivastava, A., Achanta, U., ... Harshe, G. (2018). A study of magnitude and psychological correlates of smartphone use in medical students: A pilot study with a novel telemetric approach. *Indian Journal of Psychological Medicine, 40*(5), 468. https://doi.org/10.4103/IJPSYM.IJPSYM_133_18.

Pryzbylski, A. K., & Weinstein, N. (2017). A large-scale test of the goldilocks hypothesis: Quantifying the relations between digital-screen use and the mental well-being of adolescents. *Psychological Science, 28*(2), 204–215. https://doi.org/10.1177/0956797616678438.

Rozgonjuk, D., Levine, J. C., Hall, B. J., & Elhai, J. D. (2018). The association between problematic smartphone use, depression and anxiety symptom severity, and objectively measured smartphone use over one week. *Computers in Human Behavior, 87*, 10–17. https://doi.org/10.1016/j.chb.2018.05.019.

Ryding, F. C., & Kaye, L. K. (2018). "Internet addiction": A conceptual minefield. *International Journal of Mental Health and Addiction, 16*(1), 225–232. https://doi.org/10.1007/s11469-017-9811-6.

Salehan, M., & Negahban, A. (2013). Social networking on smartphones: When mobile phones become addictive. *Computers in Human Behavior, 29*(6), 2632–2639. https://doi.org/10.1016/j.chb.2013.07.003.

Samaha, M., & Hawi, N. S. (2016). Relationships among smartphone addiction, stress, academic performance, and satisfaction with life. *Computers in Human Behavior, 57*, 321–325. https://doi.org/10.1016/j.chb.2015.12.045.

Sheehan, D. V., Lecrubier, Y., Sheehan, K. H., Amorim, P., Janavs, J., Weiller, E., ... Dunbar, G. C. (1998). The Mini-International Neuropsychiatric Interview (MINI): The development and validation of a structured diagnostic psychiatric interview for DSM-IV and ICD-10. *The Journal of Clinical Psychiatry, 59*(Suppl 20), 22–33.

Shin, C., & Dey, A. (2013). Automatically detecting problematic use of smartphones. In UbiComp 2013 – Proceedings of the 2013 ACM international joint conference on pervasive and ubiquitous computing. Doi: 10.1145/2493432.2493443.

Shin, M., & Lee, K. (2017). Measuring smartphone usage time is not sufficient to predict smartphone addiction. *Journal of Theoretical and Applied Information Technology. 95*(19), 5296–5303.

Stawarz, K., Preist, C., & Coyle, D. (2019). Use of smartphone apps, social media, and web- based resources to support mental health and well-being: Online survey. *JMIR Mental Health, 6*(7), e12546. https://doi.org/10.2196/12546.

Stone, A. A., Shiffman, S., Schwartz, J. E., Broderick, J. E., & Hufford, M. R. (2002). Patient non-compliance with paper diaries. *BMJ, 324*(7347), 1193–1194. https://doi.org/10.1136/bmj.324.7347.1193.

Thai, S., & Page-Gould, E. (2017). ExperienceSampler: An open-source scaffold for building smartphone apps for experience sampling. *Psychological Methods, 23*(4), 729–739. https://doi.org/10.1037/met0000151.

Torous, J., & Roberts, L. W. (2017). Needed innovation in digital health and smartphone applications for mental health: Transparency and trust. *JAMA psychiatry, 74*(5), 437–438. https://doi.org/10.1001/jamapsychiatry.2017.0262.

Tossell, C., Kortum, P., Shepard, C., Rahmati, A., & Zhong, L. (2015). Exploring smartphone addiction: Insights from long-term telemetric behavioral measures. *International Journal of Interactive Mobile Technologies, 9*(2), 37–43.

Trull, T. J., & Ebner-Priemer, U. (2014). The role of ambulatory assessment in psychological science. *Current Directions in Psychological Science, 23*(6), 466–470. https://doi.org/10.1177/0963721414550706.

Van Deursen, A. J., Bolle, C. L., Hegner, S. M., & Kommers, P. A. (2015). Modelling habitual and addictive smartphone behavior: The role of smartphone usage types, emotional intelligence, social stress, self-regulation, age, and gender. *Computers in Human Behavior, 45*, 411–420. https://doi.org/10.1016/j.chb.2014.12.039.

Van Velthoven, M. H., Powell, J., & Powell, G. (2018). Problematic smartphone use: Digital approaches to an emerging public health problem. *Digital Health, 4*, 1–9. https://doi.org/10.1177/2055207618759167.

Wilcockson, T. D., Ellis, D. A., & Shaw, H. (2018). Determining typical smartphone usage: What data do we need? *Cyberpsychology, Behavior, and Social Networking, 21*(6), 395–398. https://doi.org/10.1089/cyber.2017.0652.

Wood, W., & Neal, D. T. (2007). A new look at habits and the habit-goal interface. *Psychological Review, 114*(4), 843. https://doi.org/10.1037/0033-295X.114.4.843.

World Health Organization [WHO] (2015). Public health implications of excessive use of the internet, computers, smartphones and similar electronic devices. Meeting report, Main Meeting Hall, Foundation for Promotion of Cancer Research, National Cancer Research Centre, Tokyo, Japan, 27–29 August 2014. Geneva, Switzerland: World Health Organization.

Wu, A. M., Cheung, V. I., Ku, L., & Hung, E. P. (2013). Psychological risk factors of addiction to social networking sites among Chinese smartphone users. *Journal of Behavioral Addictions, 2*(3), 160–166. https://doi.org/10.1556/JBA.2.2013.006.

Yen, C. F., Tang, T. C., Yen, J. Y., Lin, H. C., Huang, C. F., Liu, S. C., & Ko, C. H. (2009). Symptoms of problematic cellular phone use, functional impairment and its association with depression among adolescents in Southern Taiwan. *Journal of Adolescence, 32*(4), 863–873.

Zimmerman, B. J., Bandura, A., & Martinez-Pons, M. (1992). Self-motivation for academic attainment: The role of self-efficacy beliefs and personal goal setting. *American Educational Research Journal, 29*(3), 663–676.