Personal Tracking of Screen Time on Digital Devices

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ABSTRACT
Numerous studies have tracked people's everyday use of digital devices, but without consideration of how such data might be of personal interest to the user. We have developed a personal tracking application that enables users to automatically monitor their 'screen time' on mobile devices (iOS and Android) and computers (Mac and Windows). The application interface enables users to combine screen time data from multiple devices. We trialled the application for 28+ days with 21 users, collecting log data and interviewing each user. We found that there is interest in personal tracking in this area, but that the study participants were less interested in quantifying their overall screen time than in gaining data about their use of specific devices and applications. We found that personal tracking of device use is desirable for goals including: increasing productivity, disciplining device use, and cutting down on use.

Author Keywords
Personal tracking; Multi-device Use; Software Trial; Qualitative Interviews; Lived Informatics; Design.

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

INTRODUCTION
Many people now regularly use several screen-based devices in their everyday lives. These include mobile phones, tablets and laptop computers. Recently, several personal tracking applications have been released that give people feedback on the use of an individual smartphone or tablet. For example, Quality Time [39] is an app for Android devices that logs and sets limits for time spent using the device, and Moments [23] is an app for iOS devices that emphasises the times and locations devices are used. Some productivity tools, such as Rescue Time [43], also support tracking of multiple device use.

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Despite there being a sizeable body of academic research in which people's everyday digital device use is logged, for example Böhmer's study of app launches on Android devices [4], little consideration has been made of whether and how data about everyday device use might be of personal interest and value to the user.

This paper describes the development and evaluation of ScreenLife, a personal tracking application that enables users to collect and view data about the use of their digital devices (e.g. time spent on a laptop, a mobile phone and a tablet). We chose to present feedback in the ScreenLife application using a metaphor of 'screen time', showing to the user when their devices were on and in active use. We have trialled ScreenLife in the wild over a 28-day period with 21 users, gaining objective and subjective feedback in the form of log traces and interview data.

The findings we report in this paper are primarily qualitative, taking interest in what people made of a representation of their personal screen time. We find that there are many potential purposes for personal tracking of this form of data, and that people will likely have diverse preferences for accessing and viewing this data. We find that getting an overall figure for screen time is less important than supporting people in understanding the details of certain devices. We also find that this kind of tracking data, and even the gaps in the data, can reveal many aspects of an individual's life.

BACKGROUND
For decades, if not centuries, people have tracked aspects of their own lives: what they eat and drink, what they weigh, the physical activity they engage in, and much more (see [10,40]). The rise of smartphones has made it easier to automate data collection and to present data back to the user. Smartphones have led to renewed interest in personal tracking, and have opened up various new possibilities (see [31,38]). Personal tracking is often associated with health and wellness (see e.g. [8,20,48]) but is by no means limited to that domain. One may track, for example, what books one reads [36], places one visits [9] and myriad other things.

Tracking digital device Use
A growing body of research in HCI is based upon the collection of user log traces from mobile phones, tablets and computers. Studies based upon logging the time spent using computers and/or specific applications have been around for quite some time (e.g. [32,41,42]). More recently,

