Digital Wellbeing Applications: Adoption, Use and Perceived Effects

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Abstract

Increasingly, mobile applications enable people to monitor and regulate their smartphone use in the support of digital wellbeing. Herein we report a mixed-methods study involving the collection of both quantitative and qualitative data from a student sample conducted with the aim of investigating, firstly, the adoption of applications designed to support digital wellbeing, secondly, the factors that influence the continued use of such applications and, thirdly, the effects users perceive these applications to have on their digital wellbeing. The outcomes of this study highlight the importance of individual motivations and the need to understand digital wellbeing as more than simply the use of an application but, rather, a subjective consideration of the place of digital media in an individual's life. The present study provides a rich descriptive account of the temporal variability, person-specificity, and device-contingent nature of digital wellbeing.

Keywords: Digital Wellbeing, Screentime, Behaviour Tracking, Self-Regulation

Digital Wellbeing Applications: Adoption, Use and Perceived Effects

A growing number of smartphone applications enable users to track and regulate their smartphone use. Examples of such applications include those provided at the operating system level—*iOS Screen Time* and *Android Digital Wellbeing*—as well as stand-alone applications such as *Forest: Stay Focused* and *Moment*. Using applications to monitor and regulate media use can, for some, form part of a phenomenon broadly conceptualised as *digital wellbeing*. Vanden Abeele (2020, p. 13) considers this concept to refer to the "subjective individual experience of optimal balance between the benefits and drawbacks obtained from mobile connectivity." For many, this involves becoming more intentional with how digital media are used (Roffarello & De Russis, 2019), and aligning device use with general goals (Parry et al., 2020).

While various third-party services have been available for a number of years, following recent updates, exposure to, and possible adoption of, applications designed to support digital wellbeing is now a widespread possibility. In 2018, Apple launched iOS Screen Time, which tracks the time users spend with various application categories as well as overall device usage. Additionally, users can set limits, which are enforced by the application, on the time spent with particular applications, categories of applications, or the device itself (Apple Newsroom, 2018). In the same year, Google launched Digital Wellbeing which provides similar functionality to its iOS counterpart (Google, 2018).

Although studies in other domains have generated much knowledge about the user characteristics, features, and outcomes that predict use of behaviour tracking applications (Lee & Cho, 2017; Putri et al., 2019), in the context of digital wellbeing, little research has been conducted to understand the factors that motivate continued use. Given the ubiquity of smartphones in both developed and emerging economies (Silver, 2019) and, in addition to the myriad benefits that these devices provide (Vanden Abeele et al., 2018), the possibility of adverse effects (Tarafdar et al., 2013), there exists a need to understand how smartphone applications can be used to support individuals' in their digital wellbeing.

Self-Monitoring and Digital Wellbeing Applications

A growing body of research investigates applications relating to digital wellbeing through a variety of quantitative, qualitative, and design-led approaches (Roffarello & De Russis, 2019; Oeldorf-Hirsch & Chen, 2020; Parry et al., 2020; Rooksby et al., 2016; Saariketo, 2019). Studies in related areas have used various adoption models to investigate user motivations and behaviour. Such models include the *Technology Acceptance Model* (TAM; Davis et al., 1989), which emphasises perceived usefulness, attitudes, and behavioural intentions; the *Unified Theory of Acceptance and Use of Technology* (UTAUT; Venkatesh et al., 2003), which explains behaviour through performance and effort expectancies, social influences, and facilitating conditions; and the *Uses and Gratifications* (U&G; Blumler & Katz, 1974) approach which focuses on the needs gratified through technology use.

The U&G approach, in particular, provides a useful lens through which the motivations for using digital wellbeing applications can be investigated. Use is explained in terms of a technology's capacity to gratify a user's needs (Blumler & Katz, 1974). These needs serve as motivations for adoption and continued use. Many studies have used this approach to investigate use of other classes of behaviour tracking applications (e.g., Lee & Cho, 2017; Putri et al., 2019). In addition to use itself, integration of technology into routines is a central concern. Acknowledging the *Technology Integration Model* (TIM; Shaw et al., 2018), integration can be understood to reflect not only frequent use, but also consistent patterns of use and, in the context of digital wellbeing, reliance.

In an early study, Rooksby et al. (2016) assessed the efficacy of an application that enabled users to monitor their media use. Through log and interview data these authors found that, while there was limited interest in tracking overall device use, participants expressed interest in quantifying their use of specific applications, especially to support productivity and reduce excessive use. Further insight into experiences with media use monitoring has been provided in a qualitative study by Saariketo (2019) in which participants used an application to monitor their smartphone use. Through individual interviews Saariketo (2019) found that monitoring was driven by participants' curiosity and a motivation to learn about their use patterns. For some, as also found by Parry et al. (2020), this awareness served as a catalyst for rearranging usage patterns and aligning behaviour with goals. Despite this, while some were surprised, many felt that the information provided by the application was irrelevant or uninteresting, commenting that they were already aware of their usage patterns. Saariketo (2019) observes that her findings indicate that, while perhaps initially enthused by monitoring of smartphone use, many are subsequently indifferent.

In a review of 42 Android applications related to digital wellbeing Roffarello and De Russis (2019) found that, while a majority of applications include features which support monitoring of device use, they rarely include features that restrict device or application access. Analysing user-reviews for these applications, these authors show that, although a variety of use cases were reported, digital wellbeing applications were most frequently used for time-management, impulse-control, and to support productivity and concentration while studying or working. Building on these findings Roffarello and De Russis (2019) developed their own application and assessed it over three weeks. No within-subject effects were found for ‘problematic use,’ self-regulation, device unlocks, or application launches. The authors did, however, find a decrease in overall device usage and the number of applications used. Despite indicating a preference for features that enabled them to block specific applications, a majority of participants dismissed restrictions and only occasionally monitored their usage.

