

# Demand Around the Clock: Time Use and Data Demand of Mobile Devices in Everyday Life

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## ABSTRACT

Motivated by mobile devices' growing demand for connectivity, and concern in HCI with the energy intensity and sustainability of networked services, in this paper we reveal the impact of applications on smartphones and tablets in terms of network demand and time use. Using a detailed mixed methods study with eight participants, we first provide an account of how data demand has meaning and utility in our participants' social practices, and the timing and relative impacts of these. We then assess the scale of this demand by drawing comparison between our fine-grained observations and a more representative dataset of 398 devices from the Device Analyzer corpus. Our results highlight the significant categories of data demanding practice, and the identification of where changes in app time and duration of use might reduce or shift demand to reduce services' impacts.

## Author Keywords

sustainability; data demand; ICT; demand designed into practices.

## ACM Classification Keywords

H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous

## INTRODUCTION

Mobile devices (e.g. smartphones, tablets) are increasingly integrated throughout our daily lives to support the “*accomplishment of social practices*” [28]; this has implications for the energy intensity of practices: the energy demands, not only of the devices themselves, but of the Internet and communications infrastructures, and cloud services that compose the information services we increasingly access and rely upon [31]. The quantifiable energy and emissions associated with this “*demand for network connectivity and online services*” [19, p.2729] is known as data demand. Data demand is effectively *designed into practices* through its embedding in technologies and apps that we use to support them.

Despite substantial efficiency gains in both the Internet core network and cloud data centres, the backdrop for our work is

one of unprecedented and ongoing growth in demand for mobile technologies and related services. The increasing ownership and usage of mobile digital technology is contributing towards a predicted growth in European smartphone traffic from 1.2 GB to 6.5 GB per month, per user [7]. Coupled with this, initiatives driving growth in access to services, such as the UK Government's aim for 95% of UK premises to access “*superfast*” (35 megabit) broadband by 2017 [21], furthers opportunities for demand through higher-bandwidth transmissions (e.g. higher definition video [6], the adoption of ultra HD and 4K video content [22, p. 115–6], the deployment of HD voice [7])—a vicious cycle that has the potential to place *even more* reliance on cloud or Internet services.

In this paper, we establish the data demand relating to everyday practices that involve mobile devices. We identify the most data (and thus associated energy) intensive practices (e.g. watching, listening and social networking) at a level finer than surveyed in existing work, such as Sandvine [30]. We explore the relative demand intensities of the practices, and identify the times of day at which they are most prevalent. Additionally we contrast data demand and time use for communication to the time use and environmental impact of SMS and phone calls; and examine the data demand of “*hidden*” non-interactive system updates, backups and background processes, calling out their relative impacts. This analysis is facilitated by: (1) a quantitative and qualitative investigation of eight Android device users, juxtaposed with (2) a quantitative investigation of 398 Android devices. We summarise by contributing new implications for future HCI design.

## RELATED WORK

The time use of applications on mobile devices has been extensively studied in prior work. Böhmer et al. discovered that the average duration of use for an application lasts only 72 seconds, yet the average use of devices totals to 59 minutes per day [4]. Interactions with devices have been found to range from 10–250 seconds [9], with each session more likely to be for a new interaction rather than for following up a previous interaction [40]. Other detailed investigations have included: revealing how users revisit their smartphones and applications [16]; the analysis of users' attention span for web browsing on mobile phones within different contexts [23]; identifying different yet common patterns of smartphone users (e.g. “*Screen Checkers*”) [41]; and, exploring the differences of smartphone usage sessions in various places (e.g. home, office) [37]. We extend this work, however our goal is not to characterise use of such devices, but rather to quantify the data demand and associated energy impact from the everyday practices of users.

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The importance of taking a “*holistic view*” of the impacts of media and ICT (including mobile devices) has been previously stressed by Bates et al. [2]. Such a view should include manufacture and distribution (embodied emissions), direct energy use (e.g. electricity consumption), indirect impacts and the practices that encompass use of these technologies. While this work goes into details surrounding embodied emissions, direct energy and practices, indirect impact (i.e. data demand) is not quantified. However, with up to 90% of the use phase energy consumption of mobile technologies being due to data demand [15] we cannot afford to ignore the indirect impacts just because a large proportion of energy is “*hidden*” in the communication network, content delivery networks and data centres behind such services.

Addressing the embodied impacts of manufacture, HCI researchers have been discussing the importance of extending the lifetime of use of mobile digital technologies (e.g. [11, 13, 26]), and we would wholeheartedly endorse the core messages of longevity and avoiding designs that lead to premature obsolescence and obviate reuse—especially given forecasts predicting continued escalation in adoption of digital technologies (e.g. growth in the number of living room connected devices [27]) and growth in network traffic [7]. Our goal in this work, however, is to probe the connection between device use in social practices [28, 38] and its growing impact as a consequence of overall and peak demand [25].

The role of ICT in supporting social practices can be seen to reduce some environmental impacts whilst increasing others. Hilty explores these opportunities, with first-, second- and third-order environmental effects of ICT [14]. The impact of manufacture, distribution and disposal is linked to negative first-order environmental impacts of ICT, whilst second-order impacts encourage positive environmental effects through their influence on processes of production, transport and consumption [14]. Third-order effects are the long-term “*adaptations of behaviour and economic structures*” [28, p. 349] which can lead to rebound effects. Considering, as we see in this paper, that mobile ICT can loosen the spatial and temporal constraints surrounding practices [28], it is important to uncover the underlying times and places of use to better understand practices and demand.

Time of use of data demanding digital technologies in the home has been previously studied by Kawsar and Brush. They collected logs from 86 home routers, supplemented with 18 interviews and 55 surveys. They show that: there is higher activity in the afternoons and evenings for social networking and video watching [17, Figure 4]; tablets are used more frequently than smartphones [17, Figure 2]; and, screen size and usage context influence device preference for social networking [17, Figure 7]. These findings are important to consider when attempting to reduce the intensity of data demand, however, this study doesn’t link its findings to energy or other impacts.

Personal communication via home broadband has been a focus of prior work: Chetty et al. [5] study the effects of broadband in 12 US households, focusing on users’ experiences with bandwidth caps and ISPs’ monthly “*use it or*

*lose it*” data plans. They reveal directions for more bandwidth sensitive designs, moving away from “*all you can eat*” plans. Furthermore, their study highlights that people can be “*mindful consumers*” but have difficulty managing bandwidth [5, p.3029]. Other work that studies everyday life and Internet connectivity has primarily explored the effects in terms of: wellbeing (e.g. digital gaming effects [34], aloneness [39]); social expectations and negotiating friend and family relationships [1]; the relationship between productivity tools and busyness [18]; and the effects of email on productivity [20]. Whilst these studies focus on how ICT can affect everyday life, they do not quantify the data demand of the practices they observe, nor link this demand to time use.