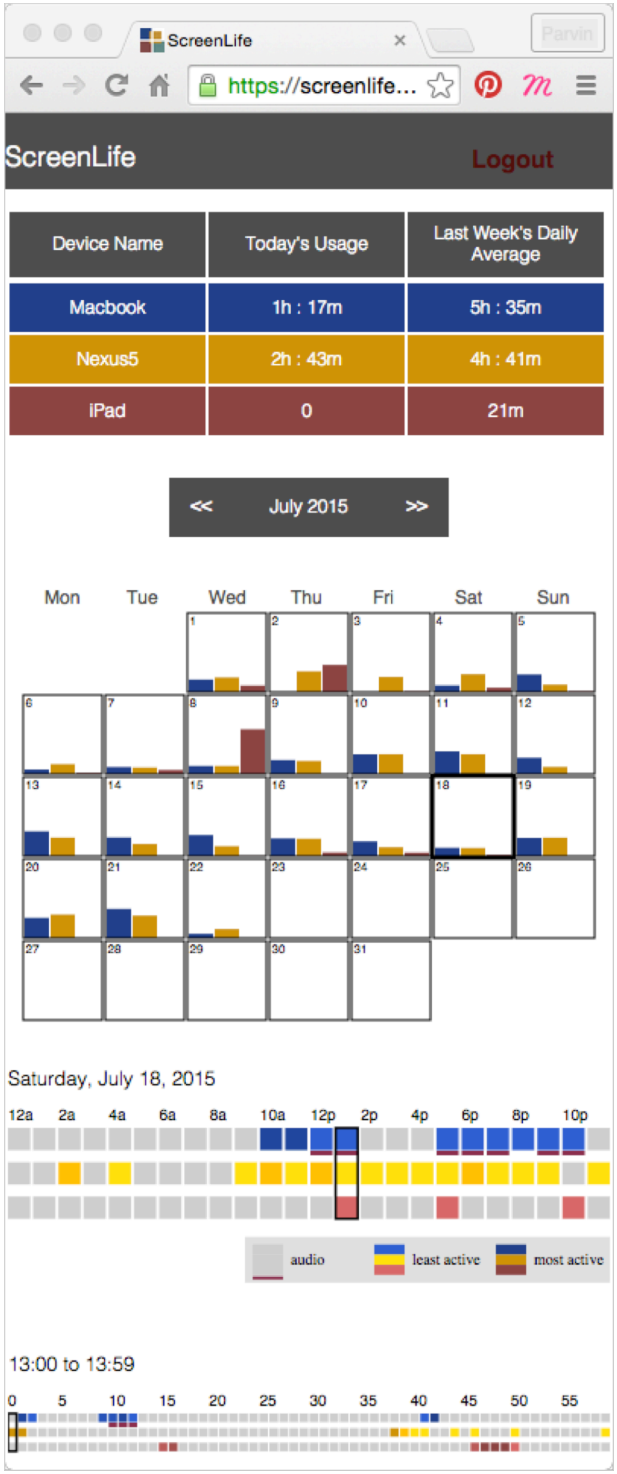

Figure 1: ScreenLife in Browser Window (P11's data shown).

several studies have collected data about how mobile devices are used, especially smartphones. For example there have been studies of when devices are unlocked/locked and what apps are launched [28,4,5]; of how battery power is consumed [16,17,15]; of people's communication patterns [49]; of security preferences [1]; of everyday connectivity [30]; and of people's locations when using devices [13]. Church et al. [7] give an overview of this area of research and discuss how these studies contribute to a broader understanding of device usage behaviours.

Most studies in this area are conducted by installing logging software on users' devices. This software need not necessarily have a user interface, and there have been several studies in which none is given (e.g. Do et al. [13], Falaki et al. [15], Karlson et al. [26], Lord et al. [30], Lee et al. [28]). In other cases, particularly where an app is to be released through an app store and no incentive is given for installing the app, an interface has been provided (and indeed the interface serves as the incentive to install and retain the app [7]). Böhmer et al. [4] and Parate et al. [37] created recommender widgets for users to launch apps, Ferreira et al. [16] and Athukorala et al. [2] created battery tracking software for end users, and Wagner et al. [49] created a personal analytics style interface offering a range of information about the use of one's device.

With the exception of Ferreira et al. ([16][17]) and Athukorala et al.'s [2] discussions of the design of battery tracking applications, the user interfaces for these applications are not typically discussed and evaluated in depth. There are some other studies in which data has been shown to users in an interview situation, for example the work of Carrascal et al. [5] and Lord et al. [30]. A consequence of the lack of work here is that little is known about what information users might want to see about their everyday device use. A better understanding of this would not only help us create better personal tracking applications, but as Church et al. [7] point out, is also likely to help persuade more users to install and use apps developed for tracking studies in HCI.

Tracking multiple digital device use

The work in HCI and related fields on tracking digital device use predominantly focuses on individual devices. Karlson et al.'s [26] study of the use of mobile and desktop Windows devices by information workers is one exception, although no user interface was provided and only four of their participants were interviewed.

Multi-device use has been more roundly explored in qualitative studies: Jokela et al. [25] have conducted a diary study of multi-device use; Rooksby et al. [47] and Holz et al. [21] have looked at how mobile devices are used when watching television; Oulasvirta & Sumari [35] and Dearman & Pierce [12] have studied multi-device use by information workers. Whereas much of the design emphasis in HCI has been on integrating devices and media, studies of multi-device use find that devices are often used in parallel or sequence for unrelated tasks.

Personal tracking

Personal tracking is often associated with three areas: the quantified self, personal informatics and behaviour change.

The quantified self is typified, in Choe et al.'s [6] words, by "*extreme users*" who wish to track and quantify as much as possible about their own lives. Similarly, personal informatics, as set out by Li et al. [29], suggests that people should collect as much data as possible and then use this to make insights into their lives. In previous work, we [46] have pointed out that mainstream, everyday use of trackers does not necessarily resemble the quantified self or personal informatics. Data is rarely separated from applications, and people do not engage in a dispassionate data science of everyday life (and indeed sometimes get things wrong [27]). Rather, personal tracking is enmeshed in people's everyday lives, outlooks and desires [14]. We have also pointed out that there is much more to tracking than behaviour change, with people finding all sorts of interests and uses in trackers.

With ScreenLife we are not trying to encourage end users to become data scientists or to modify their behaviour. Rather we have developed an application that presents data that can be flexibly interpreted by users, and upon which we can gain feedback and criticism. ScreenLife resembles what Hutchinson et al. [22] term a 'technology probe' in that (a) we kept the functionality intentionally basic (e.g. by providing simple visualisations of screen time, as opposed to detailed information about app launches, location and so on) and (b) the design does not emphasise particular purposes such as productivity or reducing device use. As such, ScreenLife should not be considered a prototype, but as a disposal probe that is used to gather data and opinion. The complexity of developing for four operating systems, and of combining and presenting data consistently, made this a probe-based approach appropriate for our study (as opposed to using a general app store release as recommended by McMillan et al. [33,34]).

We conducted a trial of ScreenLife "*in the wild*" on users' own devices as they go about their everyday activities. As Brown et al. [3] argue, the purpose of such trials is not to gauge users' 'likes and dislikes' or to assess the usability of the application, but to gain feedback and insight.