In a recent study focusing on the iOS Screen Time feature Oeldorf-Hirsch and Chen (2020) used the TAM to investigate various user characteristics, use predictors, and differences in device usage between users and non-users. Through an online survey, this study shows, firstly, that only 48.1% of those surveyed (*n* = 405) use the feature and, secondly, that both perceived usefulness and perceived ease of use predicted positive attitudes about the application, intentions to continue using the application, and actual use of application. Despite this, Oeldorf-Hirsch and Chen (2020) found that participants who used Screen Time did not report any less smartphone use than those who did not. The study also indicates that those who are generally more mindful are not more likely to use Screen Time and, in addition, they find the feature to be less useful than those who are generally less mindful.

Current Study

To address current knowledge gaps we conducted a mixed-method study with the aim of investigating, firstly, the adoption of applications designed to support digital wellbeing, secondly, the factors that influence the continued use of such applications and, thirdly, the role users perceive these applications to play in their digital wellbeing. Targeting a student sample, quantitative data were collected with an online-questionnaire and, following this, qualitative data were collected with individual semi-structured interviews. For the quantitative component of our investigation, to consider adoption, user differences, and perceived outcomes we embraced an exploratory frame and posed the following research questions:

- RQ1: *What are the levels of awareness and adoption of smartphone applications targeting digital wellbeing among students and do personal and device characteristics predict these levels?*
- RQ2: *Which applications and features are most commonly used to support efforts to achieve digital wellbeing?*
- RQ3: *Do users of digital wellbeing applications report lower smartphone use than non-users?*
- RQ4: *Do users of digital wellbeing applications perceive them to be useful and/or effective?*
- RQ5: *For non-users of digital wellbeing applications, what motivates intentions to use in the future?*

Adopting a confirmatory stance, building on previous research in this regard, we hypothesized that: *Information seeking motivations* (H1); *consciousness of negative outcomes associated with smartphone use* (H2); *the desire to align behaviour with goals* (H3); *and desires to change behaviour* (H4) *will positively predict self-reported integration of digital wellbeing applications into daily life.*

For the qualitative aspect of the study, we adopted an inductive approach and posed the following research question: *What role does self-monitoring play in students' experiences of digital wellbeing?* (RQ6). With this question, we place particular emphasis on students' perceptions of digital wellbeing applications and how these applications affect their smartphone use and digital wellbeing.

In accordance with recent calls for greater transparency in Communication research (Dienlin et al., 2020), following IRB approval, prior to data collection, we pre-registered our research questions, hypotheses, and methodology for both the quantitative (https://osf.io/n3c2p?view_only=357262128e774814a83fb79300939428) and, acknowledging recent debates about the pre-registration of qualitative methods (Haven & Van Grootel, 2019), the qualitative (https://osf.io/kazdt?view_only=2139551dc24e4a17804264196f7da659) components of our study. Additionally, all materials, quantitative data, and analysis scripts are available through the OSF (https://osf.io/9ry6t/?view_only=a4a062bb14734545ab73c913c37a298b).

Participants and Procedure

The study involved a sample of undergraduate students at a large university in South Africa. Previous research shows that students at such institutions are comparable to their Western counterparts when it comes to media use (Broughton et al., 2019; Chokalingam et al., 2019). Invitations to complete an online survey were emailed to all undergraduate students at the institution. To ensure that our analyses were adequately powered, we conducted an a priori power analysis using G*Power (Faul et al., 2009). Given the generally small effect sizes observed in Communication research (Dienlin et al., 2020), we planned to be able to detect at least an effect of $f^2 = .05$ with 80% power and $\alpha = .05$. For a multiple regression analysis with four predictors, we required a minimum sample size of $n = 244$. Notably, we planned to conduct this analysis only with respondents who were users of digital wellbeing services. Therefore, given Oeldorf-Hirsch and Chen's (2020) finding that 48.1% of those queried used these services, we targeted a sample of at least $n = 500$.

Data collection occurred over two weeks, with 5648 respondents accessing the survey. Of these, 3772 incomplete responses and 16 responses for which consent was not provided were removed, leaving a sample of $n = 1860$. While those who indicated that they do not own a smartphone (0.59%) were removed, 58.30% use an Android smartphone and 41.70% an iPhone. Thus, the final sample included 1849 students. Corresponding to the demographics of the institution, the sample included more female (62.67%) than male (36.88%) respondents (0.65% use other gender descriptors). The mean age of respondents is 20.53 years ($SD = 1.87$), and 43.10% are in their first year of study, 25.20% their second, 20.50% their third, and 11.20% have been enrolled for four or more years.

Survey Measures

As there are no existing scales specifically concerning motivations for use of digital wellbeing applications, items were developed based on the literature on technology use and adoption, previous studies of digital wellbeing, and research concerning personal analytics in general. All items were piloted with a student sample and, where appropriate, we performed assessments for internal consistency and confirmatory factor analyses. All items are available through the OSF.

To understand if use of personal analytics or mental health related applications predicts use of digital wellbeing applications respondents indicated if they regularly use applications for 1) health and fitness or 2) mental health (e.g., mindfulness) purposes (for both: yes/no). To assess whether use of digital wellbeing applications is associated with differences in self-reported smartphone use, using a slider ranging from zero to 960, respondents provided an estimate of the amount of minutes that they spend on their phone during an average day.