Closest to our research, Lord et al. have quantified data demand and explored how mobile devices are integrated into the performance of practices [19]. However, this work does not examine the time use of practices and their relationship to data demand. Unlike Lord et al., we compare the impacts of phone calls and SMS to the data demanded by communication apps, and provide insights into why users spend time away from their devices. Our study is informed by *both* quantitative analysis of app usage data, along with complementary qualitative participant accounts that are used to explore nuance in the findings. This research also adds to Lord et al. through investigating Android devices rather than iOS, and provides an increased understanding of the data demanded through practices on a large, quantitative scale.

More recently, Preist et al. [24] discuss how current design paradigms encourage infrastructure demand through defining high expectations of users. These include ensuring access to services during times of peak demand and handling high quality media. Using prior research, the paper sets out a number of questions upon which service designers should reflect, in regards to their services’ environmental impact. Through investigating the current data demanded through practices in our research, we aim to further the information presented by Preist et al. by indicating which practices in everyday life are the most demanding, or have the most potential for demand decrease, in terms of data and time.

## METHODS AND PARTICIPANTS

To investigate the integration of mobile technologies into the performance of social practices [28, 36], a two-phase study was carried out for understanding the use and demand of Android devices. In the first phase, we gathered and analysed quantitative and qualitative data from eight Android device users using the Device Analyzer data logger (Device Analyzer is developed at The University of Cambridge<sup>1,2</sup>); this records device-use data such as screen state, power state and app data usage. Logging was followed by face to face interviews to discuss the data. In the second phase, we correlate these findings with log data drawn from the large-scale dataset the Device Analyzer team at Cambridge have collected. Throughout the paper we refer to the former dataset as Eight Participants, and the latter as Atlantic Archipelago.

<sup>1</sup><https://play.google.com/store/apps/details?id=uk.ac.cam.deviceanalyzer>

<sup>2</sup><https://deviceanalyzer.cl.cam.ac.uk>

The devices investigated in these datasets are the participants' own, rather than devices given out specifically for the study.

### Phase 1: Demand in detail

We recruited participants by promoting the study via local and University mailing lists and snowballing methods, and approaching previous study participants via email. Whilst no incentives for participation were given, eight participants agreed to take part. These participants were studied between October 2014–January 2015. We use consistent pseudonyms throughout the remainder of this paper.

The participants are a mixture of undergraduate students (Harry, Mark, Victoria), postgraduate students (Holly, Xander), and full-time employees (Tim, Bob, Amanda). Two of these participants were tablet users (Holly, Xander), whilst the remaining six were smartphone users. A summary of the participants and their device use is shown in Table 1.

This phase of the study was split into quantitative data gathering and qualitative interviews. For the data gathering, the Device Analyzer was installed on each participant's Android device, where one device was studied per participant. Although the participants did own other devices (e.g. Mark owned an iPad, Holly owned a Windows phone, and Xander owned an iPhone), these were not studied as this research is an important first step for associating data demand with practices; however, multiple device studies will be essential within future work. The quantitative logging phase lasted for a minimum of 14 days for each of the participants (mean 29 days), except for Xander where only 11 days of data was captured due to problems charging his tablet abroad. The duration of each participant's logging period is shown in Table 1.

Semi-structured interviews were carried out with each participant to discuss typical practices that included mobile device use, approaches to mobile and Wi-Fi connectivity, power management, charging, and times of use. In order to foster deeper discussion of the devices' integration into everyday life, graphs created from their logged data were presented to them; these included visualisations of their device use, battery level, charging habits and a break-down of app usage<sup>3</sup>. During each interview, we encouraged discussion surrounding the meanings and competence associated with the device as well as the social practices in which the mobile devices featured. The interview questions were tailored to account for differences between phone and tablet devices, and the interviews lasted from 38 mins–1 hour and 25 mins (median 56 mins). Each interview was fully transcribed, independently open-coded by two researchers, and then consolidated and re-coded for emerging themes.

To relate the devices' data demand and time use across practices, we manually categorised all of the apps and processes used across Eight Participants, totalling to 1121 apps<sup>4</sup>. It is important to note that these categories are not practices themselves, as the categories (e.g. "browsers") may cross multiple practices. Where we graph the categorised time use and data demand from devices in both datasets, we omit devices who

were not "active" for each category, i.e. were not seen to be used, or exhibit data demand. Rather than analysing broad aggregates like existing studies [30], we present use and demand this way, as we want to compare categories' average usage, and identify where we might shift practices' reliance upon different categories of apps. However, to expose the prevalence of these categories, we show the number of devices contributing in brackets on relevant plot legends (Figures 2–7); in these plots, we average across days for each device and then average across devices. Throughout the paper, we define *time use* as the number of times an app had foreground status when the device screen was both on and unlocked.

### Phase 2: Scale of demand

The second phase of the study links the findings of our observational study with a large device population. This consisted of quantitatively analysing Android device use from a large-scale dataset collected by the Device Analyzer team. 30,000 devices have contributed to the corpus, of which we selected a partition of 398 devices to carry out our analysis. We selected devices which: (1) contributed data for at least 14 days with the latest data collected on or after 1st January 2014, (2) had a network-based location in the UK or Ireland for at least half of the contribution days, and (3) used apps or demanded data during their logging period. Interesting insights from the first study phase (e.g. the impact of watching, the use of different communication mediums) helped us identify app groups and practices of interest. As with Eight Participants, we manually categorised apps used by devices in Atlantic Archipelago.

### Limitations

It is important to point out that the time use of some categories of apps we account for may be less than that actually used: Device Analyzer logs the foreground priority of apps every five minutes, meaning that an app can be used and yet not be still in the foreground when sampled. Apps which are used quickly (e.g. communication apps which are more likely to be "micro-used" [10]) will be missed more often than apps used for longer periods of time; this is a limitation present in both datasets. However, the five-minute sampling interval only applies to counting when apps are in the foreground; data demand, phone calls and SMS uses are logged in real-time and hence are accounted for accurately in our method.

Device Analyzer users typically *do not* give permission for app names on their devices to be shared with researchers outside of Cambridge. To prevent the identification of participants from their app use profiles, we do not analyse app use for any apps installed on less than 50 devices to maintain an anonymity set. We generated a list of the 404 apps that were installed on at least 50 of the 398 handsets. Of these 404, we had already classified 247 for Eight Participants; the remaining 157 apps were then categorised in the same way. We discard information relating specifically to apps not appearing on this list. This technique has the advantage of consistency between the two datasets but the disadvantage that demand and time use for unpopular apps in Atlantic Archipelago are not recorded. Despite this, we were able to capture 72% of the total data demand of Atlantic Archipelago devices using the categorised apps, and 59% of the total captured time use.