SCREENLIFE

The ScreenLife application has two general components: a logger that monitors and records when a device is in use, and an interface to provide users with a visual representation of screen time across their logged devices. We implemented ScreenLife loggers for four platforms: iOS, Android, Mac, and Windows (meaning it will work on iPhones, iPads, Android phones, Android tablets, Mac computers, and Windows computers). The visual interface is implemented in HTML5 and JavaScript. The logger and interface are packaged together on mobile devices in the form of an app. On computers, the logger is installed as an app and the interface is accessed via a web browser.

Logging screen time

ScreenLife has been designed to collect data about when a device is 'in use'. Compared to related studies that analyse individual app launches or attempt to classify types of behaviour this is a relatively high level abstraction about device use, although one that readily allows the comparison and juxtaposition of different classes of devices.

On mobile platforms, we consider a device to be in use if the screen is on. This led us to collect data on when the screen wakes and sleeps, and when the device is locked and unlocked. On Mac and Windows computers, we are conscious that a screen can be on without the device being in active use. We therefore collect sleep and wake events but also data about whether the keyboard, mouse, or speakers are in use. After a minute passes without any events on these I/O channels, we consider the device not to be in use until the occurrence of the next event.

ScreenLife loggers run continuously in the background and automatically launch at startup on each device to ensure continuous logging. However, users are able to disable or enable logging through the app's settings. Such continuous monitoring is not readily supported on iOS, and the method we use to keep ScreenLife running has a battery cost on these devices. Otherwise the application is (in theory) of low cost to the battery and processors. Each logger periodically uploads usage logs securely to our server.

The Interface: Quantifying screen time

ScreenLife creates a visual presentation showing usage data for each of the user's devices, and can display this aggregated data on any platform (e.g. if the user has ScreenLife loggers on three devices, she can view the combined data on any of these). On mobile platforms, ScreenLife is installed as an app that can be launched from the home screen, and within which the interface is displayed. On Macs and PCs, a ScreenLife icon is inserted into the OS's menu bar or system tray, so that clicking upon it opens the interface in a browser.

On first launch of ScreenLife, a user is asked to create a username and password, and is directed to a device registration form. On launching ScreenLife on additional devices these login credentials are entered during registration, allowing us to associate multiple devices with a single account. Through registration, the user is also asked to provide a name for each of his/her devices. Users are not required to provide credentials on later openings of the web interface.

The main interface for ScreenLife is shown in Figure 1. A summary table at the top of the page lists the registered devices of the user, showing usage of each device in the current day and the average daily usage during the past seven days. Each device's data is presented with a different colour in a separate row, with the same colour being used to display data associated with this device in all sections of the interface. Under the summary table is a month view, each square cell of which corresponds to a single day within that month. Within each day cell, vertical bars show each

device's usage. Using the left and right arrows on the top, users can navigate between different months.

This month view presents a high level overview of activity, but users are able to drill down into particular periods of interest. Each day cell in the month view is clickable, which loads a more detailed view of the selected day's usage at the bottom of the page. The day view is presented with rows of 24 squares, each row corresponding to one of the user's devices and each square corresponding to device usage in a single hour of the day, starting on the left with 12 am. The colour of each square reflects the amount of device usage within that hour. A grey cell shows an inactive hour, while an active hour is coloured with a shade of the device colour, with the lightest shade corresponding to 1 to 15 minutes and the darkest corresponding to 45 to 60 minutes. Users can also drill down further to the active minutes within each hour, with the minute-square colours again corresponding to the activity within that minute. Finally, clicking on a minute reveals the active seconds within that minute.

The period during which audio was playing on each device is shown by a red line below each cell in the hours, minutes and seconds views of the interface.

Design choices made in developing Screenlife

The ostensibly simple idea of displaying when a screen is on or off necessitated us to make several design choices that have had consequences for the study. These have included whether to include device wake events occasioned by a notification arriving as screen time. It also led us to consider active screen-time of a computer as opposed to time away.

In this paper, we conceptualise the time using devices as 'screen time'. Our use of the term relates primarily to the use of computers and mobile devices. We acknowledge that this term is often associated with watching television. For example in public health research, screen time is seen as a sedentary behaviour and studies often ask people to self–report their time spent watching a television and using a computer. In audience research, more sophisticated methods have been created for logging television use, and latterly, digital devices. Effective advertising is a key concern in that area. Screens are ubiquitous in developed countries [19,24] and it is difficult if not impossible to quantify our overall screen time. Moreover, judgements about what counts need to be made. Even when we are in the presence of screens we do not necessarily look at them [11], and what and how to log the usage of screens in part comes down to the purpose of logging. In our study we have chosen to log time when a screen-based device is being 'actively used'.

THE STUDY

We undertook a trial of ScreenLife in Summer 2015. We recruited 21 students (10 male, 11 female) to install the app and use it for 28 full days or more. The app was installed on a total of 48 devices (see table 1). Participants were compensated with a £25 payment, which was given to them at the interview before we asked any questions. The study was granted ethical approval by the University of Glasgow College of Science and Engineering.

