

Energy efficiency of mobile handsets: Measuring user attitudes and behavior

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ABSTRACT

The purpose of this research is to understand the behavior and expectations of mobile handset users towards energy consumption. We analyze mobile handset monitoring traces from subsequent years with $N = 253$ and 105 , and questionnaire studies with $N = 155$ and 150 . The data allows us to study both the actual behavior of the users and their explicit attitudes, expectations, and experiences. Additional difference to prior work is the use of longitudinal data from multiple years and a user sample that is much larger than in earlier studies. We present hypotheses drawn both from literature and from our own experience, and use the datasets to support or refute them. Our results indicate that mobile device users need more detailed and clearer information of the battery status and energy consumption. Moreover, users want to understand how different applications and services affect the energy consumption and to learn what they can do to control it.

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1. Introduction

Advanced mobile handsets (“smartphones”) have become commonplace during the past years. Applications and services using Internet technologies previously available only for devices with limited mobility, such as laptops, are now readily accessible on devices fitting our pockets. Unfortunately, the battery performance and energy efficiency of small-scale mobile devices has not progressed at a desired pace (Robinson, 2009), resulting in users having to frequently recharge their devices and to pay considerable attention to battery consumption. The purpose of this research is to understand the behavior and expectations that mobile handset users have regarding energy consumption.

Better understanding of user behavior helps in multiple ways in developing new technical solutions that better match the user expectations. First, developing more energy-efficient devices and applications is an obvious engineering problem. Knowledge on the influence of energy consumption on application usage allows allocation of development resources to the most important issues. Second, making energy consumption more explicit to users can increase their satisfaction. With additional feedback, users can adjust their behavior and take proactive measures to manage the energy consumption of their device and the applications running in it.

We study user behavior and attitudes with two approaches: questionnaires and usage monitoring. The benefit of questionnaire study is that users’ opinions can be asked for all kinds of issues, even ones that do not yet exist or are not readily

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measurable. On the other hand, users may give misleading answers especially about their own behavior, for example to show commitment to predominant social norms, and to communicate an ideal reflection of oneself (Robson, 2002). Moreover, users may find it difficult to imagine the cases depicted in the questionnaire, or misunderstand the questions asked (Robson, 2002). Monitoring studies are harder to implement, but as they observe how people are behaving, the probability of getting reliable results from the users' behavior is higher (Robson, 2002).

Mobile handset monitoring is a fairly novel method to conduct monitoring studies. The main advantage is that as users carry their mobile handset with them almost all the time, a broad set of data with good granularity can be collected unobtrusively (Smura et al., 2009). The main disadvantage is the presence of potential privacy concerns. Monitoring panels have previously been used to study both mobile device and service usage (Smura, 2008; Verkasalo, 2009), and social network formation (Eagle and Pentland, 2006; Karikoski and Nelimarkka, 2010).

Energy consumption of mobile applications, devices and networks has been measured from a variety of perspectives, including different access networks (Balasubramanian et al., 2009; Mahmud et al., 2004), context-aware battery management (Ravi et al., 2008), voice over IP (Gupta and Mohapatra, 2007), location-aware applications (Anand et al., 2007), a video streaming application (Xiao et al., 2008), data sorting algorithms (Bunse et al., 2009), and ad hoc and peer-to-peer systems (Feeney and Nilsson, 2001; Gurun et al., 2006; Kassinen et al., 2009; Kelenyi and Nurminen, 2008a,b; Nurminen and Noyranen, 2008). However, user attitudes and behavior were not directly assessed by these studies.

McCalley and Midden (2002) found that products giving feedback about their energy consumption and having a means to set an energy conservation goal motivate their users to save energy. Vallerio et al. (2006) demonstrated how Graphical User Interface (GUI) design can improve energy efficiency of a mobile device. Abrahamse et al. (2007) noted that giving consumers more information about their energy consumption resulted in energy savings. This article also contributes to the line of studies assessing the effect of feedback on energy consumption behavior.