<sup>3</sup>Some sample visualisations are provided as supplemental material.

<sup>4</sup>A listing of all 24 categories and example apps falling into each category are provided as supplemental material.

Participant (Gender, Age)	Device (Monthly Data Plan in MB)	Study Duration in Days	SMS Sent / Received Totals (Daily Avg. Sent / Received)	Phone Calls Count / Duration in Seconds Totals (Daily Avg. Count / Duration)	Data Demand Total in MB (Daily Avg. in MB)	Notable Categories (Daily Avg. Data Demand in MB)
Holly (F, 23)	Samsung Galaxy Tab 2 (Wi-Fi only)	28	N/A	N/A	3838 (137)	Watching (72)
Harry (M, 23)	Samsung Galaxy S2 (500)	42	138 / 147 (3 / 4)	33 / 2555 (1 / 61)	5644 (134)	Watching (2), Online Dating (15), Social Networking (96)
Mark (M, 21)	Samsung Galaxy S4 (500)	46	315 / 327 (7 / 7)	32 / 2979 (1 / 65)	8359 (182)	Online Dating (3), Social Networking (145), Communication (13)
Victoria (F, 20)	Sony Xperia S (500)	21	189 / 263 (9 / 13)	82 / 12743 (4 / 607)	441 (21)	Social Networking (1)
Tim (M, 33)	Sony Xperia SP (250)	31	26 / 39 (1 / 1)	80 / 32761 (3 / 1057)	14431 (466)	Watching (5), Social Networking (334), Communication (10)
Bob (M, not given)	HTC One (2000 - 'unlimited')	17	58 / 79 (3 / 5)	22 / 1540 (1 / 91)	1199 (71)	Watching (5), Social Networking (26), Communication (3)
Amanda (F, not given)	Samsung Galaxy S4 Mini (unknown)	39	63 / 56 (2 / 1)	209 / 30126 (5 / 772)	931 (24)	Communication (0.02)
Xander (M, 24)	Asus Google Nexus 7 Tablet (Wi-Fi only)	11	N/A	N/A	4622 (420)	Watching (144)

Table 1: A summary of the Eight Participants and their device use.

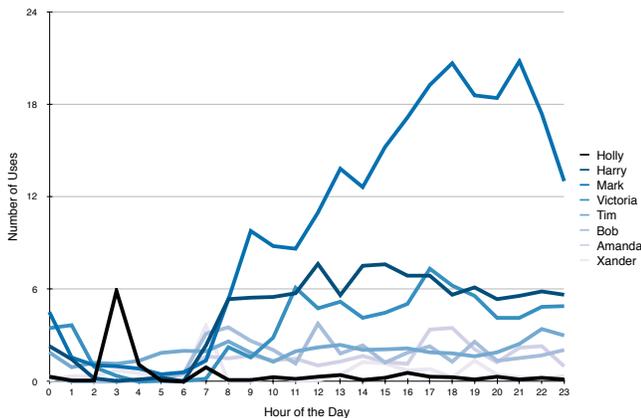


Figure 1: The device use (averaged across days) for Eight Participants, estimated by the number of device screen on times.

## OVERVIEW OF TIME USE AND ENERGY CONSUMPTION

Routines around mobile devices from Eight Participants typically start in the morning with the checking of current news and events (Tim, Xander, Bob, Harry), exercising (Tim), social networking (Bob, Xander, Mark, Harry), and online dating (Harry). Whilst all the participants maintain a regular work day (roughly between 9am–5pm), use of devices continued throughout the day, specifically for smartphone users. This use during the working day varies between participants. For some, their device was sometimes used to aid with their work (Mark, Holly, Xander) and communicate with colleagues (Bob). Whereas for others, mobile devices were used whilst at work or university for checking the time (Amanda, Victoria), filling in free time (Xander, Bob), communication with friends (Harry, Mark, Victoria, Bob, Xander), and social networking (Mark, Tim, Bob, Holly); participants blur the lines between work and non-work practices, cf. [28].

Evenings were typically filled with social networking and communication, alongside more media-rich activities for entertainment-related practices. These included watching TV or movies (Holly, Xander), shopping (Tim), and browsing the Internet (Xander). This was similar to weekends, with communication, hobbies and social networking occurring more regularly. Examples of regular weekend use included keeping up to date with sporting events (Tim), organising outings and visits (Amanda), and bird watching (Harry). A summary of the participants' hourly device use is shown in Figure 1.

In reporting our measurements throughout this paper, we list data demand in megabytes (MB) or kilobytes (KB)<sup>5</sup>. The daily average data demand of Eight Participants devices ranges from 21–466 MB (Table 1), and was 316 MB for an average Atlantic Archipelago device. This data demand is generated by: (1) user interaction with an app that requires connectivity, (2) apps demanding data in the background, and (3) automatic and scheduled updates and backups.

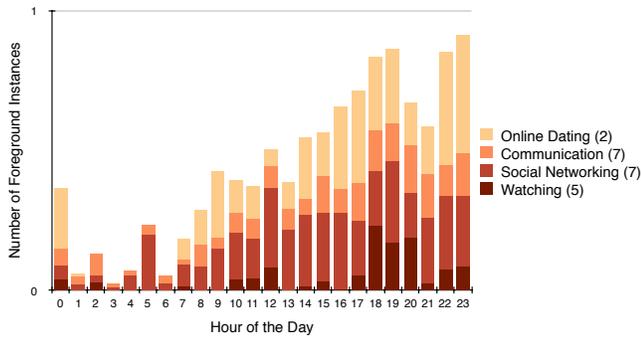
For each gigabyte of data, the energy consumption associated with the Internet infrastructure, core Internet networks and data centres can be estimated to 200 watt-hours (Wh). This coefficient is a compound of three contemporary estimations drawn from the literature [31, 32, 33], assuming a mixture of text and video traffic; we use this coefficient throughout the paper to measure energy consumption. Using this estimate, the daily average energy consumption from the data demanded by the Eight Participants devices ranges from 4–91 Wh, and is 62 Wh on average for a Atlantic Archipelago device. To put the energy consumption from data demand into perspective, the energy required to charge participants' devices in Eight Participants ranges from 5–20 Wh per day<sup>6</sup>. Furthermore, using coefficients estimated by Berners-Lee [3] and converted using the Government emission conversion factor 2016 of 0.52 kg CO<sub>2</sub>e/kWh (including scope 3 emissions), we estimate that the energy consumption for a minute of phone call corresponds to 109.6 Wh, with 0.027 Wh corresponding to a text message.