For adoption and awareness of digital wellbeing applications we first asked respondents whether they knew about such applications (yes/no) and, following this, to characterise their engagement as either ‘never’, ‘ceased’, ‘occasional’, or ‘regular’. To determine which applications and features are most commonly used, those who indicated either occasional or regular use (classified as users) were asked to select 1) the applications and 2) the features that they use from provided lists. For both items, respondents could augment the list with additional options. For these same respondents, to assess use integration, motivations, and perceived value, we developed items on the basis of technology use and adoption literature, and previous studies in this domain. For these items responses were provided through 7-point Likert scales (1 = strongly disagree, 7 = strongly agree). For integration and each of the four motivations we presented four items, with responses being independently averaged to produce overall values. Integration items concerned intentions to continue using, use-frequency, integration into daily life, and reliance. For perceived outcomes of using digital wellbeing applications, responses for three items which concerned the value of the data provided, the effectiveness at behaviour change, and the effectiveness at supporting productivity were collected. Finally, for respondents classified as non-users, we presented a single use-intention item for which they could respond either ‘yes’ or ‘no.’ These respondents were then presented with the motivation items (rephrased to pertain to future use intentions and not actual use).

Interview Procedures

Given the need to produce data with individuals who have experienced the phenomenon of interest (Creswell, 2013), those who reported either occasional or regular use of digital wellbeing applications in the questionnaire could indicate their willingness to be invited for an individual interview (*n* = 322). Noting Creswell’s (2013) prescriptions, we targeted a sample of 20 individuals, and randomly selected respondents for the interviews.

The interviews were conducted with online videoconferencing software by researchers previously unknown to the participants. Each interview lasted approximately 40 minutes and was recorded. Based on the research question an interview guide was developed to direct the semi-structured interviews (available through the OSF). This guide included questions to enable participants to describe their understanding of digital wellbeing, use of relevant applications, the factors that have motivated or averted use, and the perceived outcomes of such applications for their digital wellbeing.

Analyses

All quantitative analyses were performed with the *R* programming language (v. 3.6.3; R Core Team, 2013), with an alpha level of .05. To address RQ1, we calculated the proportion of respondents who were 1) aware and 2) reported either occasional or regular use of digital wellbeing applications. Next, we considered the effects of age, gender, use of fitness and mental health applications, and device type by computing either independent samples *t*-tests or *chi*-square tests as appropriate. RQ2 was addressed by summarizing the proportion of users reporting use of the relevant applications and features. To address RQ3 we analysed the difference in mean reported smartphone use between users and non-users with an independent samples *t*-test. For RQ4, we evaluated the proportion of users who expressed either agreement or disagreement with the statements provided. For RQ5, we conducted a binary multiple logistic regression predicting use-intentions by non-users for the four motivations posed. To test H1-4, we used a multiple linear regression predicting integration of digital wellbeing applications with the four motivations targeted. All composite variables were evaluated for internal consistency and single-factor model fit.

For the qualitative analysis, the transcribed interviews were analysed using CAQDAS software. Our inductive thematic analysis, following Braun and Clarke (2006), began with the identification and coding of potentially relevant statements. The first author created an initial codebook after reviewing the transcriptions. The research team reviewed these codes and provided suggestions for additional codes. Two coders then followed an iterative coding process. Coded statements were clustered into themes which enable the provision of rich descriptions of students' understanding and experiences of digital wellbeing.

Noting that findings from qualitative designs are influenced by the lens through which the researcher(s) have produced and interpreted the data, and that such research requires bias clarification (Creswell, 2013), we acknowledge that our own experiences with digital wellbeing applications are either non-existent or they have been futile. While our experiences are diverse, generally, initial high-hopes have faded to neglect and relapse to entrenched behavioural patterns. To attempt to account for this possible bias and remain faithful witnesses to the participants, we tried to bracket our experiences by, firstly, posing broad open-ended questions which were followed with focusing questions for elaboration, secondly, involving a group of researchers with diverse experiences, ages, opinions on digital wellbeing, and educational backgrounds in the research process and, thirdly, using reflexive journaling to express our interpretations during the analysis process and aid us in understanding our own evolving perspectives on the data.

Findings

Quantitative Findings

Use of Digital Wellbeing Services. While 80.48% of respondents indicated that they are aware of digital wellbeing applications, only 36.94% reported either occasional (27.80%) or regular (9.14%) use. In contrast, 63.06% of respondents indicated that they have ceased using (16.12%) or have never (46.94%) used such applications. Those who reported occasional or regular use were classified as users (n = 683), while those who did not were classified as non-users (n = 1166).

For respondents who indicated either male or female, gender did not predict awareness ($\chi^2(1) = .17$, $p = .68$) but it did predict use of digital wellbeing applications ($\chi^2(1) = 13.24$, $p < .001$), with 40% of female respondents compared to 31.52% of male respondents classified as users. Although awareness differed by age ($t(430.55) = 2.45$, $p = .02$, $d = .19$), use did not ($t(1530.08) = .42$, $p = .67$, $d = .02$). Neither awareness ($\chi^2(3) = 6.04$, $p = .11$) nor use ($\chi^2(3) = 2.13$, $p = .55$) were influenced by year of study. Users of mental health applications (23.91%) were not more likely to be aware ($\chi^2(1) = .85$, $p = .36$) of digital wellbeing applications, but they were more likely to be users of these services ($\chi^2(1) = 21.17$, $p < .001$), with 46.15% using digital wellbeing applications compared to 34.04% of those who do not use mental health applications. Use of fitness applications (49.11%) was associated with both awareness ($\chi^2(1) = 9.51$, $p < .01$) and use ($\chi^2(1) = 21.94$, $p < .001$) of digital wellbeing applications. For all of the above comparisons the effect of these variables on awareness or use was small to negligible. In contrast, the effect of device type (Android or iPhone) on awareness ($\chi^2(1) = 85.11$, $p < .001$) and use ($\chi^2(1) = 93.98$, $p < .001$) of digital wellbeing applications was substantial, with 27.74% of Android owners classified as users compared to 49.81% of iPhone owners.

