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METHODOLOGICAL ARTICLE

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Use of passive sensing to quantify adolescent mobile device usage: Feasibility, acceptability, and preliminary validation of the eMoodie application

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Abstract

Utilizing the built-in features of smartphones, a novel app "eMoodie" (www.emoodie.com) was developed which passively collects information on app and smartphone/tablet usage including duration and time of use. Youth in the US and UK participated in piloting and validating eMoodie. In the first study, we evaluated the feasibility and acceptability of eMoodie in a sample of 23 parent–child dyads (N = 46), with children ages 10–12 years. Children downloaded eMoodie onto their device, which collected information on their screen time and app usage for seven consecutive days. Children responded to notifications via eMoodie to complete ecological momentary assessments (EMA) on wellbeing and digital media use. In the second study, caregiver-child dyads participated (N = 526) in a study conducted in Edinburgh, Scotland. Early adolescents (ages 11 to 14) participated in a remote study using eMoodie involving an EMA component, questionnaires, and passive sensing data collection over a 7-day EMA study. To examine the preliminary validity of using eMoodie, we evaluated whether app-enabled research may alter the behavior being studied. As youth are increasingly using mobile devices, capturing objective use and evaluating the correlates of such use on development grows ever more important. Remote data capture will be essential to continuing developmental research that cannot be facilitated in face-to-face settings due to the ongoing pandemic. As the first empirical investigation into the utility of an app that objectively measures adolescents' smartphone use, we summarize lessons learned in implementing this novel methodology and future directions for the measurement of mobile media.

KEYWORDS

adolescents, mobile technology, privacy, smartphone addiction, smartphone habit, smartphone usage, social media, social networking, students, wearable device

1 | INTRODUCTION

Children and adolescents are using mobile devices (e.g., smartphones and tablets) at increasing rates, despite growing concerns regarding the potential long-term effects on children's health (Lissak, 2018). Indeed, since the start of the Coronavirus pandemic (COVID-19), children are online nearly twice as long as they were before the pandemic (i.e., 3 hr prior to the pandemic to 6 hr during the pandemic, as of April 2020; Parents Together, 2020). Parents are concerned about this increase in screen time; in particular, 85% of parents expressed

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concern specific to their children's use of mobile apps, social media, and gaming. Although it is still unknown how children will be affected by the pandemic and the transition to virtual/remote learning and socialization, prior research indicates that certain aspects of children's digital media use may exert negative impacts. For example, the research on mobile device use suggests that disrupted sleep and sleep duration may be affected by nighttime use of mobile media or excessive mobile device use (Domoff, Borgen, Foley, & Maffett, 2019). Similarly, various aspects of mobile device use may associate with poorer mental health (Barlett, Gentile, Barlett, Eisenmann, & Walsh, 2012; Raudsepp, 2019) and academic functioning (Domoff, Foley, & Ferkel, 2020), particularly when such use interferes with sleep (Domoff, Borgen, & Robinson, 2020; Raudsepp, 2019; Vernon, Barber, & Modecki, 2015; Vernon, Modecki, & Barber, 2017). Research on how the pandemic affects children's well-being will benefit from considering the role of digital media and mobile device use on children's physical and mental health.

2 | MEASUREMENT OF MOBILE DEVICE USE

Although evidence is emerging that mobile device use is linked to the mental and physical health of children and adolescents (see Domoff, Borgen, et al., 2019 for review of physical health correlates and Domoff, Borgen, and Robinson, 2020 for a review of behavioral health correlates), there are barriers to further study of the specific associations. One of these barriers faced by researchers and clinicians is the lack of objective measures of mobile device use (see Ellis, 2019 for a review of the limitations of current assessment of smartphone use). Commonly, when attempting to measure the prominence of screens in an individual's daily life, youth or their caregivers are asked to estimate the amount of time spent with technology (Rideout & Robb, 2019). Although this is the most straightforward approach, research has suggested that this type of retrospective reporting is typically inaccurate in providing a true measure of how often youth utilize screen-based media devices (at least for cellphone use, Boase & Ling, 2013; television and video game use may be more accurate as they are often used for blocks of time).

Adolescents and older children may be able to provide a report on their own technology use, but parents are often recruited to describe habits of young children, which may increase inaccuracy (Radesky et al., 2020). When asking youth directly, other factors may affect the validity of their reporting; youth generally under-report sedentary behavior and as with other problematic behaviors, there are likely concerns about possible repercussions for overuse of screens (Adamo, Prince, Tricco, Connor-Gorber, & Tremblay, 2009; Del Boca & Noll, 2000). That said, it is worth noting that the problems in self-report and parent-report may be less important than is commonly assumed. For example, although parents and children seem to give very different answers about media use, with remarkably divergent point-estimates, they both appear to provide *valid* responses (c.f., Busching et al., 2013; Gentile, Nathanson, Rasmussen, Reimer, & Walsh, 2012). Nonetheless, objective measures of private media, such as cellphones and tablets, are needed. Additionally, children's technology use patterns fluctuate rapidly, with new sources frequently being introduced into their daily lives (Vizcaino, Buman, DesRoches, & Wharton, 2019). Measures created to assess time spent with one type of screen media device may completely overlook the newest technology "fad" that is occupying the majority of youths' screen use.