## DATA DEMAND IN EVERYDAY LIFE

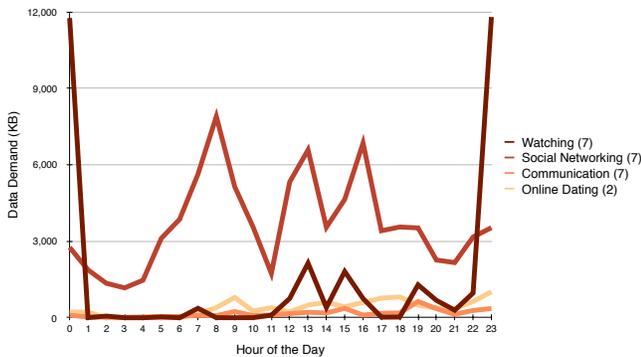
In this section we explore the relationship between time use and data demand for the most significant categories of apps used by Eight Participants: watching, online dating, social networking and communication. Through examining the qualitative data gathered from the interviews, we provide accounts of their practice use in everyday life, relating this to the time use and demand of app categories. The section finishes by showing when automated updates and backups make large contributions to data demand.

<sup>5</sup>Throughout we use the MB notation to represent 1,048,576 bytes or 1 Mebibyte (MiB), and the KB notation to represent 1024 bytes or 1 Kibibyte (KiB).

<sup>6</sup>Based upon the amount of time spent charging per day and the capacity of the battery collected using the Device Analyzer.



(a) the hourly number of foreground instances for categorised apps



(b) the hourly data demand of categorised apps

**Figure 2: The distribution of time use and data demand hourly across notable categories for Eight Participants. The most demanding category, social networking, is ever present throughout the day (41% of overall data demand). Watching is less continuous, but is still demanding (16%) due to the data intensity of video media. Like social networking, communication apps are used regularly, but represent less data demand (2%).**

### Watching and downloading asynchronously

Video watching played a significant role in the lives of six of our participants (Holly, Mark, Harry, Tim, Bob, Xander), and was seen to cross practices (e.g. Holly watching TV or movies on-demand in bed, Xander watching content stored on his tablet, Bob watching DIY tutorials on YouTube). For Tim, BT Sport is used on Saturdays to watch the football, forwarding video to his TV but not using the app interactively. Whilst he explained how he listens to YouTube playlists when exercising in the morning, he was unable to recount what he else he would use YouTube for throughout the day, “*I dunno... I do use, I do use YouTube a lot*”. This app demanded a total of 41 MB of data during his study. Like Tim, Harry watches videos on YouTube, whereas Mark focuses on Sky Go.

Holly’s watching time use and data demand consists of watching catch up TV via video-on-demand apps. This watching occurred typically at midnight, corresponding with her explanation of how she would watch TV on her tablet when going to bed. This watching in the evening was a common activity for Xander too, who is also a tablet user. He described how watching video is a part of his evening routine: “*There’s like a stage where you’re going to bed and you’re like ‘no I’m really going to bed now’, the laptop is turned off... so I watch quite a lot of TV on [my tablet]*”. Xander’s watching use occurred between 17:00 and 20:00,

yet his watching data demand occurred later between 22:00 and 01:00 with very little time use within these later hours. When discussing watching with Xander, he explained that he primarily watches video that he has pre-loaded onto his tablet via his VPN app. This gives an insight into why increases in time use for watching do not always correspond with increases in its associated data demand.

Watching also occurs more spontaneously. Tim mentions that he sometimes watches videos that appear on his Facebook feed, “*if there’s like videos on Facebook that people post I sometimes watch them as well*”. Xander also streams from his web server directly to his device, “*I stream stuff through like a web server, I think it goes through [MX Player]*”. With apps such as the browser supporting watching, and social networks allowing the sharing and linking to videos, it is likely that the data demand and time spent watching is higher than we have attributed. This could be the case for Holly, as she mentioned she would use her browser for watching streamed content. Although we cannot assume that all the data demanded by Holly’s browser use is directly associated with watching, it contributed 55 MB to her daily data demand.

### Online dating and obsessive data

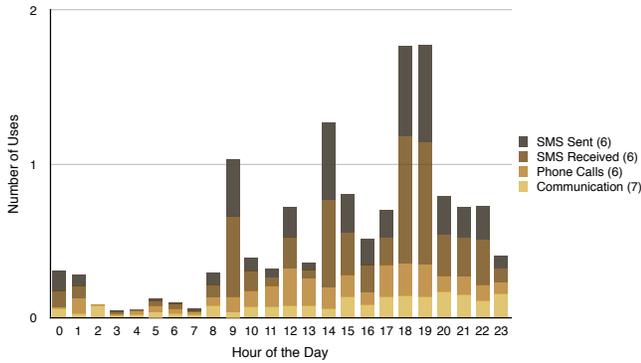
Harry and Mark use online dating (OKCupid and Tinder by Harry, Tinder by Mark) apps regularly throughout the day, with the peaks in the morning (09:00) and again in the evenings (22:00–23:00) (Figure 2a). Whilst Mark’s daily use of Tinder halted in the middle of the study, Harry made his online dating part of his “*obsessive checking*” routine, “*I generally have a bit of a pattern of like Facebook, and Twitter, and Rare Bird Alert, and sometimes Tinder*”. This routine explains why online dating is perhaps most similar in time use to social networking and communication.

Even though the demand arising from online dating may only be from two of the participants, this category is interesting to consider as it is relatively data intensive (e.g. online dating contributed to 11% of Harry’s daily data demand), with demand throughout the day for communication being comparable (Figure 2b). Ten years ago, online dating would have primarily been carried out on a desktop or laptop computer; but mobile devices have come to allow (through dating apps) for the activity to be carried out in any space and at any time.

### Social networking and communication

Social networking in many cases replaces older but less data intensive forms of connecting with others (e.g. messaging via SMS), but usually also adds richer (and more data demanding) media including images, URLs, and videos. This category was used consistently throughout typical waking hours (Figure 2a), yet its associated data demand was constantly high across all 24 hours of the day (Figure 2b).