User attitudes and behavior regarding energy efficiency in mobile devices and related applications and services have been investigated in only a few studies. Banerjee et al. (2007) examined the context of recharging the batteries of both mobile phones and laptops. They collected traces using a passive logging tool and interviewed their subjects ($N = 10$, all engineering students). Rahmati and Zhong (2008) investigated the interaction of users with mobile phone batteries, which they call "human–battery interaction." They did a survey among high school students in China, India and the USA ($N = 350$), and used mobile phones equipped with logging software in field trials among students ($N = 21$). Bloom et al. (2004) and Harter et al., (2004) studied how users accepted energy-saving user interfaces on a mobile device (both $N = 12$). Heikkinen and Nurminen (2009, 2010) studied with questionnaires consumer attitudes towards different aspects of mobile peer-to-peer services, and towards energy consumption of mobile handsets and services ($N = 196$ and 150 , respectively).

A characteristic feature of this research in comparison to other studies is the large sample size. We analyze handset monitoring traces from subsequent years with $N = 253$ and 105 , and questionnaire studies with $N = 155$ and 150 . The four datasets allow us to examine our data in different ways. Observations made with handset monitoring traces of a year can be validated with the data from another year. Questionnaire studies can be combined with the monitoring studies to see if users' actions matched their stated behavior. Finally, datasets from different years allow seeing trends and year-on-year changes.

In order to concretize our findings we have formed hypotheses drawn from literature or our own experience and used the datasets to support or refute them. We hope that the hypotheses provide useful guidance for handset manufacturers as well as for application and service developers.

Our results indicate that mobile application, service, and device providers should place more emphasis on user interfaces able to communicate the battery status and the energy consumption in more detail to the end-user. Furthermore, the user interest towards energy-saving settings evident from our questionnaire studies suggests that users of advanced mobile handsets are sensitive to energy consumption, motivating the efforts of mobile application, service and device providers to optimize it.

Whether the user interest towards saving energy is due to mere reasons of convenience (for example, to prevent the battery running out of power on a critical moment) or due to genuine interest towards conserving the environment is an interesting question. At the moment, it appears to be primarily a matter of convenience, and only secondarily a matter of environmental impact. However, as energy savings correspond to convenience, it is within the users' interest to optimize the energy consumption of their mobile devices.

The energy consumption of a mobile device is small compared to the energy consumption of ICT infrastructure: according to different estimates (Koomey, 2008; Baliga et al., 2007; Etoh et al., 2008), the electricity consumption of data communication infrastructure and data centers is between 10 and 100 times higher than the energy consumption of mobile handsets. Although mobile device operation is only a small part of the estimate on global carbon footprint of mobile communications (Fehske et al., 2011), possible cumulative savings on recharging the batteries of mobile devices can be substantial. This is even more so in developing countries, where the energy consumption share of portable devices in a household may be almost triple compared to developed countries (Somavat et al., 2010).

It is up to manufacturers to optimize both recharging and utilization of batteries, and the standby power consumption of rechargers. Maintaining user satisfaction is a strong incentive for recharging and battery consumption optimization. Standby power consumption of chargers is less evident to users, as the monetary cost of recharging is negligible to most consumers, although it may constitute almost half of the total power consumption (Hawley and Economou, 2010). Thus, optimizing

standby power consumption of chargers is dependent on the environmental responsibility of manufacturers, and on related regulation (Hawley and Economou, 2010).

The rest of this article is structured as follows. In Section 2, we introduce our two methods, handset monitoring panels and questionnaire studies, and our four datasets related to them. In Section 3, we present and analyze our results related to battery life, battery recharging, and application usage. In Section 4, we summarize our findings, discuss the limitations of the study, and present ideas for future research.

2. Methods and samples

Altogether four datasets were collected among Finnish handset users (see Table 1): from two handset monitoring panels conducted in 2007 and in 2008 (referred to as P07 and P08, respectively), and from two questionnaire studies done in 2008 and in 2009 (referred to as Q08 and Q09, respectively). The panels were designed to gather real-time mobile handset usage data, whereas the complementary questionnaires provided answers to questions left open by the panels.

2.1. Handset monitoring panels

Our first method of data collection is handset monitoring panel. In the panel, panelists install monitoring software to their mobile handsets. The software we use is developed for the Nokia Symbian S60 Third Edition platform, limiting our sample to the users of a subset of mid- to high-range mobile handsets from a single manufacturer. The software runs as a background process and tracks different aspects of handset usage and status, including application and service launches, battery charge level, and battery recharge events. The tracked data also contains anonymized user identifiers and time stamps. The data is submitted daily from the handsets to centralized servers for analysis.