Despite the common focus on measuring the amount of time that youth spend with screen media devices, research suggests that this is not the most important factor when considering an individual's physical and mental health (Domoff et al., 2019). Instead of only measuring number of hours spent using a mobile device or watching television, measures of media use also need to assess the context and content of these hours (Barr et al., 2020). Depending on when and where youth are using screen media (i.e., the context), this use could interfere with important daily activities, including schoolwork, socializing, and sleep. Research supports that use of screen media in these important contexts negatively affects academic performance, development of relationships, and sleep quality (Domoff, Borgen, et al., 2019; Domoff, Borgen, & Robinson, 2020; Gentile, Berch, Choo, Khoo, & Walsh, 2017; Richards, McGee, Williams, Welch, & Hancox, 2010).

In addition, it is important to consider which applications are being used, and how children are using them (i.e., the content). Mobile device applications, images, and videos that are not age-appropriate have a vastly different impact on children than educational programming created specifically for their age group (Supanitayanon, Trairatvorakul, & Chonchaiya, 2020). Additionally, some youth may be experiencing support and developing friendships through social media, while others are victims of cyberbullying (Hamm et al., 2015). Clearly, clinicians and researchers not only need an accurate method for measuring amount of time that youth spend with screen media devices, but also the content and context of their use.

3 | NOVEL MEASURES OF MOBILE DEVICE USE

A potential and emerging solution to these shortcomings may exist in the form of in-the-moment assessment and passive sensing technologies—both of which are part of the broader category of experience sampling methods. In particular, ecological momentary assessment (EMA), a term more commonly used in clinically relevant research, makes use of ecologically realistic, real-time sampling of current behaviors and experiences. This data may be gathered by way of interval-based responses that take place while youth are in their natural environment (see Dunton, for a review of these methods for physical activity). Deploying these techniques may represent a viable solution to reduce recall bias and improve ecological validity (Russell & Gajos, 2020). The EMA methodology has been validated in adults and children for a variety of health-related behaviors, which have been traditionally difficult to assess via retrospective self-report (Wen, Schneider, Stone, & Spruijt-Metz, 2017). Relatedly, mobile technology-based (e.g., smartphones, wearable sensors) EMA has

been successfully used to measure a variety of behavioral health outcomes, in children as young as 7 years (Heron, Everhart, McHale, & Smyth, 2017). For example, EMA may serve as a viable measure of children's physical activity patterns (Liao, Skelton, Dunton, & Bruening, 2016).

While there is an emerging body of research related to the implementation of EMA in the measure of the aforementioned topics in adolescent and child health (mainly physical activity), there remains a dearth of studies specific to passive methodology and the measure of mobile device and app usage—particularly among older children and adolescents. Passive-sensing data collection from smartphones makes it possible to tap into data being aggregated on devices to measure when, and for how long, phone users are using the device and/or different apps. This method can provide objective data on smartphone use and more specific details as to what type of media (e.g., social media versus gaming) is being used by adolescents. For example, Yuan et al. (2019) described the development and utility of a passive sensing app for measuring adults' (i.e., parents') smartphone screen time (SST) and, recently, Radesky et al. (2020) piloted an app to measure mobile device usage in young children. Additionally, the Comprehensive Assessment of Family Media Exposure (CAFE) Consortium has proposed a novel approach for assessing a multitude of digital media use among family members, including a passive sensing feature (see Barr et al., 2020 for this innovative approach). These seminal studies indicate that passive sensing as a method for measuring SST is feasible and acceptable to adult participants and parents of young children. Despite this, there remains a significant gap in the literature pertaining to the use of passive sensing for the examination of mobile device and app usage among adolescents. Taken together, we are unaware of any empirical investigations of passive sensing apps that quantify mobile device use among adolescents. Given the ubiquity of smartphones and tablets among youth, filling this gap in the literature is imperative for research on mobile devices.

4 | STUDY AIMS

Although there is compelling support for using passive sensing techniques to quantify adults' (Yuan et al., 2019) and young children's device use (Radesky et al., 2020), there is a need to examine this methodology in older children and adolescents. Indeed, besides these examples, passive sensing to quantify mobile device has only been piloted in adults (Bagot et al., 2018). Additionally, in-the-moment-self-report of digital media use through EMA on mobile devices may aid in the research on content and context of adolescents' digital media use. As such, utilizing the built-in features of smartphones, a novel app "eMoodie" (www.emoodie.com) was developed that passively collects information on app usage and SST including duration and time of use, and has an EMA feature that is programmed with built-in gamification design features (www.emoodie.com; Banga, 2017). Since this is the first empirical evaluation of the use of a passive sensing/EMA app to quantify adolescents' smartphone use, it is critical to assess the practicality and adequacy of using eMoodie. One issue at stake is whether participating in a mobile-based EMA study leads to increases in SST due to the fact that when an individual answers an EMA notification, this may prompt further phone usage since the individual is now engaged with the device. Moreover, the attention devoted to monitoring the smartphone for notifications may also alert the participant to other notifications and activity that may otherwise be ignored.