Figure 1 summarises the applications (panel A) and features (panel B) reported to be used to support digital wellbeing. Overall, the most used application is iOS Screen Time, followed by Forest: Stay Focused, Huawei Digital Balance, and Android Digital Wellbeing. As depicted in Figure 1, although 43.63% of users indicated that they use features that disable notifications, the features most frequently reported concern usage tracking: overall weekly usage (65.74%), weekly application category usage (43.63%), and daily overall usage (41.00%).

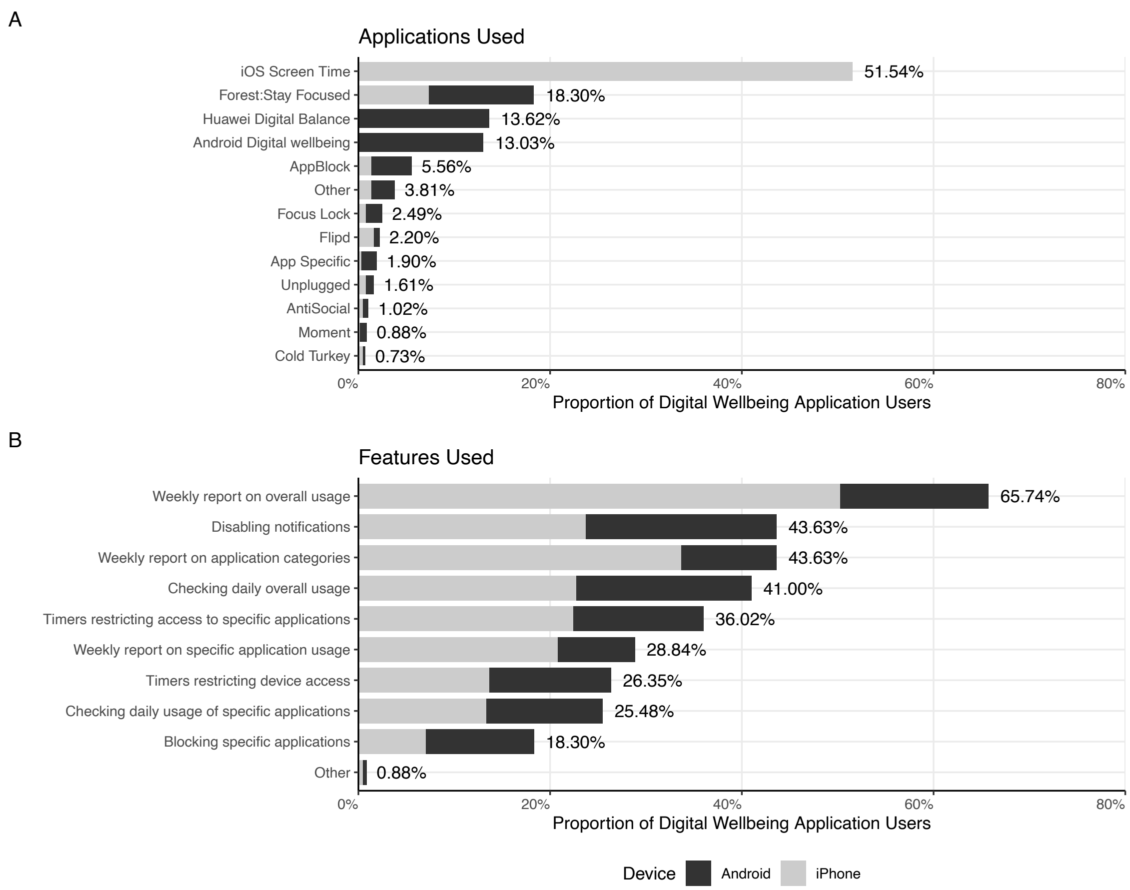

Figure 1. Summary of digital wellbeing applications and features used.

Outcomes of Digital Wellbeing Services. No meaningful difference in self-reported smartphone use in minutes was observed between users (M = 330.49, SD = 170.93) and non-users (M = 337.75, SD = 193.14) of digital wellbeing applications (t(1569.6) = .84, p = .40, d = .04). As shown in Figure 2, 68% of users indicated that the data provided by the applications were interesting and useful. However, only 52% perceived such applications to be useful for helping them change their behaviour and 51% reported that digital wellbeing applications help them to remain on task and focus on their work. For the latter two outcomes, a quarter of respondents do not regard digital wellbeing applications to be useful for behaviour change or task- or focus-management.