ID	Gender	Age	Summer activity (all participants students)	Laptop	Phone	Tablet
1	M	24	Employed: office	Mac	And.	-
2	F	21	Employed: developer	Mac	And.	-
3	F	34	Dissertation project	Win.	-	iOS
4	M	27	Dissertation project	Win.	And.	-
5	M	19	Employed: electronics	Win.	And.	-
6	F	23	Trainee at hospital	-	iOS	And.
7	F	20	Employed: nightclub	Win.	And.	-
8	F	25	Unemployed	Mac	iOS	iOS
9	M	22	Unemployed	Win.	And.	And.
10	F	24	Dissertation project	Mac	And.	-
11	M	23	Dissertation project	Mac	And.	iOS
12	M	23	Dissertation project	Win.	And.	iOS[3]
13	F	22	Unemployed	Win.	And.	And.
14	F	21	Dissertation project	Win.	And.	-
15	M	24	Dissertation project	Win.[1]	And.	And.
16	M	18	Employed: factory	Mac	iOS	-
17	F	25	Dissertation project	Mac[3]	And.	-
18	M	24	Dissertation project	Win.	And.	-
19	M	21	Employed: tutor	Win.	And.	iOS[2]
20	F	22	Employed: manual	Mac	And.	iOS[2]
21	F	22	Employed: developer	Win.	iOS	iOS

Table 1: Trial Participants (Notes: [1]dual boot window/linux; [2]iPad shared between P19 & 21; [3]failed installations (x2); Win = Windows; And = Android)

We selected the participants from a pool of 76 applicants. The key selection criteria were that a) the trial should be gender balanced, b) participants should own and use two or more eligible devices, and c) the participants should be able to travel to our laboratory for deployment and an interview. The participants were not representative of the applicants (of which 64% were male, 72% used a Windows laptop, and 50% used both a Windows laptop and Android smartphone). Our sample is one that we believe is sufficient to gain insight into multi-device personal tracking, but clearly it is right to be cautious about how our work may generalise. It should also be noted that the timing of the study meant that the undergraduate students were on their summer break, and the postgraduate students were working on their dissertation projects. The study also overlapped with Ramadan, which was observed by several participants.

Data collection and interview

We collected two kinds of log data from participants during the trial. Firstly, the data logged by ScreenLife itself in order to display usage back to the user was collected by us and used as research data. We also logged user interaction (UI) events while users used the interface.

Each participant was interviewed after having run ScreenLife for 28 full days or more. 20 interviews were carried out face-to-face and the other using a video conferencing tool. The interviews were semi-structured. An interview schedule (i.e. a list of questions) was developed, but was not used to direct the interview. The interviews began with an open question "*What did you think of the app and our study?*", and the schedule was checked at the end to see if anything was missed.

Analysis

All the interviews were transcribed and were triangulated with the log data we had collected. The interview data was analysed using a framework approach [18,44]. This approach has been developed for use by multidisciplinary teams collecting heterogeneous data. It is qualitative-researcher led, but is designed to involve and be accountable to people with expertise in other areas (such as software development). We began with open coding of the interviews, and then created a framework with six broad codes and twenty-five sub-codes. The analytic themes presented in the next section have been worked up from framework.

FINDINGS

Before we present findings relating directly to ScreenLife itself, we will give some relevant contextual information about how device use was organised by the participants. Our findings here echo those from studies by Jokela et al [25], Dearman & Pierce [12], and Oulasvirta & Sumari [35] on multi-device use.

We found it is not specifically an inherent quality of a device that entails it is used for a particular task at a particular time. The fact is that most of the people in the study had a choice of devices. For example one could write on their laptop or on a library computer, one could read or watch a film on one's laptop or a tablet, one could access social media and news sites on any device. However, we noticed that people had preferences for using particular devices for particular tasks, and that these preferences were regularly contingent on:

- The physicality of a device
- The age and state of repair of their devices
- The risk of a device being damaged or failing

Echoing Oulasvirta and Sumari [35], we found physicality was an important determining factor in multiple device use. Several participants in the study discussed not wanting to carry a laptop with them because of the weight. Therefore they would use tablets or University computers when out of the house, even if their laptops were superior to those. One participant also described preferring to work at desktops to laptops because it was better for her posture. Another factor was the age and state of repair of a device. All but two of the participants did not own a set of new, up-to-date, high-end equipment. Rather they had devices in various states of repair. Devices do not seem to be bought all at once, but rather a laptop might be bought one year, a mobile device another, and so on. For example, P15's laptop battery was broken and so he would use his tablet when out of the house. P14's laptop fan was too noisy, making that device useless for Skype and watching videos and so she would use her phone. P20 had problems with the audio on her mobile phone and so used her iPod Nano for music. P3 had abandoned her iPhone because it was old, slow and had broken audio; she found her iPad mini could meet her needs until she could afford a new phone. P13 had a cracked screen on her phone, and so would play games on her tablet. For other participants, the organisation of device use had more to do with risk. P18 used University computers to write his dissertation because he worried his laptop might fail. P21 had bought a new laptop, and so started to use her iPad when cooking because it became her less valuable device.

What Jokela et al. [25] term "sequential use" of devices characterises the majority of multiple device use by our participants. Particularly for those who had jobs or were working on dissertation projects, the participants seemed to move through sequences (e.g. of using a device on the move, of using another at work, and then perhaps another in the evenings). There were also examples of what Jokela et al. term "parallel unrelated" use. For example some participants would use one device to listen to music while using another to do something else, and many said they checked social media on a mobile device while using a computer. When it came to social media, there were some striking differences in outlook on multi-device use. Some preferred to view social media such as Facebook within the web client, whereas others preferred to use their phone (or were blocked from using social media on work computers by their employer). For some, having a mobile device near a computer is a convenience, yet for others other, a distraction.