The purpose of this manuscript is to evaluate the feasibility (i.e., compliance with downloading and using the app) and acceptability (i.e., adolescent ratings of app features and usability) of the eMoodie app in a sample of 23 parent–child dyads (N = 46), with children age 10–12 years (data collected during Spring 2018 through Spring 2019). In a second study, 263 caregiver-child dyads participated (N = 526) in 2017 in Edinburgh, Scotland. In this study, early adolescents (ages 11 to 14) participated in a remote study using eMoodie involving an EMA component, questionnaires, and passive sensing data collection over a seven calendar day period, and one parent/caregiver completed a questionnaire pack online. Feasibility and accessibility were also evaluated in this sample using compliance statistics and adolescent ratings. Finally, the development of passive sensing applications or smartphone-enabled EMA research should consider whether the methods influence adolescents' mobile device use. As such, a final aim of this study was to evaluate whether using eMoodie alters the behavior being studied (i.e., SST) in participants in Study 2.

5 | METHODS: STUDY 1

Study 1 piloted the use of the eMoodie application (app) to examine its feasibility and acceptability among US adolescents and their parents. The Central Michigan University Institutional Review Board granted approval for this study. Twenty-three caregiver-child dyads in the Midwest participated in this study in 2018 to 2019 (N = 46). After consenting, participants completed surveys and other measures within the lab. Before leaving the lab, children downloaded the eMoodie application to their smartphone or tablet, which monitored device use and administered EMA surveys twice daily, over seven consecutive days.

5.1 | Participants and procedure

Families were recruited via flyers displayed at health clinics and child day cares, emails sent to university email lists, and advertisements posted on Craigslist. To be eligible, the child had to fall within the target age group (10.00 to 12.99 years), have no major medical concerns or developmental delays, have access to a mobile device (tablet or smartphone) that uses applications, be born at 37 weeks or later (i.e., not born prematurely), and have no major dietary restrictions (relevant to other aspects of the study not germane to current manuscript aims).

The majority of child participants were identified as White (91.3%, n = 21), with two child participants (8.7%) identifying as biracial. The majority of caregiver participants identified as White (95.7%, n = 22). Approximately half of the child participants were male (56.5%, n = 13), and the average child participant age was 11 years and

8 months (*SD* = 10.66 months). The majority of participating caregivers were mothers (87.0%, *n* = 20). The majority of caregivers had a 4-year college degree (39.1%; *n* = 9) or had more than a 4-year college degree (47.8%, *n* = 11).

Of the 23 participants, 15 (65%) had an Apple (iOS; *n* = 13) or Android device (*n* = 2). The remaining participants did not indicate the operating system (*n* = 2) or had other mobile devices not compatible with eMoodie or for whom new app downloads were not permitted on their device (*n* = 6). As newer iOS and Android versions were released throughout the study, there were a few occasions where the app was simply not compatible with the operating system newly installed. Of the sample with eMoodie installed on their device (*n* = 16), approximately half of the participants used both WiFi and data plans to go online (*n* = 7), nearly half had only WiFi capacity (*n* = 7), and one participant primarily used data to go online (*n* = 1 did not complete this question). Results are presented on the sample with eMoodie installed on their device (final *N* = 16 caregiver-child dyads).

During the dyads' initial appointment for participation, caregivers completed written questionnaires with a research assistant while another research assistant completed questionnaires with the child in an adjacent, but private, room. After the data collection, child participants were instructed to download the eMoodie application on their mobile device. Caregiver-child dyads were instructed on how to use the eMoodie application prior to leaving the appointment. Approximately 1 week after the initial lab visit, research assistants visited the participants at home, to assist the child in uninstalling the eMoodie application and to complete the feasibility and acceptability measures. Parents were compensated $25 after completing baseline surveys. If participants completed the home-based data collection (e.g., eMoodie app, EMA items, etc.), they were provided with an additional $5 and the child participants were offered a prize worth ~$10.

5.2 | Measures

eMoodie App. eMoodie automatically logs phone usage data, other application use data (e.g., social media applications and games), and accelerometer data, which provided objective data on smartphone usage and activity. No content entered within the used applications was collected (i.e., the app does not track what is said or posted on social media). Android operating systems provide an output of individual apps used as well as timestamps of use, whereas iOS provides SST with logging of time when device is being used (but without the granularity of which apps are used).

5.2.1 | EMA

The eMoodie app was programmed to notify participants to complete EMA surveys twice daily (morning and evening). To enhance completing the EMAs, gamification features of eMoodie were used. Specifically, participants collect points from completing surveys which in turn unlock puzzle pieces to uncover a picture underneath (see Figure 1). Germane to the current study, we asked, "Did you go to bed with this phone or tablet last night?" and "After you went to bed last night, did you use your phone or tablet to go on any websites?", with response options of yes or no. Participation in the study was "gamified" such that the completion of EMA surveys gives users points, and certain thresholds allow participants to "unlock" puzzle pieces which gradually uncover a picture with a riddle underneath (see Figure 2).