The monitoring software logs battery level only when an event occurs. An event can be caused by battery level falling below a threshold (for example, one bar drop in the battery display) or by user action (e.g., connecting handset to charger for recharging). We have estimated the battery levels on 5-min timeslots using linear interpolation to calculate values between logged events. In Nokia Symbian S60 Third Edition handsets, battery level display is not linear. Instead, the scaling is as follows: 50–100% of remaining battery power is displayed to the user as level 7, whereas levels 1–6 are evenly distributed among remaining battery power (i.e., $50/6 = 8.3\%$ units per level at levels 1–6, meaning for example 33.4–41.7% remaining battery power at the level 5, and 0–8.3% at the level 1).

We identify different mobile applications based on their logged name. We group the applications to different classes, out of which only user-initiated classes are included in this study, because our intention is to study user behavior, not automated functions.

We used the handset monitoring method in two controlled panel studies in Finland in 2007 and 2008. To motivate the panelists, we gave each a 20 euro gift certificate and the opportunity to enter a prize draw. The panelists used their own handsets and downloaded and installed the monitoring software themselves. Panelists paid the potential additional data charges related to sending the monitoring reports to the server. We mitigated privacy concerns by making the data collected automatically anonymous.

The first panel, to which we refer as P07, began in November 2007 and ended in February 2008. On average, a panelist had 50 active days in the panel. To account for an active panelist (i.e., for a panelist presumably having the monitoring software installed to a primary, active handset), the panelist had to have more than 20 active days in the panel. A day was classified as active if the panelist generated at least one event during the day. We sent invitations to participate to 13,500 customers of three Finnish mobile network operators, out of which 253 ended up as active panelists. Most active panelists are male (81.7%), employed (68.0%), and 20–39 years of age (73.3%).

The second panel, to which we refer as P08, began in October 2008 and ended in December 2008. This time we sent 10,000 invitations to the customers of three Finnish mobile network operators. We recruited 105 eligible panelists with an average of 31 active days in the panel. Each panelist had more than 20 active days during the panel. Again, most active

Table 1

Summary of samples in handset monitoring panels (P07 and P08) and questionnaires (Q08 and Q09).

	P07	P08	Q08	Q09
<i>N</i>	253	105 ^a	155	150
<i>Gender</i>				
Male	81.7%	73.3%	78.1%	88.7%
Female	18.3%	20.0%	21.9%	11.3%
<i>Status</i>				
Employed	68.0%	64.8%	69.0%	11.3%
Student	19.6%	18.1%	18.7%	86.7%
Other	12.3%	10.5%	12.3%	2.0%

^a Seven out of 105 respondents did not provide their demographics.

panelists are employed (64.8%) males (73.3%) with mean 35 years of age (25th percentile 28 years, and 75th percentile 40 years).

The demographics of both panels demonstrate a bias in the selection of the panelists, as young males are overrepresented in the samples. Reasons for this might include, for example, having the motivation, a suitable device, and sufficient technical skills required for installing the monitoring software to participate in this kind of studies. At the time of the studies, the Symbian S60 Third Edition handset population was estimated to be from 9% to 15% of the total handset population in Finland (Kivi, 2009), and therefore we considered reaching an unbiased sample to be unfeasible. Although distributing new devices with pre-installed monitoring software to a representative set of panelists could have been possible, the fact that the panelists used their own devices was seen as more important to avoid abnormal usage due to, for example, initial excitement or unfamiliar user interface. Although the knowledge of having monitoring software installed to a device could alter some users' behavior from normal, we believe that our samples represent with reasonable accuracy the Finnish users of advanced mobile handsets.

2.2. Questionnaires

As our second data collection method, questionnaires were used to collect two different datasets, using a web-based questionnaire platform. Before both deployments, we did a pretest with a convenience sample ($N = 15$).