Generally, communication has lower levels of data demand (Figure 2b) than other categories. This is in part due to the lower time use of communication apps within specific time periods such as mid-late morning (e.g. 09:00–11:00) (Figure 2a), and also due to the extensive use of text (i.e. email, instant messages) without multimedia attachments. However, Mark often sent large email attachments to work colleagues, making his daily communication demand the largest of the participants (Table 1). Although communication apps are



**Figure 3: The distribution of communication time use hourly for Eight Participants. Hourly communication use consists of the number of: SMS sent and received, phone calls, and times communication apps were in the foreground.**

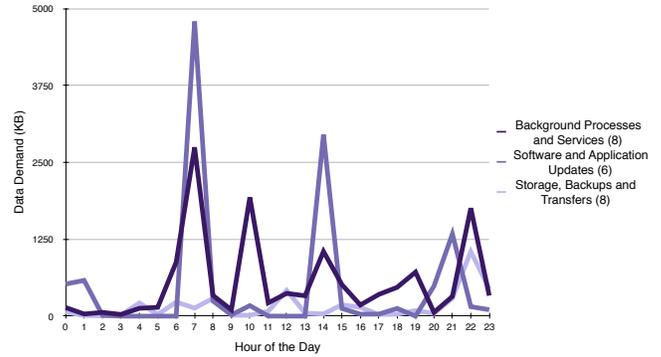
used consistently throughout the day, SMS and phone calls are still an important means of participants’ communication with others (Figure 3). Whilst phone calls were prominent around lunchtime (12:00–13:00) and early evening (17:00–19:00), SMS was a more popular medium for communication throughout the day. Both sent and received SMS were used significantly in the morning (09:00), after lunch (14:00) and after work (18:00–19:00).

Mobile device notifications were seen to reinforce a perceived urgency to reply to messages, particularly when communicating with friends or family. This urgency regularly led to quick replies and short bursts of two-way communication, especially when participants had more free time (e.g. Victoria is more likely to reply quickly if she’s free), and even feelings of anxiety for Bob: *“I feel that you should respond to texts as soon as you can. But then you don’t want to end up in a situation where you’re like text, text, text...”*

When discussing communication apps, Xander mentioned that he prefers to use Facebook Messenger as he can see if his sent messages have been read. Instead of using this app, Victoria uses her browser for Facebook when connected to Wi-Fi, due to problems that she had faced with her phone’s cellular connection (e.g. 3G/4G). She explained how she only really uses Facebook to send messages when she has additional content that wouldn’t necessarily be sent over SMS (e.g. photos, links to websites). Bob and Amanda also used communication apps for sharing multimedia to support them in maintaining family relationships (e.g. Bob uses video chat to show his parents his son due to them living abroad, Amanda uses WhatsApp to see pictures of her partner’s grandchild). This indicates that preferences for communication use can vary based on the content users want to send (e.g. images) or receive (e.g. confirmation that messages have been read).

#### Hidden demand: updates and backups

Apps and services relating directly to updates and backups accounted for 7% of the participants’ daily aggregate data demand. This demand arises in the following scenarios: (1) updating an app or the OS, (2) downloading new apps from the app store, and (3) syncing and backing up of data to a server or Cloud service (e.g. syncing documents to Dropbox). Peaks (e.g. 07:00 for updates, 22:00 for backups) and troughs



**Figure 4: The distribution of data demand hourly across the “hidden demand” categories for Eight Participants.**

(09:00 for both) form the data demand for these categories (Figure 4), a trait shared by background processes (e.g. peaks at 07:00, troughs at 09:00). Although the reasons for the demand by these background processes is unknown, it accounts for 7% of the participants’ daily aggregate demand. This highlights how demand is buried deep in the design of mobile device operating systems and their supporting processes.

Both software and apps can perform updates and backups without users’ knowledge. For some, these updates are seen negatively, e.g. Bob gets frustrated when updates take a long time and prevent him from using his device. Xander manually manages his tablet updates, with automatic updates turned off; this does not mean updates do not happen at all however, as he updated and downloaded apps before his trip abroad, contributing to 56 MB of his daily data demand. Mark also manages his upgrades, choosing to update when there are updates available for several apps instead of updating them individually. Victoria however, actively avoids updates as she’s worried she’ll lose all the text messages stored on her phone, explaining why she was one of the two participants who didn’t contribute to the demand of updates (Figure 4).

Although we are able to differentiate specific apps for updates and backups, these can sometimes be hidden within the data demand of categories such as social networking. This was the case with Tim and his automatic uploads of videos and photos to the Google+ app. As Tim takes a large quantity of photos on his smartphone, this app demanded just under 10 GB during his study, indicating that the demand from updates and backups crosses multiple categories and is therefore likely to be more than we have estimated here.

#### A REFLECTION OF USE THROUGH TIME

This section analyses the Eight Participants accounts to help uncover how the patterns of use support everyday practices, and how these patterns (and their deviations) can contribute to time use peaks and troughs (Figure 2a). These themes are important to explore, as they arise from mobile device hardware and software design: effectively encouraging convenience and ease of use that has implications for data demand. Currently encouraging more use increases data demand, specifically peak demand, which in turn raises expectations around infrastructures and services that influence growth in data demand and surrounding environmental impacts. This paradigm is visualised by Preist et al. [24, Figure 1].

### Filling time and notifications

Harry checks social networks, communication apps and bird watching news throughout the day. He views this pattern as “*obsessive*” and has noticed that he uses his phone more frequently now he has Twitter, stating that “*Twitter keeps you up to date with what’s going on in the world all the time*”. His checking is likely contributing to his higher device time use (Figure 1). Mark, the participant with the highest device use (Figure 1), is a sporadic checker of his smartphone too, particularly when news feeds are announced that he is interested in (e.g. every “*two to three minutes*” during weekend football games). Tim is also a frequent user of his phone, where he checks notifications “*when they flash up*” to see what they are, even though he isn’t supposed to use his phone at work.

Obsessive checking, reactions to notifications, and pressures to work can be seen to fill time; this supports the finding by Lord et al. [19]. Having time to fill, along with the increased multitasking supported by digital technologies are “*enabled by the partial decoupling of many practices from previous time and space constraints through the use of ICT, contribute to a more densely packed everyday life*” [28, p.356]. A more densely packed everyday life can be seen to increase the use of digital technology, which in turn leads to increased demand. However, we have shown that there are some exemplars where our participants increase the frequency in which they “*obsessively*” fill time (e.g. Mark filling time more when there’s football on, Tim checking even though he’s not supposed to). We also observe that notifications and filling time in the case of Harry can encourage him to travel to another place when there are bird sightings: “*if there’s something around locally or whatever and I’ll go off*”.