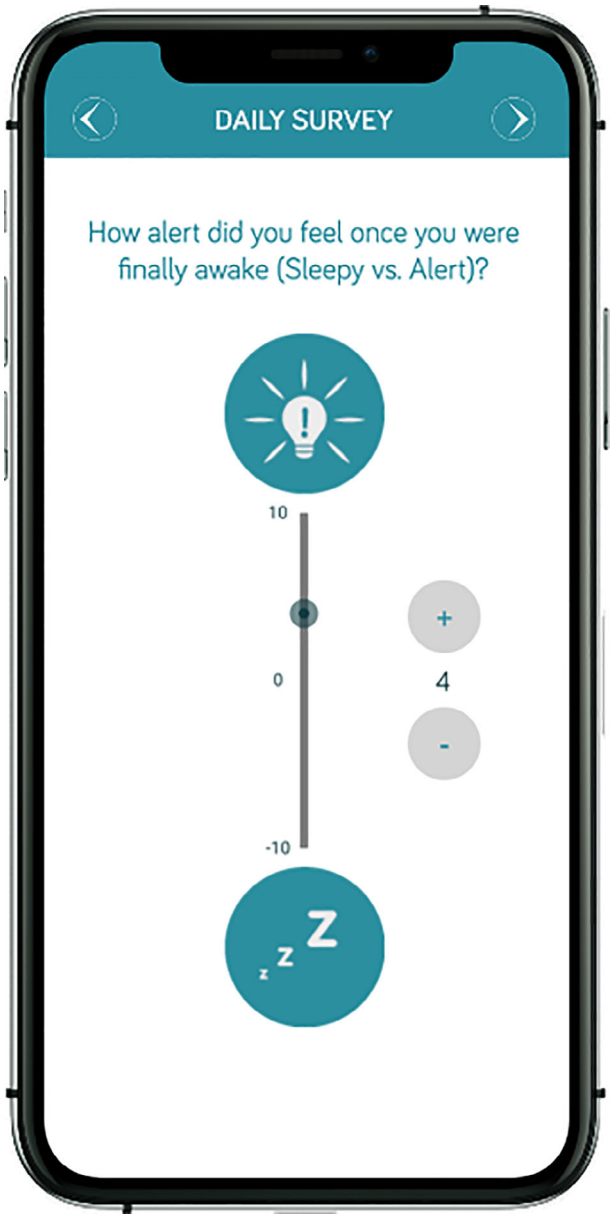

FIGURE 1 Screenshot of question screen

5.2.2 | Acceptability of eMoodie

After using eMoodie for 7 days, participants reported on ease of: downloading/installing eMoodie; of using eMoodie overall; and of

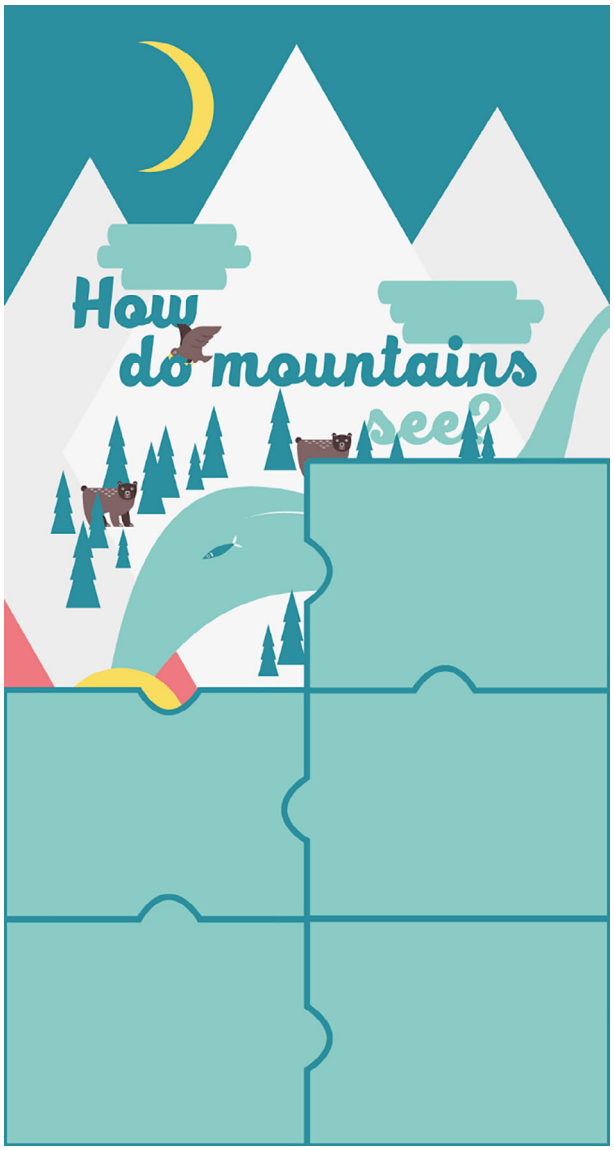

FIGURE 2 Screenshot of puzzle

using eMoodie to answer in-the-moment (EMA) questions. They responded to these questions on a 5-point Likert scale from very easy (1) to very hard (5). Participants were also asked whether they had difficulties in using eMoodie (yes or no) and if there were ways to improve the app or its usability (in an open-ended response format).