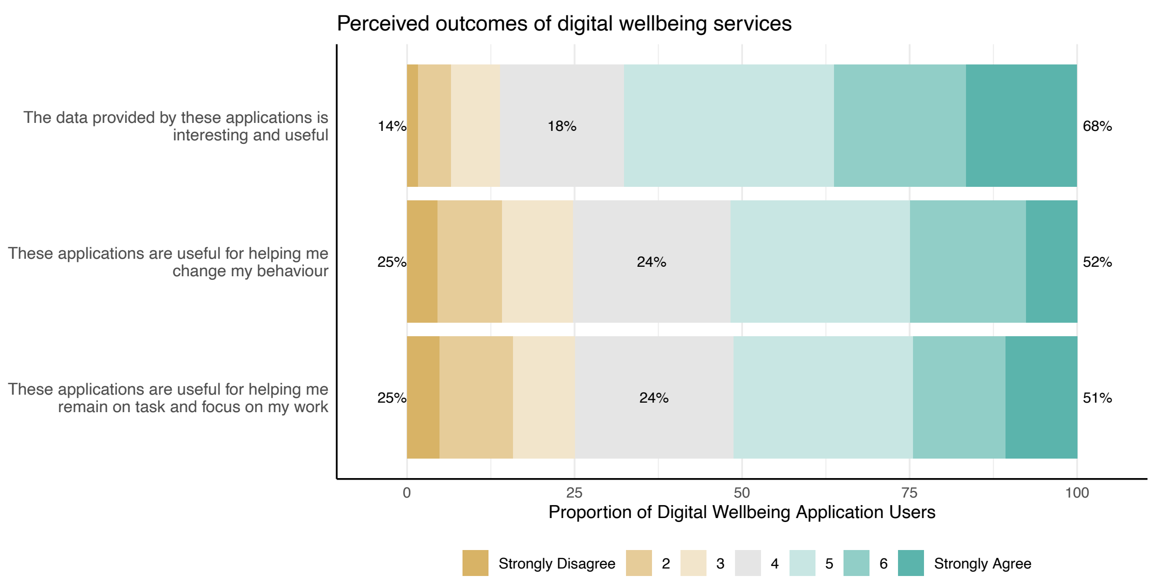

Figure 2. Perceived outcomes of digital wellbeing applications.

Motivations for Using Digital Wellbeing Services. Table 1 provides a summary of the descriptive statistics and zero-order bivariate correlations for the integration and use-motivation variables for users of digital wellbeing applications. All variables were internally consistent and approximately symmetrical. As indicated by the CFI and SRMR outcomes the fit for the single-factor model for each variable was acceptable. All motivations were positively correlated and, with the exception of the association between behaviour alignment and behaviour change motivations, all relations were small to moderate in magnitude.

Table 1. Descriptive statistics and zero-order bivariate correlations for study variables.

Variable	Descriptive Statistics					Correlations				
	M	*SD*	*α*	*CFI*	*SRMR*	1	2	3	4	5
1. Integration	3.72	1.52	.88	.98	.03	-				
2. Information Seeking	4.32	1.49	.87	.97	.04	.46***	-			
3. Negative Outcomes	4.93	1.52	.86	.98	.02	.10**	.20***	-		
4. Behaviour Alignment	4.36	1.48	.91	.97	.03	.53***	.42***	.29***	-	
5. Behaviour Change	4.18	1.42	.87	.95	.04	.53***	.44***	.29***	.82***	-

Note. * $p < .05$; ** $p < .01$; *** $p < .001$. CFI = Comparative Fit Index; SRMR = Standardized Root Mean Square Residual; α = Cronbach's α.

To test H1–4, we conducted a multiple linear regression to predict use integration based on the four motivations ($R^2 = .37$; $F(4,678) = 100.36$, $p < .001$). Table 2 summarises the outcomes of this analysis. Supporting our first, third, and fourth hypotheses, information seeking ($B = .28$, $p < .001$), behaviour alignment ($B = .28$, $p < .001$), and behaviour change ($B = .23$, $p < .001$) motivations all positively predicted integration of digital wellbeing applications. However, in contrast to H2, experiences of negative outcomes associated with smartphones did not positively predict integration of digital wellbeing applications ($B = -.10$, $p < .01$).

Table 2. Multiple linear regression predicting integration of digital wellbeing applications.

Motivation	*B*	*SE*	*t*	*p*	95% CI
Information Seeking	.28	.04	7.96	< .001	[.21, .35]
Negative Outcomes	-.10	.03	-2.98	< .01	[-.16, -.03]
Behaviour Alignment	.28	.06	5.01	< .001	[.17, .38]
Behaviour Change	.23	.06	3.99	< .001	[.12, .34]

Note. *B* represents unstandardised regression coefficients.

To address RQ5, we conducted a binary multiple logistic regression, the results of which indicate that, together, the four motivations accounted for a significant amount of variance in future-use intentions among non-users (Nagelkerke Pseudo $R^2 = .31$; $\chi^2(4) = 297.90$, $p < .001$). Overall, 60.72% of non-users indicated that they intend to use digital wellbeing applications in the future. Of the four motivations, only information seeking ($M = 3.88$, $SD = 1.50$, $B = .63$, $p < .001$) and behaviour alignment ($M = 4.71$, $SD = 1.43$, $B = .25$, $p < .01$) were significant predictors of use intentions, while negative outcomes associated with smartphones ($M = 4.87$, $SD = 1.57$, $B = .02$, $p = .62$) and behaviour change ($M = 4.33$, $SD = 1.42$, $B = .05$, $p = .52$) were not.

Qualitative Findings

We present the qualitative findings in three sections, first focusing on participants' evaluations of their smartphone use, before considering digital wellbeing and the role that applications play in its support.

Subjective evaluations of smartphone use. Interviewees generally shared the view that their smartphone use benefits them in various ways and that these benefits outweigh the negative aspects they associate with their devices. The ability to maintain social connectedness was emphasised as the most valuable affordance smartphones offer. A majority of interviewees also mentioned the role their phones play in the management of their day-to-day activities with features such as calendars, alarms and note taking applications considered essential to their ability to successfully navigate their tasks and responsibilities.

P17: *"I think the fact that everything can be on there and that it is equipped to handle all of your personal life affairs, whether it's like messaging, emailing or academics, just the fact that it's convenient and it's all there and it can be handled from one portable device."*

While emphasis fell on these positive aspects, all interviewees were cognisant that their smartphone use can lead to various negative outcomes. A majority of interviewees noted that they perceive certain types of use as unproductive. Many expressed their desire to regulate such use more effectively and rather use the time to pursue more important or rewarding goals.

P13: *"I feel like I'm not really using my time constructively due to my phone. I've come to realize there's a lot of things that I would rather be doing than like being on my phone. Going through Instagram and just explore memes are funny and everything, but they're not really constructive uses of your time at all."*

Many interviewees stated that their phones frequently distracted them from other activities (e.g., socialising or studying), while a smaller subset of interviewees associated feelings of envy, self-judgement or fear of missing out with social media use.