"If I'm working on the laptop I might be emailing on my phone because it's more convenient, or Facebook or messenger … I'll check my phone rather than checking the email on my laptop because its more convenient" (P10)

"It's like I use the iPad for a few minutes and then put the iPad away cos its distracting me" (P12)

"Parallel related" use was less common. P3 spoke about using her tablet to read PDFs while writing on a laptop, and three participants spoke about talking with family and partners on Skype using a mobile device resting against their laptop screen. P12 spoke of staying up until 3am to watch his national team play football in the Copa America.

"I said to my girlfriend, ayy, lets watch Columbia's match [together on Skype]. So she was watching it on the TV. I was watching on the laptop." (P12)

The organisation of device use in everyday life then, is not a matter of one kind of device being good for one thing, and another kind of device being good for another. Rather how devices are used together, and how they are used sequentially during the day is contingent upon user preferences, their life world, their willingness to carry equipment, and the various states of repair of their devices. The issue here is that the appropriateness and value of the use of a particular device at a particular time is not an inherent quality of the device's functionality, but rather manifests according to a range of factors including the individual user's values and preferences. These values and preferences pervaded our participants' opinions and perspectives on personal tracking of digital device use.

The value of tracking screen time

When we installed ScreenLife, we did not advise the participants on there being any correct way or purpose for using it. Rather we told them they were "*free to use it as much or as little as you want*" and that we were "*interested in what you think about it*". The initial question of the interview "*what did you think of the app and our study?*" was also designed to be as open as possible to opinions and ideas.

We found in the interview that the participants had flexibly and diversely interpreted what the purpose of ScreenLife was or could be. The interviewees discussed:

- Understanding device time
- Cutting down on device use
- Increasing device use
- Disciplining device use
- Managing devices
- Tracking everyday activities

Understanding device time: All but two of the participants had never used a tracker similar to ScreenLife before (P18 had used Quality Time, and P12 had used a productivity tool). So, for most participants this was the first time they had been confronted with data about their use of their devices. For participants such as P20, the data was "*shocking*". For others such as P2 and P21 the data was "*interesting*". P21 in particular spent a lot of time scrutinising her data.

For P2 and P5, there was no further purpose for the app other than gaining an understanding of device time.

"I noticed that it's pretty much the same every day. There's no sort of variant. So after that was just sort of like, well, I know." (P5)

For the other nineteen participants, the data pointed to some purpose beyond merely quantifying time spent on devices.

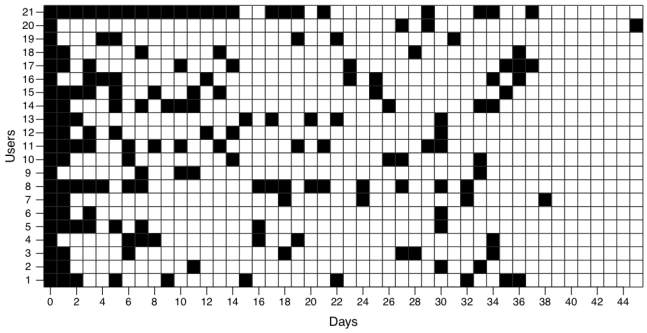

Figure 2: Interactions with ScreenLife. Each marked square represents a day that the ScreenLife interface was opened at least once. Day zero is relative to the day we installed the app.

Cutting down on device use: Many of the participants thought they could or should cut down on technology use. For P1 this was to cut down on overall amount of time he spent looking at screens. He explained this in terms of *"my eyes"*, specifically mentioning YouTube and Facebook as things he ought to spend less time looking at. P1 thought that things such as listening to music on his devices should not be counted, as this is not using his eyes. P1 explained that cutting down on viewing time, as opposed to cutting down on using devices to listen to music, would enable him to spend more time reading a textbook for an exam he would take at the end of the summer.

P1's perspective was fairly unusual, in that every other person that wanted to cut down on technology use wanted to cut down specifically on the use of their smartphone or tablet. For example, P12 explained:

"I'm not as critical of my time I spend on my laptop as I do on my other devices. Any time I do on my laptop, I'm usually working or watching a movie, so I'm not doing anything that's a huge time sink. Most times I'm on my phone it's just games and social media, and I'm just critical of those activities." (P12)

Increasing device use: Several participants also talked about increasing device time. In particular, several participants felt they ought to be spending more time working. This was generally something that went hand in hand with spending less time on mobile devices, although in some cases participants also felt they could read more on their tablets. This perspective was held by the participants that were working on their dissertation projects:

"The laptop, you see how many times you are spending really, in your studies. ... I need to increase .hhhh" (P3)

This perspective was also held to an extent by the students that were unemployed during the summer. The unemployed students would express guilt about the lack of laptop use.

Disciplining device use: Several participants also discussed the appropriate use of technology. This was neither to cut down nor to increase, but to not use a device in certain situations. One example, in which ScreenLife was of little

use, was P7 and P20 thinking they and their friends should be spending less time on devices when socialising. But two cases that were brought up where ScreenLife might at least have potential were a) eliminating phone use during the night, b) eliminating phone use when doing a work related task on a computer, but not when watching a film.