5.3 | Data analysis

To determine the feasibility of using eMoodie, rates of downloading the app and completing twice-daily EMAs were calculated (via frequencies/percentages). To evaluate acceptability, mean scores of acceptability ratings were calculated on ease of downloading/installing eMoodie and the ease of using eMoodie overall and completing EMA items. Frequencies/percentages were calculated on whether participants had difficulties in using eMoodie.

6 | RESULTS: STUDY 1

6.1 | Feasibility

Of the 16 participants with eMoodie-compatible devices, all consented to installing eMoodie (100%). Additionally, all participants retained eMoodie on their mobile devices until their participation ended (~7 days after lab-based data collection). Regarding completion of evening EMAs, 11 of the 16 participants completed at least 7 days (69%); four completed 5 or 6 days (25%) and one completed 4 days (6%). In terms of completion of the morning EMAs, 10 of the 16 participants completed at least 7 days (63%), four completed 5 or 6 days (25%), and two completed 3 days (13%).

6.2 | Acceptability

Most participants reported that using the eMoodie overall was very easy (n = 11; 69%) or somewhat easy (n = 2; 9%). Similarly, participants reported that using eMoodie to answer EMA items was somewhat easy (n = 14; 61%) or neutral (n = 1; 6%). Participants reported that downloading/installing eMoodie was very easy (n = 11; 69%) or somewhat easy (n = 1; 9%). Only one participant endorsed that they had difficulties with the eMoodie app interfering with device use. Thirteen participants did not recommend changes to improve eMoodie (with two not responding). One participant requested to make eMoodie "more fun."

Regarding if there was anything participants liked about the app, four participants reported enjoying the points and puzzle (i.e., gamification features; "that it gave u points like a game"); and three participants provided general positive responses ("its great;" "everything was good;" "it was easy to use"). One participant enjoyed the EMA evening items ("It helped me contemplate my day in the… evening"). Other participants did not indicate anything they liked about the app (n = 5).

7 | METHODS: STUDY 2

Study 2 also aimed to examine the feasibility and acceptability of using eMoodie within a developmental sample, and given its larger sample, aimed to validate the use of eMoodie to study media use and its potential impact on emotional and mental health outcomes in typically-developing early adolescents. The project was granted ethical approval by a research ethics committee from the Department of Clinical Psychology at the University of Edinburgh. Two hundred sixty three caregiver-child dyads participated in the study which was run across four iterations in 2017 in Edinburgh, Scotland (N = 526). Early adolescents (ages 11 to 14) from the first two grades of secondary school (i.e., S1 and S2) were recruited from three high schools to participate in the seven calendar day EMA study, and one parent/caregiver completed a questionnaire pack online.

7.1 | Participants and procedure

Students were recruited in conjunction with delivery of Online Safety and Cyberbullying Workshops which were conducted with children from eligible grades at participating schools. They were shown a recruitment video (Banga & Razakova, 2017) and had the ability to ask questions afterwards. If interested, they were given information and consent packs, and were encouraged to show the video to their guardian. Informed consent was provided in writing by both the child and one parent/caregiver. Inclusion criteria was limited to being enrolled in either S1 or S2 grade levels, and the child having access to either their own or a family member's smartphone or tablet device meeting the operating system requirements for the app to function properly (Android version ≥5.0; iOS ≥8.0). Research assistants were available in person at lunchtime and afterschool to both collect consent forms and assist with the installation of eMoodie on participants' phones. At the time of the app's installation, the child provided consent within the app, thus giving them another opportunity to ask any clarifying questions. Youth had the opportunity to earn £30 in vouchers as remuneration for their participation based on three different metrics: (a) £10 for completing a minimum of 75% of EMA surveys; (b) £10 for completing all study questionnaires; and (c) £10 for uncovering the entire puzzle behind the picture (see Figure 2).

All three high schools were located in central Edinburgh, and therefore, due to postcode catchment policies linked to school attendance, children came from very similar socioeconomic status (SES) backgrounds across the three schools. The majority of participants came from middle to upper SES households (+£50,000, 54.0%). Participants ranged from ages 11 to 14 (M = 12.88, SD = 0.72), and the gender of the sample was split two-thirds to one, female versus male (see Table 1). The sample was predominantly composed of Caucasian children from a British nation (74.9%) or other White background (11.4%), with a smaller proportion of the sample from Asian British/Asian (3.4%), Black British/Black (1.9%), and other (8.4%) ethnic backgrounds (as per ethnicity categorizations from the NHS Demographics form). The breakdown of Android versus iOS devices by study participants was 34.8% and 65.2%, respectively. The vast majority used their own personal device during the study period (98.6%).

TABLE 1 Descriptive statistics of the data set

Variable/feature	
Age (years)	12.88 (0.72)
Sex	Male: 33.5%; female: 66.5%
Ethnicity[a]	
Caucasian	74.9%
Other white background	11.4%
Asian British or Asian	3.4%
Black British or black	1.9%
Other	8.4%
Household income	
0–£20,000	9.2%
£20,001–£35,000	11.5%
£35,001–£50,000	10.3%
£50,001–£80,000	26.8%
'+£80,001	27.2%
Prefer not to answer	14.9%

[a]From NHS demographics form.