The first questionnaire, to which we refer to as Q08 (see also Heikkinen and Nurminen, 2009), was done in conjunction with the handset monitoring panel P08, thus partially having the same participants. Some respondents to the questionnaire did not generate acceptable data to the handset monitoring panel. However, we include all valid responses to the questionnaire in the sample ($N = 155$). Most panelists are male (78.1%), employed (69.0%), and 25–34 years of age (43.2%).

The second questionnaire, to which we refer as Q09 (see also Heikkinen and Nurminen, 2010), was done independently of the handset monitoring panels. It was marketed to participants of a “studia generalia” lecture series on telecommunications targeted to both undergraduate and graduate students of Aalto University, Finland, in October 2009. Altogether we gathered 150 valid responses from the 195 registered participants, implying a 77% response rate. Most respondents were male (88.7%) students (86.7%) with mean age of 25 years (10th percentile 20 years, and 90th percentile 29 years). The respondents were motivated with a possibility to enter a prize draw.

Both questionnaire samples are biased compared to the general population. However, we believe the technically oriented nature of the questionnaires was more suitable towards a population with sufficient skills of operating and understanding concepts related to advanced devices. Therefore, the responses should be considered to represent the opinions of a technologically aware segment of Finnish mobile handset users.

3. Results

The results from the measurement panels (P07 and P08), and the questionnaire studies (Q08 and Q09) are summarized in Table 2. We have collected hypotheses from the literature and present new hypotheses based on our own research. We indicate whether each of our measurements strongly supports (++), supports (+), partially supports and partially rejects (+–), rejects (–), or strongly rejects (––) each of the hypotheses.

3.1. Battery life

3.1.1. Users are reasonably good in estimating energy consumption of mobile services

In order to analyze how well users are able to estimate the energy consumption of different mobile services, we compared users' replies with measured energy consumption. With the data from Q08 we observe that users are reasonably good in estimating energy consumption of mobile services. We use cellular voice call as the comparison point. Most panelists, in Q08, think that downloading video (62% agreed), Internet browsing (66%), downloading music (66%), and navigation (68%) consume more energy than making a call with identical session duration, whereas listening to music offline (62%) and viewing video offline (50%) consume less.

For comparison, we calculated the average power consumption of these activities with Portelligent's measurement data (Portelligent, 2009) from several advanced handset models (Apple iPhone, Blackberry Storm, HTC G1 Android, Nokia E71, and Nokia N96). According to these data, the power consumptions of music and video downloading (both 1.4 W), as well as those of Internet browsing and navigation (both 1.3 W), exceed the voice call power consumption (1.1 W). The power consumptions of two offline activities, listening to music (0.6 W) and viewing video (0.8 W), are below the voice call power consumption.

Comparison of user perceptions and measured values shows that the estimates of the majority of the panelists are in line with the measurements. Our result differs from Rahmati and Zhong (2008), who found that most users have problems in estimating the power consumption of different use cases. In particular, they found that users cannot correctly point voice calling as a large power consumer, but do incorrectly point text messaging as one. We can suggest a number of reasons for the difference. First, our technically oriented sample in Q08 is likely to have better skills than average users in estimating the energy consumption of the different use cases. Second, the sample of Rahmati and Zhong was heavily biased towards

Table 2

Summary of hypotheses.

Hypothesis	Source	P07	P08	Q08	Q09
<i>Battery life</i>					
"Users have inadequate knowledge on system power characteristics"	Rahmati and Zhong (2008)			–	
"Many users are unaware of the mere existence of power-saving settings"	Rahmati and Zhong (2008)				–
"Power-saving settings remain largely unused"	Rahmati and Zhong (2008)				–
"Existing battery indicators are inaccurate and inadequate"	Rahmati and Zhong (2008)				++
"Battery indicators of higher resolution lead to higher user satisfaction"	Rahmati and Zhong (2008)				++
"Current UIs for power-saving settings are inadequate"	Rahmati and Zhong (2008)				++
Users do not allow new app or service features to reduce battery life				+	+–
<i>Battery recharging</i>					
"The majority of recharges occur with a significant portion of the battery remaining"	Banerjee et al. (2007)	– –	– –		–
"Charging is mostly and equally driven by context and battery levels rather than low battery alarms"	Banerjee et al. (2007)				+
"Users demonstrate significant variation in battery use and recharge behavior"	Banerjee et al. (2007)	++	++		+
Two types of users exist: "those who regularly charge their phone, regardless of the charge level" and "those who charge their phones based on charge level feedback from the battery interface"	Rahmati and Zhong (2008)	++	++		+
Users do not unplug the charger rapidly after recharging		++	++		
<i>Application usage</i>					
Propensity to launch applications depends on battery level		+	+		
No significant differences exist on launch patterns between app classes at different battery levels		+	+		