Managing device use: P6 felt that ScreenLife gave her little value in thinking about her everyday life, but thought it had potential as something to help her manage her devices. In particular she wanted to use something like ScreenLife to correlate app use and battery time.

"It's interesting. It might be of a curiosity, but it has no impact on how I would change my behaviours … it would be interesting if it was connected to battery life." (P6)

Tracking everyday activities: Others talked about ScreenLife in terms of tracking their activities. An unanticipated use stated by P16 was that ScreenLife served him as a memory aid—he was doing shift work at a factory, and he could see what days he had worked and when he left the house.

"I think most of the time I used it for erm, if I couldn't remember what time I did something. But I know if I looked at it I could figure out what that was. That's probably not as intended." (P16)

Others also talked about being able to see and remember things they had done, for example when they had gone to bed or woken up or when they had had time away.

These purposes of ScreenLife were not necessarily mutually exclusive. Nor were these purposes necessarily borne out by the participants; the ScreenLife design was minimal and did not offer anything but basic support for things participants were interested in. Indeed the participants gave us advice on how to improve the app with relevance to their favoured purposes, such as support for goal setting, or for enabling users to define the activities they had used their devices for. A common suggestion was that ScreenLife should offer more detail, particularly about what apps and websites were used.

Making sense of screen time data

Figure 2 shows the days on which the ScreenLife interface was viewed on one of the participant's devices at least once. In this section we will explore when and why ScreenLife was accessed, and what was looked at.

Interest in overall time spent: Several participants reported being mainly interested in the overall figures for daily and weekly device use, rather than the drill-down detail. P18 for example was specifically interested in the amount of time he spent each day on his smartphone. He wanted to use ScreenLife to reduce the use of his smartphone during the summer months.

"I thought going to check every time like, every days, … I must do discipline yes… Basically to see how much time I spent" (P18)

In the end however, P18 was neither disciplined with his use of his device or with ScreenLife itself. He said we should have provided notifications every day to remind him he needs to focus. Similarly, P3 suggested it would be better to send reports rather than require people to remember to check. However, her idea was for a monthly summary rather than a daily nudge. Her rationale for a monthly report was that it would help her know if she was getting her money's worth from her devices.

"It would be really good if by the end of the month lets say, it gave you a report" (P3)

Interest in the details of use: Other participants were far more interested in drilling down into the data about the hours, minutes and seconds for which they had used their devices. P21 viewed ScreenLife very frequently for the first half of the trial, probing and scrutinising the data. She explained:

"So I would go into the app, like every day to see if this is working fine" (P21)

Other interviewees also discussed their interest in drilling down into the data, although they did not scrutinise it to the extent that P21 did. In some cases the drill down data served a similar function to the daily total given at the top. It allowed participants to see how much time they spent on devices:

"Most of the time I just checked the blue, the blue whether its very dark or…Yeah, or its like light blue." (P17)

An interesting and unexpected repercussion of our presenting this hourly view of interaction was that participants oriented to their use of devices not just in terms of an overall total but developed the concept of a 'free hour'– this being a square on the hourly view that was not coloured.

"I actually had no hour where I did not touch my phone." (P15)

This idea is striking for us because it is contingent on our design decision to present the data in this particular way. This design was not inevitable, but one of several options we explored. This leads us to wonder what different ideas or practices would have emerged if we designed the interface in an alternative way.

Interest in the general idea: For P20, ScreenLife was not something to be checked regularly or scrutinised in detail, but rather something to make her more mindful of technology use. It was something to prompt thinking:

"I think I only checked it a few times in the beginning of the study … I sort of began to think about, more about how I use my computer and iPad and phone I'd say." (P20)

The calendar view: Several people were actually interested in both the overall totals and the drill-down detail. However, no one was particularly fond of the calendar view in the centre. It did lead one participant to discuss being able to mark up Ramadan and look for differences. For P2, she could clearly see a gap of a few days where she had taken a holiday.

Problems making sense of the data: It must be said that not all participants found the interface easy to understand. One person appeared to add up the time for their two devices when stating a figure for overall screen time. Some reported problems understanding that different shades were used in the hourly view to represent how much usage there had been during that hour:

"It took me a while to know this all, this yellow is related to this orange, and this yellow, and it is the notebook" (P14)

In sum, the participants developed different rhythms and practices of viewing and making sense of the data. Some oriented to different temporalities of tracking. Some wanted an 'everyday' app to scrutinise and give reminders. Others wanted something slow. Some wanted something to use for a week or two out of interest, others something specifically to help them through their busy dissertation period or slack summer. Others saw ScreenLife as something that accrued and fed back data more slowly. Some interpreted the interface in unexpected ways, for example orienting to having a 'free hour' from device use.

Seeing everyday life in screen time data (and non-data)

ScreenLife offers an abstract representation of screen time, showing the times when a device is in active use. Nevertheless, the participants were able to see many aspects of their everyday life in the data.