7.2 | Data analysis

Similar to Study 1, we examined feasibility based on the compliance statistics associated with the completion of EMA surveys, questionnaires (12 in total), and passive sensing data capture. In addition, we examined quantitative (i.e., frequencies) and qualitative feedback from adolescents on their experience of using eMoodie, and participating in an EMA study with a high participant burden (due to the frequency rate of surveys and time required to complete questionnaires). Feedback also included technical feasibility related to the performance of the app, which is an important consideration in EMA studies where individuals are using their own device as opposed to the same homogenous device provided by researchers to participants.

In examining the feasibility of using mobile devices to conduct a study when the main dependent variable is screen-time and/or smartphone usage, it is important to evaluate whether SST rates change as a result of participating in an EMA study. Using objectively collected app usage data from the smartphones of study participants (which, when summed, is a measure of SST), we compared mean levels of SST on days prior to the study versus days during the study. A paired-samples t-test was run to examine potential differences between pre- and during- study SST levels. In order to rule out the time when participants filled in EMA surveys with eMoodie, it was only possible to use the subsample of 47 participants with Android phones from our full sample (N = 263) because that level of detail in the data output is not available with iOS.

8 | RESULTS: STUDY 2

8.1 | Feasibility

Some participants (n = 9) with older devices (e.g., iPhone 4S) and operating systems unsupported by the app were unable to receive notifications, but still completed the questionnaires. Thus, compliance statistics for the completion of EMA surveys versus questionnaires are calculated with different sample sizes. Passive sensing data was collected from 93% of participants (n = 254). Compliance for the completion of EMA surveys across the entire study was 77.8% based on 10,022 completed EMA surveys, whereas 92.2% of questionnaires were completed, for a total of 3,010 questionnaire entries. The combined compliance rates across both the EMA and questionnaire components of the study was 85.0%. A more detailed discussion of the compliance, engagement, and gamification statistics for this validation

study can be found in Banga, Razakova, Clain, Quale, and Schwannauer (2020).

8.2 | Acceptability

The total number of notifications per day (7), the total length of the EMA survey, and the addition of the questionnaire completion component of the study made participation in this study time intensive. Nonetheless, at least three quarters of participants rated that participation in the study was acceptable across the various questions, except for ratings of the number of notifications per day, which performed at a two-thirds acceptability rating (63.5%) (see Table 2).

Participants also had the opportunity to provide qualitative feedback on the app (see Table 3). Because there was a gap of a number of months between running the study in the spring and then later in the fall, we were able to use the feedback provided to fix further technical issues in the app. In particular, there was an issue with the points system in the gamification set-up whereby some participants' point totals would be altered after they had uncovered all the puzzle pieces. This was due to having lowered the total number of points necessary for completion of the puzzle in comparison to pilot testing such that this was an unknown issue going into the first iterations of the study. In the fall studies, this was not reported as an issue, as reflected in the substantial drop in reported issues for this category (46.0% in the spring as compared to 11.0% in the fall studies). Overall, 26.1% of participants reported a technical problem across the four iterations of the study, with 90.5% of participants having completed the "End of Study" questionnaire. Fewer errors were reported by participants with iOS devices as compared to Android due to the fact that all iOS devices are produced by Apple and there is therefore, a greater uniformity in performance. In comparison to the question on error reporting, there were no substantive patterns of feedback for the other qualitative question. Positive feedback included respondents reporting that they had fun participating: "I think this was a really smart idea and I enjoyed participating in the study."

TABLE 2 Acceptability survey questions and answers

Question and answer options	% answered
Do you think the number of notifications per day was reasonable?	
Too few	7.1
Ok number of ratifications	63.5
Too many	27.8
Way too many	1.6
Was the last notification of the night (between 8:00 and 9:00 PM) too late for you given your bedtime?[a]	
It was fine	81.0
Too late	15.1
Way too late	4.0
Do you think the total number of days was ok for this type of study?	
Too few	16.7
Ok; it was reasonable	77.8
Too many	5.6
Way too many	0.0
Do you think the time it took to fill out the experience survey was reasonable?	
Reasonable amount of time	76.2
Too long	19.8
Way too long	4.0
Do you think the time it took to fill out the questionnaires was reasonable?	
Reasonable amount of time	77.8
Too long	19.8
Way too long	2.4

[a]A notification was sent out at a random time during this interval each night.

8.3 | Validity using SST

Only weekdays were used in the analysis because weekend SST differs significantly from weekday SST, and there were comparatively fewer weekend days prior to the study available for analysis. We used individual weekdays rather than average across participants in order to maintain the true variance in the data.

Statistically, there was a significant difference in SST before the study (M = 120.97 min, SD = 66.80 min) in comparison to during the study (M = 131.98, SD = 61.60); $t(46) = 13.31$, $p < .05$. While the difference is statistically significant, the real world difference is arguably negligible particularly when considering the size of the SD and the overall mean difference (~11 min). Moreover, calculation of Cohen's effect size (d = 0.17) yielded a slightly lower value than what is typically considered to be a "small" effect size (d = 0.2) (Cohen, 1992).