Conceptions of digital wellbeing. The amount of time spent on one's smartphone emerged as a key dimension of interviewees' conceptions of digital wellbeing. Many related this to a person's ability to effectively self-regulate and achieve a balance between excessive use and personal goals.

P14: *"If you spend enormous amounts of time on your phone then your digital wellbeing is going to suffer so I don't think it is healthy to spend four hours per day on your phone. During the holidays I am now probably spending about three hours per day on my phone which isn't healthy."*

In addition to use volume, some interviewees argued that digital wellbeing also depends on the nature of use, arguing that many forms of use support rather than detract from wellbeing. In this regard interviewees emphasised forms of use which aligned with the achievement of personal goals by, for example, enhancing the user's productivity, sense of belonging or creativity, as well as presenting opportunities for relaxation and escape from academic or other stressors.

> P9: *"I think it's how much time you spend on your phone, but also how you spend the time on your phone when you're on your phone. So do you use your phone for just social media? Do you use it for games? Do you use it for any purpose other than social media? I don't know how to explain it, but digital wellbeing is just, how do you use your phone to better yourself."*

When describing digital wellbeing interviewees sometimes referenced their emotional experiences during or after smartphone use as a means of gauging how their digital spheres impacted their general wellbeing. Here, again, a sense of the purpose seems to dictate affect. The use of applications for utilitarian purposes (planning, note taking, scheduling etc.) tends to evoke positive emotions and a sense of purposefulness. However, when use is perceived as unproductive or loafing, negative affect is experienced. This also applies to social media which, some interviewees argued, promotes wellbeing when used purposefully but harm wellbeing when the user fails to regulate it.

> P15*: "Digital wellbeing is very important and everyone should really take it very seriously to make sure that they have control and a good relationship with their phone. They should check how they feel after they put their phone down and how that makes them feel. If they're more happy or if they are sad or depressed or whatever."*

Adoption and use of digital wellbeing applications. While the interviewees were selected based on their reported use of digital wellbeing applications, differences in the motivations for, and patterns of, adoption and use of these applications are evident. Across interviewees, however, the primary use case involved monitoring of smartphone use.

> P2: *"When I get the notifications it tells you your screen usage is 15% up from last week or whatever. So I kind of have an idea of where I've increased but I always go there to check and see the facts not just my gut feel. [...] so I do actually go into the analytics because I feel like they help me hold myself more accountable."*

Interviewees' monitoring of their smartphone use is primarily grounded in a desire to be informed about their own usage patterns. For some, this information seeking is prompted by a general curiosity about their behaviour while, for others, it is prompted by a need to gain an objective indication of their usage patterns. In many cases, interviewees reported that they started monitoring their smartphone use in response to fears related to overuse or experiences of overuse. For other interviewees, however, initial adoption was not prompted by specific needs. Rather, the default settings on their device exposed them to data on their usage.

> P1: *"A few years ago during my exams I was wondering how much time I spent on my phone, so I went to look and it was quite [a lot] more than I expected. Ever since then I have kept my eye on it just to make sure I do not stay on my phone for too long every day."*

For other participants, monitoring of smartphone use is driven by a desire to manage their media behaviour. Developing an objective understanding of their usage is viewed as an important step in bringing their smartphone use in-line with their intentions.

> P14*: "If you can't measure it, you can't manage it. It is just much easier to see the raw facts in front of you than just relying on your intuition which could very easily be unreliable."*

Two patterns characterise participants' monitoring of their smartphone use. The first—active and regular—involves checking of smartphone usage statistics regularly throughout the week (and even the day for some). For interviewees whose monitoring can be characterised in this way, knowledge of their own smartphone behaviour is important, not only for the management of their smartphone use, but also for their general time management, behavioural alignment, and self-conception. Such knowledge enables them to balance the benefits they associate with their devices with the subjectively negative effects of poorly regulated use. For these participants, it is important to maintain awareness of both overall and application-specific usage. For the latter, time spent on social media applications is particularly important to monitor.

P20: *"I like that Screen Time tells you that this is how much more or how much less you have spent this week or over this period. I like that it tells you for social media apps, this is how much use you have had for productivity or social. [...] So it really narrows it down very nicely. So you can see where every bit of your time is going."*

The second pattern—passive and occasional—describes participants who only monitor their smartphone behaviour with weekly reports automatically provided by their device. For interviewees whose monitoring can be characterised in this way, awareness of media use is not of particular importance. The information gained does not influence their device use.

P13: *"I used the Screen Time app that the iPhone has, but not actively. It just tells me at the end of the week how much time I've spent on my phone, but I just go like, 'Oh, that's a bit of a problem.' And then I just keep on doing what I was doing before."*

While most participants did not report changes in their smartphone monitoring during the pandemic-related lockdown of 2020, a small proportion reported that spending time at home was an impetus for monitoring their media behaviour.

P10: *"I probably only started doing it during lockdown because that's when I found that I had the most free time. In a lecture there's stuff going on and you kind of have to concentrate, but just being at home the whole time, there's nothing really stopping you from going onto your phone. That's why I thought, before things get out of control, just monitor it."*

Considering the outcomes the interviewees associated with monitoring their usage, it is evident that knowledge of actual usage patterns provides a sense of being in control of media behaviour. There is, however, disagreement on the extent to which monitoring impacted actual usage patterns. Most interviewees felt that monitoring can initiate effective regulation in an attempt to manage use levels in relation to some perceived standard that is deemed appropriate, while a minority of interviewees felt that, although the data is informative, it does not impact their behaviour.