Seeing everyday routine: Firstly, routine was grossly apparent in the data for many participants. This was particularly true for those that were working. Routine was apparent in the sense that participants could recognise and account for the overall look of their day-to-day data, for example going to and from work, watching films, and taking breaks:

"That's my internship day, so I use it in the morning when I wake up at breakfast, and when I get back after work" (P2)

"*My commute is about two or three hours long, and I'm pretty much on my phone the entire time*" (P1)

Seeing a lack of routine: For other participants, particularly the unemployed students, the absence of routine was grossly apparent and something that they seemed to want to explain or excuse. P8 explained that not only was she using her laptop very little, but also that her data from her pedometer and cycle tracker were also down. She was becoming sedentary and unproductive over the summer. P9 explained, very apologetically, about his absence of laptop use during the summer. He also gave a reason for using his phone at night rather than during the day:

"The month of fasting, Ramadan … I was using this phone to like err watch news and stuff at night, so I was like 3am, 4am I was up … so during the day, just sleep ah hah" (P9)

Similarly, P8 felt she had to explain the presence of data during night time hours:

"My sleep pattern is weird so eh heh heh heh," (49)

Seeing detail in the data and absences of data: Although ScreenLife gave a high level representation of time on devices, this was often translatable by participants to specific activities. For example, P15 pointed out of his mobile phone data that "*whenever I have a longer block in one go*" it would almost certainly be him on Skype. He joked about using this as evidence in his relationship:

"Maybe I will have proof for my girlfriend that, she's nagging I don't Skype enough, and I could say see here, on this date." (P15)

However, it was not just the data that was meaningful to participants. The absence of data, the blank periods, could be meaningful too. The blanks might represent breaks, or time spent on a work or library computer. Most remarkably, the absences represented sleep:

"You see when one's working, or sleeping" (P10)

"Yes I've been sleeping not until 6am eh heh heh ha ha yeah. I may have a shift in my studying, like my day just shifted." (P14)

It is remarkable that it is not just the *presence* but also the *absence* of data that speaks of daily activities- the blank periods of sleep, followed by the use of a smartphone in the morning, and the closing of a laptop before going to work or going to bed.

Privacy concerns: Perhaps unsurprisingly most of the participants felt that the data was private or personal.

"They might know whether I'm going to sleep. When I woke up or something like that." (P11).

"I wouldn't share it but err, yeah, but in the same breath I'd want to see what others do." (P5)

This said, one participant felt it might be helpful if her parents could see the data in order that she stays disciplined.

"I don't know if for your parents for instance can, huh huh monitor how many units that you use. … of course I wouldn't like it, but I think it would be helpful you know, to force you to study." (P17)

We do not wish to claim that everything recorded in ScreenLife was readily explainable, but it was striking how the abstract data we collected and presented could be related to specific activities. It also striking how readily the data could (rightly or wrongly) be used to question the morality of the person's everyday life – one's sleep

patterns, how long one spends working, and more. The ScreenLife data revealed much more about the participants than we initially anticipated.

Perspectives on imperfect screen time data

We began this study knowing full well that it is impossible to capture perfect information on screen time. Therefore an aspect of our evaluation has been to explore and articulate how the users encounter and make sense of imperfect data. The data was imperfect because a) not all devices could be logged, b) there were some bugs and failures.

Not everything can be logged: We failed to install ScreenLife on two devices, an iPad owned by P12 and a laptop owned by P17. Both continued in the study, and neither appeared to miss having data about these devices. We also decided not to log a laptop owned by P6 for ethical reasons (she was using it while working with data about vulnerable people, and so was not appropriate for inclusion in an exploratory research trial). Moreover, many participants used screen-based devices that we simply could not log. Some of these were devices compatible with ScreenLife but not managed by participants. For example many of the students would use laboratory computers, and those with jobs would use work computers. Participants also used devices incompatible with ScreenLife. Several participants had televisions, with one participant regularly using it to play console games. P20, a music student, regularly used an iPod Nano to play music. They recognised that these other devices would be interesting to log, but no one seemed to think that ScreenLife was incomplete or missing something.

An interesting issue we encountered was that P15 had a dual boot Windows/Linux laptop. ScreenLife only logged when he was using Windows, thus delivering partial information about when the device was in use.

"it was interesting to see especially for my windows laptop … because I only use it for one purpose, gaming. Err so I could track myself while doing my Masters Thesis. On how much I wasted my time."(P15)

P15 felt the data would be less meaningful if it had combined his screen time for both Linux and Windows, saying that if ScreenLife did work for Linux it should treat the laptop as a separate device for each OS.

What seems to be at issue here is that having a complete picture of all screen time across every device is not necessarily desirable. The participants were not generally interested in overall screen-time, but needed the details of what they were doing with their devices to make judgements about productivity, overuse and so on.

Imperfect logs: There were also several intermittent or partial failures in the study. Firstly, we found ScreenLife had two bugs that caused it to occasionally display tablets as being on for up to 24 hours. We discovered these bugs were associated with a) turning a device off, and b) the battery depleting. This bug was present for phones as well as tablets, but we realised that tablets were disproportionately affected, not for technical reasons, but because tablets are managed in different ways to phones – they are not charged every day, and sometimes they are turned off (whereas phones generally are not). We also noticed that ScreenLife would sometimes be 'killed' on iPads. P3 said she sometimes did this for all iPad apps, and that she did not realise this would stop ScreenLife logging.

If we think of apps such as ScreenLife as a data collection, it is reasonably straightforward to detect and discard 'outlier' events such as 12 hours of apparent use of an iPad. Yet from a user's perspective, these outliers are extremely apparent – particularly on the calendar view. For some users, they were fine about something being "*obviously wrong*" (P15), particularly as it was tablet data which no one thought was the most important. But two participants, P8 and P21, repeatedly stated in interview that they were upset about their inaccurate iPad data. On discovering problems with their tablet data they felt unable to trust any of their data. For P21, it meant she no longer wanted to use the app.