### Time out from mobile technology

For some, using their device less and getting away from technology was seen as a necessary part of their everyday life. Amanda actively avoids technology in her own time: “*I’m not a slave to technology, erm I use it at work ’cause I have to, I can download, I love the fact you can have information at your fingertips but I don’t want to be on it at the end of the night*”. Figure 1 shows Amanda’s overall device use decline in the evening (18:00–23:00), with her leisure practices of dancing, walking and reading normally involving no digital technology. Bob’s work involves using a desktop computer, so he feels the need to take breaks from digital technology in the week; this explains his relatively low evening device use in comparison to other participants (Figure 1). He described how he goes for walks during his lunch break, often not using his smartphone at all. Similarly to Bob, Holly mentioned that reading from her tablet is the “*last thing you kind of wanna do*” when spending all day looking at a computer screen.

Although Victoria takes her phone everywhere she goes, and uses it throughout the day, she still likes time without her phone: “*at night time I try and just leave it, erm if I’m communicating with someone I’ll probably be on Facebook and then I’ll just try and have like rest from my phone cause I’ve had it with me all day*”. For Harry, his variation revolved around his weekend hobbies, leading him to not use his smartphone on Saturday mornings due to him being “*out bird ringing*” (attaching tags to wild birds).

### Adapting to space and context

The spaces which the participants inhabit create variation in their device use. For example, at work, Amanda has no cellular reception, so there is little point checking her phone. If Amanda wants to use her phone she has to go outside, otherwise “*if anybody needs me 9–5 they phone [her workplace]*”.

For the tablet users, use was influenced by connectivity. Holly recently had no Internet connection at home, so her tablet’s involvement in notable categories of demand was reduced (Table 1). She described how she planned her tablet use in advance, i.e. pre-loading content (e.g. reading for work, videos), to use it at home. Xander also habitually pre-loads his tablet with videos, games, maps and work materials when he knows he’ll be without connection for longer time periods. Despite this, Xander occasionally tethers his tablet with his phone when there is no Wi-Fi, and will stream video content from his home server while travelling. He described how he tends to use his tablet in spaces where he doesn’t want to get his laptop out, or physically move to his laptop or desktop PC.

Tim actively manages mobile data when he’s in spaces without Wi-Fi (e.g. when he’s using his phone as a sat-nav), yet leaves his Wi-Fi on all of the time unless his battery is running low. Victoria is unable to access mobile Internet on her device, due to a suspected problem with her phone, and is therefore limited to using the Internet on Wi-Fi only.

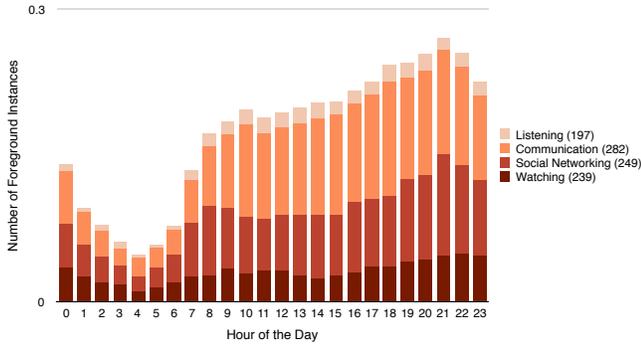
We saw that space and availability of infrastructure can both influence and limit usage. Whilst time spent in a space where a device is available can lead to usage just because it’s there (e.g. Xander using his tablet when his laptop is out of reach), availability limitations (e.g. Amanda’s poor signal at work, Victoria’s faulty phone) can significantly decrease opportunities for data demand. Participants nimbly adapted to their limited availability of infrastructure, carrying out downloading activities in places with connectivity before their period of no connectivity (e.g. Holly pre-loading to use her tablet at home, Xander pre-loading to use his tablet whilst travelling).

### INSIGHTS FROM ATLANTIC ARCHIPELAGO

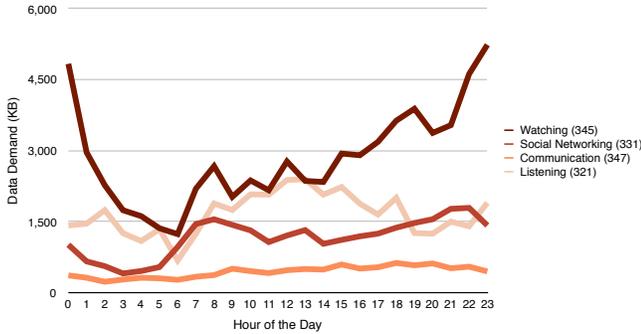
The data gathered from Eight Participants gives us a detailed account of Android device use in everyday life, and data demand and time use of associated practices. Drawing on quantitative data collected from Atlantic Archipelago, we now extend our analysis to a larger set of “*common*” Android device users to observe to what extent there are similarities and differences at a more representative scale.

The data demand for social networking and communication were continuous through the day (Figure 5b). Social networking is the more data demanding of the two with mean data demand of approximately 1.1MB/hour, around 700KB/hour more data intensive than communication ( $p < 0.01$ )<sup>7</sup>. The data demand for social networking is comparatively high to other practices in Atlantic Archipelago, yet still lower than

<sup>7</sup>We use pair-wise two-sample and k-sample permutation tests to compare the data demand associated with practices, rather than more well known statistical techniques for analysis of variance since data demand is non-normal. The permutation tests find for the alternative hypothesis, that the true mean data demand between the practices we observe, differ from one another, and that this difference is statistically significant with probability  $p < 0.01$ .



(a) the hourly number of foreground instances for categorised apps



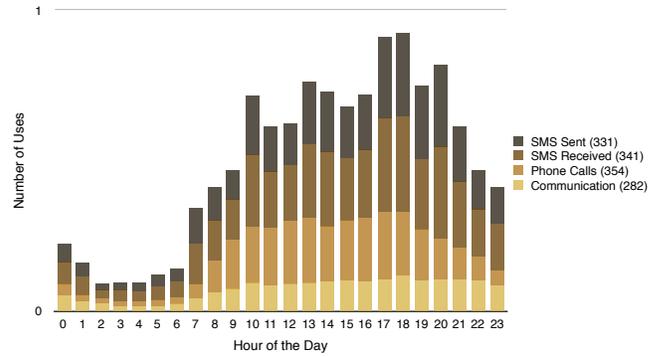
(b) the hourly data demand of categorised apps

**Figure 5: The distribution of time use and data demand hourly across the notable categories for Atlantic Archipelago. Note that communication apps are often in the foreground and are used extensively during waking hours, but exhibit a fairly continuous 24hr data demand (3% of overall demand). Watching time use is comparatively less frequent, but exhibits high data demand intensity when it is (21%). Listening to audio (11%), which was uncovered and featured extensively in our Atlantic Archipelago, is almost triple communication demand and surprisingly nearly half of watching related demand.**

that observed in Eight Participants for the same practice, with less pronounced social networking demand peaks (e.g. 08:00, 13:00) (Figures 2b and 5b). This was the opposite for the communication demand from the Atlantic Archipelago devices, where the hourly demand for this category is higher on average throughout the day (Figures 2b and 5b). The differences in demand for these two categories could be due to the differences in app time use between the two datasets. Communication apps were used more in the morning and early afternoon (09:00–14:00) for Atlantic Archipelago devices (Figure 5a), and whilst social networks were used slightly more by Atlantic Archipelago devices at specific times of the day (06:00) (Figure 5a), they were used less regularly throughout the day than the Eight Participants devices (Figure 2a).