> P14: *"If you can't measure something than you don't really know if it is a problem or not. I mean you could get a gut [feeling] but it is so much easier to realise there is a problem when you have the raw facts in front of you that you just can't deny. So, yes, it has definitely been successful for me to just realise I have been spending a lot of time on my phone and to change the trajectory of my life."*

The influence of monitoring on subsequent behaviour is seen by many to be mediated by various personal characteristics. Such characteristics—self-control, self-awareness—are seen to not only account for the outcomes associated with monitoring, but also the attitude with which monitoring itself is approached.

P7: *"I think for me, even if none of these apps existed or the iOS didn't have the built-in thing, it's more a personal thing where you kind of realise that it's becoming a bad habit, that you spend too much time on your cell phone or social media. So you kind of put things in place when you do it. And you're like, it's been a while now, put it down and try and be more interactive. [...] A lot of people that I've spoken to on a similar topic would say the same, that it's more of a personal decision that you make, nothing else is going to make you not spend that much time on your phone, on social media, unless you decide, okay it's enough now."*

The secondary use case for digital wellbeing applications involves restriction of device or application-access for designated periods to enable concentration in the support of other (often academic) goals or detachment from applications subjectively deemed detrimental (at least in excess). In this way, digital wellbeing applications become a commitment device; participants make a choice—setting a time-limit on, or disabling access to, specific applications—that restricts their future options and enables them to avoid instances of akrasia. Such intentions to improve time allocation peak around intensive periods of study like exams.

P5: *"Because now I am able to budget my time with these apps. Especially with 'Bakery'. If I know I want to achieve four hours or six hours I know how to structure my time. So, these apps have played a huge role in terms of time structuring and time management. I actually look forward to studying in a weird way. You look forward to it because you know you're going to be productive and have something to show for it."*

Participants indicated that they primarily restrict access to their entire device when they need to study. However, for those who target specific applications or application-categories, restrictions are generally applied to social networking or instant messaging services.

> P10: *"I limited my time on Instagram to be 45 minutes a day. After that, my phone shuts down Instagram and I can't go onto it anymore. Secondly, I basically make Instagram stop being available from half past ten at night until ten in the morning. Cause, often when you go to bed, then you scroll through Instagram."*

Many interviewees recounted the extent to which actively monitoring and restricting their smartphone use require considerable pro-active configuration and planning. While most reported monitoring and some reported periodic restriction during crucial study times, only a minority of participants reported continuous, long-term use of restrictive features. For such participants, it is evident that they hold a general orientation towards goal-setting and behaviour monitoring, reporting use of similar applications in other domains of their lives.

> P14*: "I use the downtime feature where you can set specific times that you don't want to be on your phone. So, mine is set so that at eight o'clock in the evening I am not on my phone anymore so that I stop. [...] I also use the app limits setting. I use that to set a limit of 35 minutes per day on social networking. [...] I set up the day I am not supposed to use my phone for more than 45 minutes. [...] I tend to keep my limits consistent regardless of whether it is exams or normal term time."*

Among participants who use restrictive features, native applications are perceived as lacking desired features and easy to bypass. In contrast, while shortcomings were still noted, most participants who use restrictive features reported using third-party applications. In these cases, there seem to be more purposeful and directed attempts to utilise restriction and goal-setting features. However, it was also reported that advertising in free versions discourages continued use, with many participants noting that they are unwilling to spend money on applications for digital wellbeing.

> P10*: "I don't use it anymore, so I kind of just stopped using them. I think it's because they had too many adverts and I don't trust buying apps."*

In addition to application-based approaches many interviewees recounted using more basic methods to support digital wellbeing. These techniques include reducing the physical proximity of the device by placing it in a different location, removing all applications perceived as distracting or harmful for their wellbeing from their phone (either temporarily or permanently), switching off mobile data, activating 'airplane' or 'do-not-disturb' modes to inhibit unwanted notifications, or simply turning the device off for a period. In many cases these approaches are used to facilitate short-term periods of concentration or relaxation during particular parts of the day or academic calendar, or longer term 'sabbaticals' from digital media.

P18: *"I have also tried to make time for myself, especially during the day, wherever I am to just switch off my phone. I'm not available for those two or three hours. During those two or three hours, no one can reach me and after that I'll switch my phone back on and continue with whatever is needed to be done or reply to whoever is looking for me. But otherwise I do like to have a little window period where I don't talk to anyone on my phone. Then I don't get bothered by whatever notifications are popping up on it."*

Many interviewees try to increase their offline activities when spending too much time on their smartphones. In such cases, rather than explicitly restricting access to their device, they would distract themselves with another enjoyable activity: pursuing offline hobbies, spending time outdoors, face-to-face socialising with friends.

P6: *"Especially with Instagram, I tend to just take the app off my phone sometimes and then I leave it for a bit, just an attempt to lessen the amount of time I'm on it. And then also I'm trying to keep busy, with other things. So little projects at home. I started painting or I'm helping with gardening or something like that. Just something else besides just being on the phone. So I'm trying to do other things and I think that's how I'm making a balance, I think between them."*

As noted, interviewees perceive exam-periods to be particularly important for their studies and, as a result, are more conscious of the distracting effects of their smartphones during these periods. As with application-based device-management, such periods are also times of greater self-regulation through non-technical methods.

P11: *"When the first assessment exams came up I felt that I cannot spend much time on my phone so I just went cold turkey on it."*

Overall, when asked to evaluate the need for applications to support digital wellbeing, respondents fall in one of two categories. Those in the first category feel that such applications are essential to supporting their digital wellbeing and that they would struggle to maintain their desired behaviour without them. This dependence seems to be rooted in the idea that it is difficult to mentally track usage, creating the need for objective feedback to support regulation.