"I looked at it here, and I thought … this is not right at all. So, after I didn't check it very often." (P21)

Faults and failures are common in field trials. It is particularly striking that the users had a very different experience of the particular bugs that manifested in ScreenLife to our own experience in the lab (where boxplots would make the outlier data invisible). It is also notable that the differing practices people have around particular devices also leads to software faults turning to failures.

Screen time on shared devices

A final point of interest is that some of the devices in the study were shared: primarily the tablet computers. P19 and P20 were a couple and shared an iPad (we did not know this when they were recruited, and we did their installations and interviews separately). P15 and P21 also talked about how they shared their tablets with their partners. The tablets also had complex ownership stories, for example P19 and 20's tablet actually belonged to P20s mother, but had been abandoned by her. P15's tablet was on long-term loan to him from a friend who had bought a new iPad. P13 had borrowed her tablet from her sister after breaking the screen on her phone. She was waiting for her contract to end before buying a new phone and returning the tablet. Not all tablets were shared, but on the whole, their status was markedly different to mobile phones and laptops.

When it came to sharing mobile phones and laptops, these were typically shared very rarely and only in the presence of the owner. For example couples or housemates might watch a video on a laptop together. Couples seemed more relaxed about sharing devices than others.

The issue raised here is of the very relevance of *personal* tracking to devices that are and are not personal. It makes sense in the main to have a personal record of a smartphone or a laptop, but a tablet is often not a personal device. In this case the log becomes a log not of the person's life but of the use of the device by various people. For this reason, and because tablets are used so irregularly, the study participants were far less interested in the data from these. P21 did remark that even if it is not personal data, it can be helpful to know about the life of the device itself. However, viewing this alongside personal data about a phone and a laptop was not necessary.

LESSONS LEARNED

In this study we were reminded that the ways in which digital devices are used are not technology-determined, but are a practical matter in people's everyday lives. Not all devices are equal, but rather they have values and meanings imbued in them by their users. Our key lessons learned from this study therefore concern both the design and the practices of personal tracking of screen time.

Personal tracking of screen time can support varied purposes: These purposes include cutting down on device use, becoming more productive, monitoring devices, and keeping a record of everyday life. Different trackers might be designed for these purposes. It might be that some trackers are used over short-term periods, e.g. during religious observances, busy periods, or breaks.

There cannot be 'raw' screen time data: Our intention was to provide simple and consistent data, but we found ourselves having to make many design choices. We also found that 'innocent' design ideas such as segmenting time by hours led users to develop concepts such as the 'free hour'. Some users wanted to build 'slow' long-term data, whereas others wanted regular notifications and reminders. Representation of screen time is therefore unavoidably a *design* issue and a dialogue between representation and practice.

People can see everyday life in screen time data: The participants could clearly see their routines and often explain of the data what it was they were doing. The absences of data also held meaning, for example showing sleep. This is potentially both a strength and weakness of personal tracking applications in this domain. Data about everyday device use can reveal much about someone's life, to the point that it raises privacy concerns.

Depth rather than breadth of screen time data is important: The participants were generally not interested in gaining an overall figure for the time they spent on screen-based devices, but were more interested in using data to see and organise their use of individual devices. If they were upset it was not about missing devices, but misrepresentation of a specific device.

Tracking of screen time is less meaningful on shared devices: Not all devices (in particular tablets) are necessarily personal, and so the data generated from these is not necessarily personal. Data from shared devices was not valued as much as from personal devices in this study although it raises some interesting possibilities for shared tracking.

The study we have presented does have limitations. Firstly, some of the people we recruited may never have thought to look for and download a device tracker:

"*I liked it, I really did cos I never thought of having some kind of app like that* " (P14);

Secondly, many of the participants would probably have removed the application sooner if given a choice:

"I feel like if it was an app that I just err say found online and if I just downloaded it, and wanted to try it out, I probably, in the shape its in right now I'd probably stop using it in a week." (P8).

Finally, the recruitment and timing of the study meant that our participants were all students at transitory points in their lives. Trials such as ours are an important part of understanding and working-up design knowledge [3,45]. Our particular cohort is as valid as any for generating insight. We do suggest though, that further work might reasonably explore the opinions and perspectives of various other types of user.

CONCLUSION

Our study shows that there is great deal of potential for personal tracking of digital devices, either of individual devices or multiple devices. Personal tracking need not be limited to health and wellbeing but can be of value and interest in many aspects of people's lives. In this research we have found that the concept of screen time is of interest to users when tracking their devices, but far from fully sufficient for the range of purposes for which people would like to put a device tracker.

In evaluating ScreenLife we have learned lessons and gained many insights that we believe are valuable for on-going design work in this area. We believe there is much potential for further innovation of personal tracking applications that give insight into everyday device use. As Church et al [7] say, improved user interfaces and user experience is likely to result in better data collection in device tracking studies. However, we suggest that HCI's interest in personal tracking should not be limited to and need not be led by data collection. It is important to address and support how people make sense of, take interest in, and organise their everyday personal lives.

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