emerging markets, probably meaning that their respondents have a much shorter experience on using handsets than our panelists. Overall, we can say that users are good in evaluating the power consumption of mobile handsets and the different applications and services running in them. This is reassuring for developers of new services and related applications: if developers tune their offerings to match the power consumption profile of existing services, or improve the power consumption of their offering, they can be quite reassured that users will evaluate their offering reasonably in terms of its power consumption.

3.1.2. Users are aware of power-saving settings and alter them

Advanced mobile handsets have several settings which affect their power consumption, including but not limited to display brightness, automatic discovery of Wi-Fi, probing for external devices via Bluetooth, and automatic fetching of emails, RSS items, and status updates in social networks. In Q09, we found that 39% of the respondents change the settings of their handsets to make the battery last longer. We can speculate this was to make the user experience more convenient. Rahmati and Zhong (2008) found in contrary that "many users are unaware of the mere existence of power-saving settings" and "power-saving settings remain largely unused." Again, this contradiction can be at least partly explained by the differences in the samples: the sample of Rahmati and Zhong is very probably less technically oriented than ours. Nevertheless, our results demonstrate the need for users to be able to alter the power-saving settings of their handsets to fit their needs. However, we believe that the pre-set configuration should be optimized to maximize the utility of the handset to the majority of users. For instance, the most battery consuming features such as Assisted Global Positioning System (A-GPS), Voice over Internet Protocol (VoIP), and Wi-Fi, should only be turned on by demand, not by default.

3.1.3. Existing battery indicators are inaccurate and inadequate

Most mobile handsets indicate battery charge level using a semi-obscure battery or bar indicator. This is not enough for some users. Rahmati and Zhong (2008) stated, "existing battery indicators are inaccurate and inadequate", "battery indicators of higher resolution lead to higher user satisfaction", and "current UIs for power-saving settings are inadequate." Our results in Q09 support this as most respondents state that they are interested in knowing more about energy consumption of mobile applications and services, and recharging the battery (see Fig. 1). Furthermore, 63% of the respondents would like to get information about the remaining operating time of their handset in minutes, a feature that is currently not commonly available. Improving battery indicators is a clear action point for mobile device manufacturers, because consumers clearly want more detailed and versatile indicators. Some tools to meet this need, e.g., Power Tutor for Android and Nokia Battery Monitor, are available. However, the preinstalled battery indicators of the mainstream mobile handsets are still rather primitive.