> P10: *"I couldn't really do it without the app. Not just because of the lack of self-control, but it's just because it's stuff you don't even think about. I didn't even realise how I subconsciously go onto Instagram. So I feel like I needed that to bring awareness to the fact that I was doing it subconsciously. I would say that I probably wouldn't have become aware of it if it wasn't for the app."*

The second, larger category includes those who believe the onus is on them to, firstly, consider their desired balance and level and pattern of engagement with their smartphone and, secondly, put in place procedures, whether application-driven or not, that support this balance. Without this reflection and pre-commitment, any application is unlikely to be successfully utilised to support digital wellbeing.

> P14: *"It definitely depends on the person themselves because you can have the best tools but if you yourself as an individual, if you're not willing to actually make a change, then it is not going to help at all. So I know a lot of people that just simply switch off the screen time, or they just ignore the statistics. So, it is definitely helpful to be a wakeup call for people but, in the end, I think it depends on the individual. If you don't act on the statistics that you are getting, then what's the use of it."*

Discussion

Our findings provide a number of insights into students' adoption of smartphone applications as a means of supporting their digital wellbeing. To follow, we briefly discuss these before outlining key study limitations.

Corresponding to Oeldorf-Hirsch and Chen (2020), our quantitative data indicate that a majority of students do not use digital wellbeing applications. This may, prima facie, indicate a low level of concern about digital wellbeing as one would expect concern to trigger some minimal level of self-monitoring. An alternative interpretation is that non-users are indeed concerned about their digital wellbeing but do not perceive smartphone applications as providing enough benefit to justify adoption, as was shown by Saariketo (2019). This interpretation is perhaps better supported by our qualitative data which suggest high levels of awareness about the potential negative effects of smartphone overuse or misuse among this population. Moreover, the finding that there is no meaningful difference between the reported smartphone use levels of users and non-users of digital wellbeing applications, in addition to corroborating Oeldorf-Hirsch and Chen (2020), suggests that many non-users manage to effectively regulate their media use through alternative (non-technical) strategies.

Of those who do use digital wellbeing applications, a majority can be described as passive-occasional users for whom objective information about their phone use patterns is interesting, but does not serve to initiate efforts to change behaviour. For iOS users such information is, by default, provided periodically which explains the higher level of adoption among students with iPhones (50%) compared to those with Android-based devices (28%). Passive-occasional use seems to be driven primarily by information seeking needs rather than a motivation to improve the balance between phone use and personal goal attainment. This may, again, result from a lack of awareness about the role of phone use in wellbeing, apathy towards the improvement of digital wellbeing, the belief that such applications are not beneficial, no experienced negative effects associated with smartphone use or, as our qualitative data suggest, some combination of these. Additionally, passive-occasional users may value the benefits of high levels of phone use over the advantages they associate with actively regulated use. However, our qualitative data suggest that situations in which the importance of personal goals become accentuated (e.g., exam periods) serve to trigger more active regulation among this group.

About 10% of students surveyed can be described as active-regular users of digital wellbeing applications. Among this group we observe a motivation to achieve an optimal balance between the advantages offered by smartphone use, the attainment of personal goals, and the potential drawbacks associated with excessive smartphone use. Unlike their passive-occasional peers, these users utilise the restriction and goal-setting features of digital wellbeing applications to support their self-regulation efforts. Our qualitative data suggest that students in this category are sensitive to the manner in which phone use can, at times, interfere with or disrupt their academic, social or other pursuits. This sensitivity, we believe, is a key driver of the motivation to manage media use through various means, including the use of digital wellbeing applications.

Consideration of our findings in their totality suggests that the success of attempts to regulate smartphone use through the adoption of digital wellbeing applications depends upon a certain level of motivation and commitment by the user, and that these factors are often dictated by personal characteristics. Much like applications which track and support other forms of health and wellbeing improvement (e.g., fitness, meditation, diet etc., Fitzgerald & McClelland, 2017), the successful integration of digital wellbeing applications seems to occur among students that are, firstly, mindful of the relationship between their behaviour and their wellbeing and, secondly, *motivated* to perform optimally in the pursuit of personal goals. Specifically, such individuals have explicitly considered the place of a smartphone in their lives and are intentional about achieving a balance between the benefits and drawbacks they associate with use of their device. There is some evidence that occasional monitoring serves to raise the user's awareness of their media use patterns and, on this basis, trigger some degree of regulation. However, in the absence of user motivation and commitment, attempts to regulate are likely to fail.

Conclusion

This study contributes to our knowledge of digital wellbeing by identifying adoption rates, use motivations, perceived effects, and experiences with applications used to support digital wellbeing. The findings highlight the importance of motivations and the need to understand digital wellbeing as more than just the use of an application. As Vanden Abeele (2020, p. 5) argues, digital wellbeing depends on a range of person-, device- and context-specific factors. This study provides a rich descriptive account of the temporal variability, person-specificity, and device-contingent nature of digital wellbeing, adding to our understanding of this phenomenon.

Notwithstanding the study contributions, several limitations merit consideration. First, the study involved a student population. To understand how the results would generalise to a non-student population, investigations among either general or specific populations are needed. Second, the study was conducted during the pandemic of 2020. It is possible that behaviour during this period may differ from others. A third limitation of the study concerns the measurement instruments used to assess integration and use-motivations. As with previous studies concerning behaviour tracking (Lee & Cho, 2017; Oeldorf-Hirsch & Chen, 2020) survey-items were produced based on existing literature. While the measures used were internally consistent, demonstrated the expected internal structure and face validity, more work is needed to further verify the construct validity of the measures used. Furthermore, while self-report measures may be appropriate for assessing motivations, measures based on digital-trace data may provide a more accurate representation of application usage than the binary measure used.

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