Despite the regular, hourly use of communication apps discovered with the Atlantic Archipelago devices, traditional modes of communication were still used throughout the day (Figure 6). In fact, SMS and phone calls dominated the communication use for all hours of the day; this corresponds for most hours with the Eight Participants devices.

Watching remains the most data demanding practice with mean data use of 2.8MB/hour, 1179KB/hour more than the next most demanding practice, “listening” at 1.6MB/hour



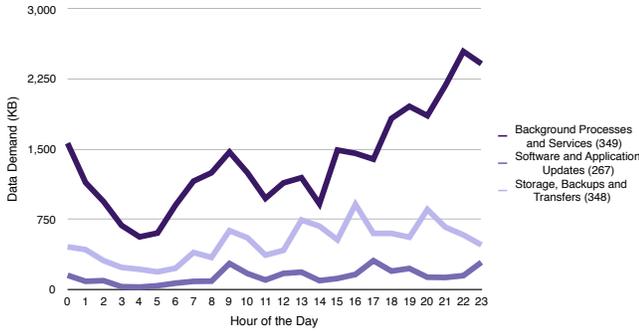
**Figure 6: The distribution of communication time use hourly for Atlantic Archipelago. Hourly communication use consists of the number of: SMS sent and received, phone calls, and times communication apps were in the foreground.**

( $p < 0.01$ ). Here we observe both differences and similarities between the two datasets. Although there are peaks of watching demand around midnight for both sets of devices, the top watching data demand peaks for Atlantic Archipelago devices are lower (e.g. 23:00–00:00) (Figure 5b). Adding to this, the overall demand through the day is much higher and more continuous (Figure 5b), rather than with obvious peaks and troughs (Figure 2b). Whilst the two datasets differ in watching time use throughout the day, evening watching (17:00–00:00) is a popular activity for both Eight Participants (Figure 2a) and Atlantic Archipelago (Figure 5a).

As no online dating app was installed on 50 or more devices, we were unable to analyse this category. However, we can say that while the category might have comparable demand to social networking for those who participate in it (as with Harry and Mark), Atlantic Archipelago indicates that it is a less common activity as compared to others (e.g. watching).

Further contrasting to Eight Participants is the category of “listening”. This is significantly more demanding in Atlantic Archipelago with a mean data demand of 1.6MB/hour, using even more data than social networking for most hours of the day (Figure 5b). According to our statistical analysis, listening uses on average 500KB/hour more data than social media ( $p < 0.01$ ). Whilst this category is demanding, it’s associated time use is extremely small (Figure 5a); this is most likely due to the ability of apps associated with listening to run in the background whilst other apps are in the foreground during use. Whilst seven of the Eight Participants did listen to music on their devices (all except Amanda), this only contributed to 0.37% of their total data demand, with Tim alone contributing to 97% of this demand due to his use of Spotify and TuneIn Radio. The low demand from the remaining participants is due to the use of offline media stored on devices rather than streamed, with participants occasionally transferring their audio files from external storage via apps (Victoria through Dropbox), via cable (Mark, Xander) and syncing to local devices through Wi-Fi (Xander).

In Atlantic Archipelago, updates and backups contributed to 4.5% of the overall daily aggregate data demand, with mean demand of a surprisingly large 1.4MB/hour. This demand is just 300KB/hour less than listening (a statistically significant difference, but only at a 5% level)—but is relatively steady



**Figure 7: The distribution of data demand hourly across the “hidden demand” categories for Atlantic Archipelago. Notably, background processes’ demand is greater in the evening, and does not exploit “off peak” hours.**

throughout the day, with troughs (04:00 for updates, 05:00 for backups) and peaks (23:00 for updates, 20:00 for backups) (Figure 7). This increased evening demand for backups corresponds with Eight Participants (Figure 4). Interestingly, the data demanded by background processes is significantly more throughout the day for a typical Atlantic Archipelago device (Figure 7) than an average Eight Participants device (Figure 4); this is particularly the case at 00:00, 09:00 and 20:00. As a result, background processes contributed to 10% of the overall daily aggregate demand for Atlantic Archipelago.

Clearly care is required when drawing inferences across datasets collected with different cohorts, such as our formative and Atlantic Archipelago datasets. Yet we note that similar categories of demand to those we identify in both our datasets have also been observed independently by others. Sandvine show that real-time entertainment and social networking are both top 5 composers of peak period traffic in Europe via fixed and mobile access, with communications also making the top 5 for mobile access [30]. Furthermore, Ericsson have reported that mobile data traffic will increase by 55% for video, 41% for social networking, and 37% for audio from 2015–2021, estimating that video will dominate at 70% of overall mobile traffic in 2021 [8]. Thus, we suggest that these trends of data demand we observe, are undeniably present in everyday practices at significant scale.

## DISCUSSION

In this section we discuss the implications of the study findings, focusing on how HCI researchers and practitioners can adapt apps and services to reduce their data demand impacts.

### Targeting the four big areas of data intensity

Half of the overall daily aggregate data demanded by Atlantic Archipelago was due to watching (21%), listening (11%), social networking (8%), and background processes (10%). This demand roughly corresponds to 30 Wh of daily infrastructure energy consumption per device. Thus, we identify these four app categories as specific targets for data demand reduction.

In line with reports of European aggregate data [30], we find that watching is the most demanding category for Atlantic Archipelago. This is particularly the case for late evenings (22:00–00:00) (Figure 5b)—just after traditional prime time viewing and before bedtime. Listening is also a crucial category to target due to its high hourly demand (Figure 5b).

Notably, listening demand peaks at lunchtime, and at 08:00 and 18:00, i.e. times at which people may be commuting to and from work whilst listening to their device (both Bob and Xander mentioned they listen to music whilst driving). While it helps that services such as BBC iPlayer and Spotify implement the “nudge” approach (i.e. defaulting to lower quality streams) described by Preist et al. [24], we would point out that it is also the *sheer number of devices demanding these services* (345 or 87% for watching; 321 or 81% for listening) and the time invested in evening watching (Figures 2a and 5a) that are important to focus on. We also draw attention to the fact that the demand for watching and listening is still significant during non-waking hours (02:00–06:00); this shows that the data demand for these categories may not always necessarily be triggered by users, or may continue when they are asleep.