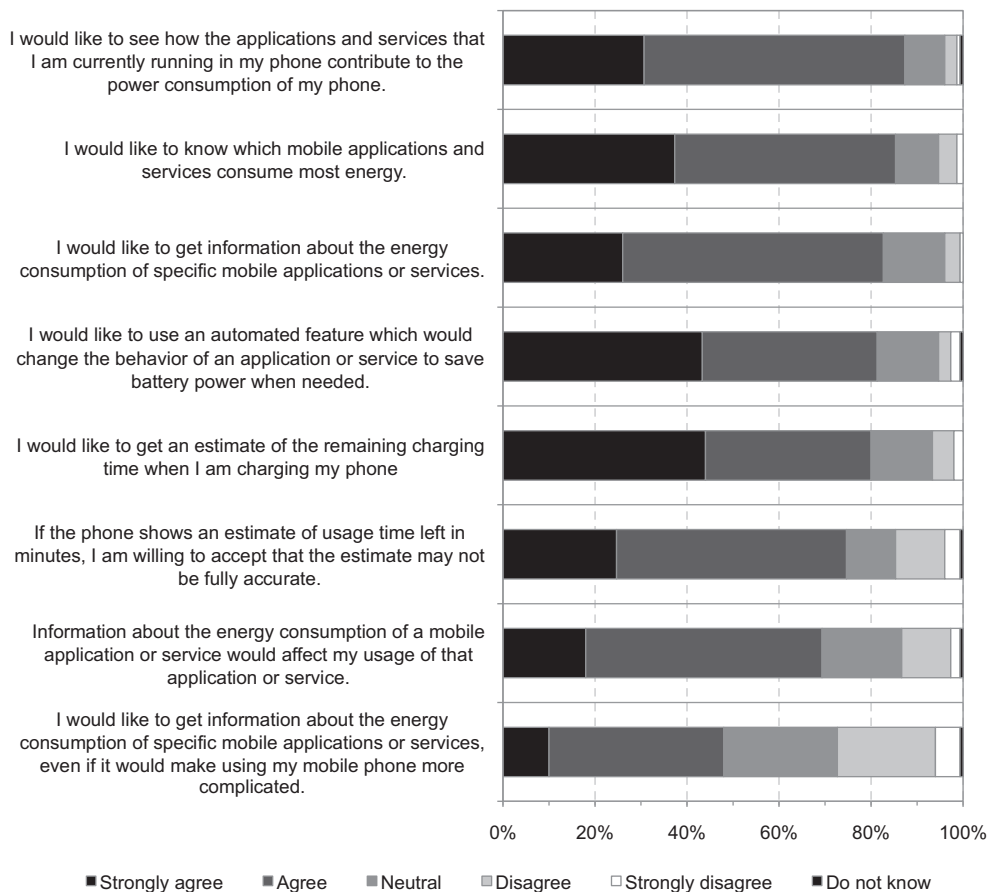


Fig. 1. Answers to statements regarding energy consumption of mobile applications and services, and recharging the battery in Q09.

3.1.4. Users do not allow new application or service features to reduce battery life

New applications and services have brought much new functionality to users of mobile handsets, but they have taken their toll in battery consumption, as many of them require constant connection to the Internet, which is a major energy consumer. In Q08, 53% of the respondents would not allow an email notification feature to increase the battery recharge interval. Furthermore, 44% would not shorten their recharge interval to be able to download new applications directly with the handset from the Internet, instead of transferring them with a cable from a computer. In Q09, receiving new email messages is more important than saving battery life to 53% of the respondents, whereas in the case of less established services saving battery life is more important (for 17% status updates of social networking services, and again for 17% new news headlines are more important than saving battery life). This means that users' sensitivity to energy consumption is high (i.e., a small change in energy consumption has a high impact on user behavior), especially in the case of using less established services.

The behavioral sciences provide one way to explain users' sensitivity to energy consumption of mobile applications and services. The Prospect Theory (Kahneman and Tversky, 1979) states that people evaluate change compared to a reference point (e.g., the status quo) non-linearly. In our context this means that users accustomed to a specific level of energy consumption (along with corresponding recharging needs) strongly disapprove even small increases in energy consumption. Therefore users are not eager to adopt new services if they increase the energy consumption. However, with an established service the situation is different because the operation of the established service is already part of the reference point. For example, in the case of email, many users assume frequent alerts of incoming messages to occur, and they are not willing to forfeit the alerts when using email with mobile handsets.

One consequence of users' sensitivity to energy consumption is that service designers should look for less energy-sensitive parties to compensate the user-side energy-sensitivity. For instance, designers may allocate more computing load on servers than on devices, thus moving the industry towards server-oriented computing ("cloud computing"). While shifting the energy consumption to other parties may be good for the mobile user, it may have a negative effect on the total energy consumption of the service. If the overall electricity consumption becomes a higher priority in the future, the server-side advantage in energy-sensitivity may disappear. If the server-side energy consumption is made apparent to the user, for example via metered pricing, it may no longer be evident that saving battery power (or maximizing convenience) is the only key driver for the user.

The total battery capacity is likely to remain very limited unless some major breakthroughs in battery or component technologies are made. Therefore users are forced to prioritize specific applications and services. Running a number of services in the background, as is common on desktop or laptop computers, does not seem to be feasible on mobile devices. Instead, we estimate that users will more decisively choose the applications and services of real importance and dedicate the battery capacity to them. Establishing the ratio between utility and battery consumption for each application is a conscious decision on partially unconscious criteria, unless explicit accessible measures for battery consumption are introduced.