The distribution of the curve was skewed for the before study and during-study usage data which is likely to have significantly influenced our results. Therefore, as a more reliable check, we modeled the curve of the distribution for the difference between the before- and during-study data. This curve was a Gaussian distribution and from this we observed that there was a 66% probability that the difference in usage between timepoints was between 8 and 23 min.

9 | DISCUSSION

The purpose of this study was to pilot the use of a novel passive sensing app, eMoodie, to quantify adolescents' mobile device use in two samples of early adolescents. Based on rates of download and use across both studies, our results suggest that eMoodie is feasible to implement with adolescents and that it demonstrated good usability. Participants reported enjoying the gamification features and, overall, the app was accepted by the child participants. The possibility to

TABLE 3 Qualitative feedback

Questions and coded categories	Spring	Fall	Total
Were there any errors or problems with the notifications, points, or any aspect of the app that you experienced during the study?			
No problems that I noticed	63	113	176
Crashing	2	3	5
Notification errors	2	4	6
Synching error	1	1	2
App unresponsive sometimes	1	1	2
Bug at end of survey—Not letting complete	1	3	4
Glitches (graphics)[a]	35	2	37
Glitches (general)	4	2	6
Total errors	46	14	62
Do you have any other feedback about eMoodie or any aspect of the study? We really want your opinion so we can make things better for future participants.			
No feedback	85	108	193
Positive feedback	9	11	20
Want to know when surveys will be	3	3	6
Personal nature of questions	1	1	2
Notifications after bedtime	1	0	1
Feedback on survey questions	2	0	2
Longer time to complete	3	0	3
Could not answer with zero	2	0	2
Compensation	2	1	3
Too many surveys in 1 day	1	3	4
Total feedback	24	13	43

[a]The problem reported by many participants in the Spring studies was fixed for Fall studies.

report qualitative feedback provided information on any ongoing technical issues which could then be fixed for future studies. It is important to note that both parents and children consented (assented) to using eMoodie; the primary barrier to not reaching 100% of the sample using eMoodie was technological. In other words, some children's mobile devices could not access the app store or were too outdated to properly install eMoodie. However, as technologies advance, we expect that this will no longer be an issue.

An additional aim of this manuscript was to examine the validity of eMoodie. We evaluated whether using the app would increase adolescents' SST in a significant manner. Although there was a statistically significant increase in SST (ranging from an approximate increase of 8 to 23 min per day), this amount is negligible, compared with the amount of time youth spend going online (especially during the pandemic; i.e., ~6 hr online each day; Parents Together, 2020). Importantly, these results suggest that using eMoodie (with gamification features and push notifications) does not have a marked impact on adolescents' mobile device use in terms of overall duration. Future research using eMoodie may inform participants of this minor increase in SST. Due to the fact that Android has the level of granularity in the output to compute times of daily individual app usage, it would be possible to calculate the average time spent using eMoodie across Android participants each day. In turn, these values can be subtracted from both iOS and Android participants to determine SST less time spent participating in the study.

Across the studies, the eMoodie app was feasible to use, and was acceptable by youth and their caregivers. Various features of eMoodie likely contribute to its utility and acceptance. For example, no GPS or social media content is collated from the app. That is, the way that eMoodie is designed, there is no possible way to identify the child (or his/her location) unless the researcher asks for identifying information within the context of the study. One way we recommend to further ensure the confidentiality of the child's data is by only collecting identifiable information from parents outside of the app (e.g., via online survey system). As such, every single data file from eMoodie are only identifiable on the server by participant number. These standards were established in line with best practices for responsible conduct for the storage of physical research data (despite being virtual).

In addition, gamification—the inclusion of gameful elements in settings outside video games (Deterding, Dixon, Khaled, & Nacke, 2011)—has been successfully applied for some time now in technologically-enabled educational settings (Domínguez et al., 2013,

and may also contribute to the favorable ratings of eMoodie by adolescents. A recent investigation by Van Berkel and colleagues (2017) employed an experiment with gamified and non-gamified versions of an EMA app in order to evaluate the impact of gamification elements on both quantitative and qualitative aspects of participants' data quality. Comparison of responding indicated that gamification resulted in slight increases in participant compliance as measured by response rates, and notable increases in data quality, operationalized through the length, verbosity, and complexity (e.g., number of descriptors) in free-text entry responses (Van Berkel, Goncalves, Hosio, & Kostakos, 2017). Thus, there is early evidence to suggest that gamification improves participant compliance and engagement.

In addition to utilizing gamification design elements as part of the study procedure, questions and answers were also programmed using icons to increase the comprehension and engagement of child participants (e.g., see Figure 1). This is a strategy that has been employed in developmental psychology for decades. Although it is feasible to implement gamification in digital research with children, it may require interdisciplinary collaboration with, for example, the art and design college of a university, in order to ensure aesthetic quality which children have come to expect in digital products such as video games and social media.