As we saw in Atlantic Archipelago (Figure 5a), others have observed that social apps are used less frequently (4.77% total app launches) than communication apps (49.5%) [4]. Despite this, the category of social networking leads to significantly higher energy demand than communication, and does so consistently throughout the day (Figure 5b). With rich media increasingly designed into social apps, such as picture-enhanced feeds and the auto-playing of shared videos and adverts, we amplify calls for reconsideration towards slow design [12, 35]. In addition to this, we propose that social media apps be designed in a way which forces users to “work” for their rich media, e.g. through reducing media previews or increasing the number of access levels to such content; this may dissuade users from simply viewing media just because it’s easily accessible (rather than particularly important), and therefore address this data intensive category. Our conversations with the Eight Participants indicated that there was often little meaning or utility ascribed to the automated picture feeds, and video adverts common to many social media apps.

Whilst watching, listening, and social networking are related to a number of areas of everyday practice, the demand from background services is *designed into the operating system of devices*. In fact, based on the app names in this category, these do not seem to support any particular activity or service. This background traffic has been observed in previous work highlighting the differences in users’ smartphone usage [9], where the percentage of data received during active device use varied from 10–90% of overall data received. Whatever this demand is actually for, it is significant throughout the day (Figure 7). We call for further exploration into the demand from background processes to understand where and how it arises, and how we can design devices to avoid this system-initiated (rather than practice-supportive) demand.

### SMS: A ready opportunity for lowering demand

Despite the consistent, hourly use of communication apps (Figures 3 and 6), the more traditional forms of communication via SMS and phone calls were still a popular way of contacting others. This traditional use dominated most hours of the day for both Eight Participants and Atlantic Archipelago (Figures 3 and 6). Using our estimates of energy consumption, the energy consumed through communication apps’ data demand is 2 Wh per day for an average Atlantic Archipelago

device; this is 10 times the energy consumed for SMS at 0.2 Wh per day on average. By shifting the many simple text messages back to SMS or low-overhead instant messaging (as opposed to apps augmented with adverts and videos), we believe that energy consumption in the communication category has the most straightforward potential to decrease.

Emphasising and going beyond Lord et al.'s suggestion to leverage traditional but lower impact phone services [19], our quantification of SMS use and communication apps suggests designers and systems architects should exploit the current utilisation and familiarity with simple SMS texting. Through design we can make it more convenient for users to switch between communication methods, in particular targeting times of day when communication app use peaks (e.g. 20:00 for Eight Participants, 18:00 for Atlantic Archipelago); this would enable the same end-goal for users at a lower energy impact. We also suggest that SMS and MMS services be revised to better suit the phone user today, such as by sending photos at a lower cost to the subscriber, catering better for group messages, and by informing users that their sent messages have been received—all reasons why some of our Eight Participants used communication apps.

### Shift and reduce peak demand

The energy consumed at peak times on the electricity grid tends to have higher carbon intensity. And as Sandvine point out [29], network operators use peak demand to plan their capacity. Building infrastructural capacity, itself, causes energy consumption and carbon emissions. Watching, social networking, communication and listening were all demanding data by Atlantic Archipelago devices in peak electricity demand hours of 16:00–20:00 (Figure 5b). Both watching and listening were particularly demanding, with pronounced peaks at 18:00 for listening, and 19:00 for watching (Figure 5b); this corresponds with “*real-time entertainment*” being the top peak aggregate traffic category for Europe (fixed and mobile access) in 2015 [30]. In addition to this, the data demand from updates, backups and background processes is notably significant within these peak hours, particularly at 19:00 for background processes (Figure 7).

Previous work discusses how services should be designed to “*reduce or avoid usage of infrastructure at peak times*”, focusing on the use of technology to shift users’ demand off peak [24]. With low levels of data demand during the early morning (03:00–05:00), we highlight that the peak demand for categories which do not require synchronous use (e.g. updates, backups and pre-downloads for watching) could easily be shifted to this time period for demand balancing. However, we argue that automatic shifts of demand off peak may not be the best strategy to reduce demand overall. The Eight Participants qualitative data shows that people already adapt to reduced accessibility of infrastructure and anticipated times of slow connectivity, either by manually pre-downloading content, or by simply avoiding device usage altogether in specific locations and times. Given this, we suggest that HCI researchers and designers look for ways to engage users to transition their practices in less energy-intensive directions, while maintaining the meaning and utility of everyday practice. Examples include coordinating with others to enjoy

programmes together, listening to locally-stored or cached music, and developing special, celebratory times (weekly or monthly) to more fully appreciate streamed media, rather than binge-watching.

### Breaks from technology as the filler of time

Countering the blurring of practices and filling time highlighted by both Røpke and Christensen [28], we have found that some of our participants actively take breaks from their technology, particularly in the evenings. This reveals how the prevalence of digital technologies in daily life can cause some users to disengage with their mobile devices. With growth in both device ownership and data demand, we must consider possible transitions to a future in which digital technologies aren’t the default filler of time.

Previous work in HCI certainly interrogates whether services could promote healthier relationships with technology [24], or propose less demanding apps for filling time (e.g. e-reader apps) [19]. We suggest that HCI researchers and practitioners engage users in reflection and experimentation on ways to spend time away from their device, and most specifically in instances where users feel like they have time to fill. This requires that we confront the dogma of “*all-you-can-eat data*” designed into apps, devices and infrastructures. However, with some of our participants seeing time away from their devices as a positive, and at times necessary, action in their everyday lives, the challenge of reducing the time use (and thus data use) of devices may be easier than expected.

### CONCLUSION

In this paper we have presented an account of the data and thus energy impacts associated with the use of mobile applications in support of everyday practices—with special consideration to patterns of time use and data demand on Android devices. Based on our quantitative exploration of 398 participants’ logs of mobile device use, correlated with detailed accounts of how time use and data demand relate to practices for 8 participants; we have identified the notable and most demanding categories of use (watching, online dating, listening, social networking and communication) alongside updates, backups and background processes. We characterise and relate the data demands of these practices across the hours of the day. From this, we are able to contribute new implications for HCI towards reducing the data demand by mobile device use beyond the device itself. These include: targeting watching, listening and social networking at particular times of the day; making the most of existing competencies with SMS; helping people transition to reduced consumption of services at times of peak demand; and building futures where time is filled in a positive and relaxing way, through the dedicated absence of mobile technologies.

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