9.1 | Limitations

A barrier to acquiring a richer array of sensing data was that the majority of the sample were iOS users. Although not a flaw with the eMoodie app, any passive sensing app not created by Apple will have limits on its ability to quantify specific app usage. Future, larger sample studies may seek to recruit adolescents who own Android devices to further validate eMoodie's unique features. Further, the demographic characteristics of the participants preclude the generalizability of our feasibility and acceptability results; future research using eMoodie may seek to assess the feasibility and acceptability in subsequent studies with racially/ethnically diverse adolescents and youth from lower-income households.

In order to facilitate remote research, particularly in the context of COVID-19 requirements for social distancing, future research with eMoodie for EMA and passive sensing should consider certain methodological approaches to enhance participant recruitment and completeness of data. In both studies, research assistants were trained to navigate components within smartphones (on both Android and iOS) to facilitate the proper configuration of settings for eMoodie. For example, many individuals have an automatic setting that if you download a new app, push-notifications are not enabled. To collect accelerometry data, iOS users have to enable "use location" even though eMoodie does not capture GPS location; this setting is nevertheless required for accelerometry data to be collected. Although the current studies did not examine the feasibility of remote recruitment or instructing the child participants themselves to configure the settings properly, it may be possible to facilitate both of these processes remotely if necessary. In the case of the pilot studies conducted to develop eMoodie using undergraduate students, recruitment, and participation was conducted entirely remotely and this was a successful approach. Due to the technical fluency of most adolescents, it would likely also be feasible in a younger age group.

In addition to push notifications as a reminder to participants, the US study also provided daily text reminders to the caregiver to increase data completeness. When using eMoodie with younger participants (children in the US sample were 10–12 years old), engaging caregivers in reminder texts may be particularly useful (especially if the child does not have their phone or tablet with them at all times). After installation, a practice survey is automatically cued for the participant to navigate through so the children could see what a typical survey would look like during the week and ask questions if needed. The children in the US study were also rewarded with an age-appropriate prize after completion of their week-long participation, which was non-contingent on their completion of EMA surveys. In the future, it may be useful to continuously monitor completion of surveys, and reward compensation based on this completion using the gamification features of eMoodie (as was done in Study 2). Finally, screening participants in advance to ensure they have a mobile device with the most up-to-date operating system installed (prior to the appointment) will reduce errors in downloading the eMoodie app.

9.2 | Future directions

Smartphone-based EMA methods are being adapted to facilitate clinical research and evidence-based interventions alike. Unlike early EMA research which was hampered by the expensive and time-consuming process of providing devices to study participants and, in turn, training participants (Hektner, Schmidt, & Csikszentmihalyi, 2007), high personal device ownership and current trends expanding to an ever younger age group solves both of these issues. Moreover, ambulatory assessment methods typically struggle with participant adherence rates (Trull & Ebner-Priemer, 2013). While passive Smartphone sensing data is not as accurate as wearable devices for measuring behaviors such as activity levels, machine learning (ML) methods are nevertheless able to model complex behavioral markers of mental and physical health symptoms (see Mohr, Zhang, & Schueller, 2017 for review). For example, high frequency phone checking behavior is a predictor of inattention and impulsivity (Kushlev, Proulx, & Dunn, 2016).

Furthermore, data capture capabilities will improve with technological advances in newer devices. In the UK study, the most common device type of participants was an iPhone 5S which is only the second model released by Apple that was equipped with an array of sensors with APIs available to developers. While promising, it is important for psychological and medical researchers to establish interdisciplinary teams with experts in computing in order to better understand methods to the best process, analyze, and visualize sensing data. For instance, the statistical toolkit of most psychologists is ill-equipped to analyze EMA data paired with passive sensing data in the same analysis because they are in different timescales (Dwyer, Falkai, &

Koutsouleris, 2018). ML is best suited for the coupled analysis of these data types (e.g., see Banga et al., 2019). The analysis of passive sensing data alone also requires pre-processing and advanced data cleaning techniques. Fortunately, in accordance with the open-science ethos, many computer scientists are making scripts to process this data available online (e.g., Andrews, Ellis, Shaw, & Piwek, 2015) and are developing open-source tools to harness the mathematical complexity of ML for psychological and clinical scientists (e.g., PRoNTO; Schrouff et al., 2013).

9.3 | Conclusion

This is the first investigation into using a passive sensing app (with EMA) to quantify adolescents' mobile device use objectively. Our studies support the feasibility and acceptability of using eMoodie's features (i.e., passive sensing and EMA) to measure various elements of an adolescent's mobile device use. Validation of the app appears promising, but more research with larger samples and preferably with Android users will be needed. Similarly, future research may seek to validate eMoodie's use in clinical samples and/or for clinical utility. As youth are increasingly using mobile devices (both before and during the COVID-19 pandemic), capturing objective use and evaluating how such use is impacting development grows ever more important.

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CONFLICTS OF INTEREST

Dr. Domoff is on the Board of the SmartGen Society, and regularly receives honoraria for speaking invitations to different academic and non-profit institutions. Dr. Domoff has received funding from the National Institutes of Health. Ms. Banga developed the eMoodie application and consults with organizations and research teams to implement eMoodie for research and clinical purposes. Ms. Banga received funding to update and manage eMoodie during the course of the study.

PEER REVIEW

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DATA AVAILABILITY STATEMENT

Data available on request from the authors.

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