3.2. Battery recharging

3.2.1. Users recharge their batteries at low power levels

The moment when users recharge the battery of their handset is important: it contributes significantly to the risk of encountering a sudden dead battery. Opposite to the findings of Banerjee et al. (2007), we find that users recharge their batteries at low power levels. In P07, 28.9% of the recharges are initiated at level 1, and 33.8% of the recharges at levels 2–4; in P08, 26.2% of recharges are started at level 1, and 34.1% at levels 2–4 (see Table 3). Partially this behavior may be due to convenience seeking: some users minimize the inconvenience of connecting a handset to a charger.

It is challenging to strike a balance between users' unwillingness and inability to recharge their batteries more often, the increasing energy consumption of mobile applications, services and devices, and the general user experience. Clearly, it would be beneficial to encourage users to recharge their batteries more often at higher power levels to guarantee a satisfying user experience even when energy efficiency is not optimal. Combining recharging with synchronizing the device with outside data sources is a partial solution; however, its efficiency is decreasing, as wireless synchronizing is becoming commonplace. Wireless recharging solutions and universal chargers could alleviate the burden of recharging mobile devices more often.

3.2.2. Recharging is driven by context and battery levels rather than low battery alarms

Understanding what drives users to recharge the battery of their mobile handsets helps to develop a better user experience by avoiding the sudden loss of battery power. In Q09, we find evidence supporting the following notion of Banerjee et al. (2007): "charging is mostly and equally driven by context and battery levels rather than low battery alarms." In a multiple-choice question, 63% of the respondents indicated that a very low-level battery indicator usually causes them to recharge, for 50% a low-level battery indicator is usually sufficient reason for recharging, and for 13% a middle-level battery level indicator is usually enough for them to recharge. For 30% of the respondents, recharging is usually part of their daily routine. For 30%, a warning sound usually causes them to recharge. In another multiple-choice question, 60% of the respondents indicated they usually recharge at night, 57% at home, 15% at work, 5% in car, and 13% whenever possible.

One possibility is that instead of providing simple low battery alarms, handsets could learn the recharging behavior of their users, and alarm their users when they estimate that a deviation from the common pattern poses a significant risk for the battery running out of energy. A more advanced and beneficial solution would be to steer users towards optimal recharging patterns from their accustomed habits. The questions remain, which recharging pattern is the most beneficial to the environment, which to a specific user, and to what extent the benefits converge.

3.2.3. Users demonstrate significant variation in battery use and recharge behavior

Understanding the differences in users' recharge behavior is also of importance. In P07 and P08, we find strong evidence supporting the notion of Banerjee et al. (2007) that "users demonstrate significant variation in battery use and recharge behavior." Some panelists recharge on most battery levels, whereas some recharge only on the lowest battery levels (see Fig. 2). Dispersion on the number of recharges by hour is also noticeable: some panelists recharge predominantly during the night, whereas others recharge more evenly throughout the day (see Fig. 3). We obtained similar results from P07 as the ones illustrated from P08. The results from Q09 discussed in Section 3.2.2 reinforce this notion. It would be interesting to know whether charging throughout the day or every night is just a habit, or a practical requirement. In any case, our finding makes it important to customize the recharging experience, i.e., to bring customizability and intelligence to the

Table 3
Recharging events by level.

Level	P07		P08	
	N	% of total	N	% of total
Unknown	82	1.0	38	1.9
1	2438	28.9	525	26.2
2	1028	12.2	224	11.2
3	980	11.6	212	10.6
4	846	10.0	246	12.3
5	583	6.9	176	8.8
6	430	5.1	137	6.8
7	2037	24.2	448	22.3
Total	8424	100.0	2006	100.0

Panelists 1-35:

Battery level						
1	2	3	4	5	6	7
13	11	8	14	16	11	20
14	5	2	9	16	12	12
16	8	6	15	2	2	5
14	3	13	9	3	6	6
7	7	7	10	2	4	14
14	4	6	5	2	3	14
7	6	3	1	5	2	17
1	1		19	2	3	14
10	3	6	2	2	4	13
11	3	4	3	3	4	10
1	11	4	2	8	5	6
4		2	2	2	3	24
6	1	4	5	7	8	5
5	1	2	4	2		21
			1	2	1	31
22	6			1	1	2
8	3	2	4			14
13	6	4	1	2	1	4
23	4	3				
	3	1	6	7	5	8
5	6	10	1			8
5	7	2	6	5	1	3
13	9	4				3
1		2	8	14	3	
1	3	5	9	3	5	1
3	4	3	3		3	10
	2	3	1	3	4	12
4	1	6	4	2	1	6
16	1	3		1		3
3	1	4	1		2	11
	3	5	3	2	3	5
4		1	1	1	1	12
4	1	1	2	6		6
5		3	6		2	3
5	2	3	2	1		5

Panelists 36-70:

Battery level						
1	2	3	4	5	6	7
3		1	3	1	1	9
8	1	2	2		1	4
12	2	1	2	1		
			1	1	1	14
	3	1	7	5		1
10		3	2			2
				2	2	13
6	5	1	1		1	3
4	2	2	1		4	4
10		2	1		3	
7	4	3	1	1		
3		2	3	3	2	3
1		2	2	3	4	4
			2	8	1	4
1	3	2	1	2	2	4
10	1	1	1			2
6	2	1		1	1	3
8	4	1				
2	7	2	1			1
1		1	2	4	1	4
2	3	1	2	1		4
			10	2	1	
7	1	1	1		2	1
5	4	1			1	2
6	1	1	2	1		2
5	3	4				
5	3			3		1
4	4			1	1	2
2	1		3	1		4
9	1					1
4	2		2	3		
1	2	3	5			
	1		1		4	5
3	1	3	2			2
4		3	1			3

Panelists 71-105:

Battery level						
1	2	3	4	5	6	7
5	1	2	1			1
2	4		2		1	1
		5	5			
6	2			1		1
1	1	1	2	2	1	2
2	2	3		1		2
3	1	2	1			2
8						1
1	1	1	3	2		1
5	3			1		
7			1			
4	2	1		1		
7	1					
6			1			1
4	2	2				
2	2		1			3
4		2				1
4	2	1				
4		3				
2		2	1		1	
3	2	1				
5		1				
2	1	2	1			
3		1	1	1		
2	1	1	2			
5						1
3	2				1	
3	1	1				
1	2	1		1		
3			1			1
4	1					
1	1	2		1		
3			1			
2						

Fig. 2. Number of recharging events by battery level per panelist in P08.

way a handset reminds its users for a need to recharge. For example, if a user usually recharges at home at night, the handset could gently remind if there is alteration from the general pattern detected by its clock and positioning mechanism.

3.2.4. Two types of users exist: regular and impulsive chargers

Next, we look at how we could characterize the differences between recharging behaviors of users. [Rahmati and Zhong \(2008\)](#) stated that two types of users exist: “those who regularly charge their phone, regardless of the charge level” and “those who charge their phones based on charge level feedback from the battery interface.” Our findings in Sections 3.2.2 and 3.2.3 support their notion.

The existence of the two types of users raises a number of questions. Is one set of behavior more appropriate than the other? And, if yes, should people be encouraged to follow a strategy for example with some timer alarms? Is one set of behaviors better for the environment causing less energy consumption for idle chargers? What are the other common features for each type of users? For instance, do the persons who charge their handsets on a regular schedule use their handsets more actively than their counterparts? Answering these questions requires further study.

3.2.5. Users do not unplug the charger rapidly after recharging

Environmental organizations and handset manufacturers are interested if users unplug their charger after recharging their handsets. Based on our panel data, the time a fully charged phone is connected to a charger exceeds the actual recharging time. In P07, the idle time, during which handsets are connected to a charger after completion of recharging, is 55.4% of the total time handsets are connected to a charger. In P08, the corresponding relation is 60.5%. [Table 4](#) shows the following durations: from connecting a handset to a charger until disconnecting it (total duration), from connecting a handset to a charger until completing the recharge (recharging duration), and from completion of the recharge until disconnecting the charger from the handset (idle duration). Note that the total column also contains uncompleted recharges (thus, the sum of recharging and idle columns does not match the total column for both number of events and hours). The

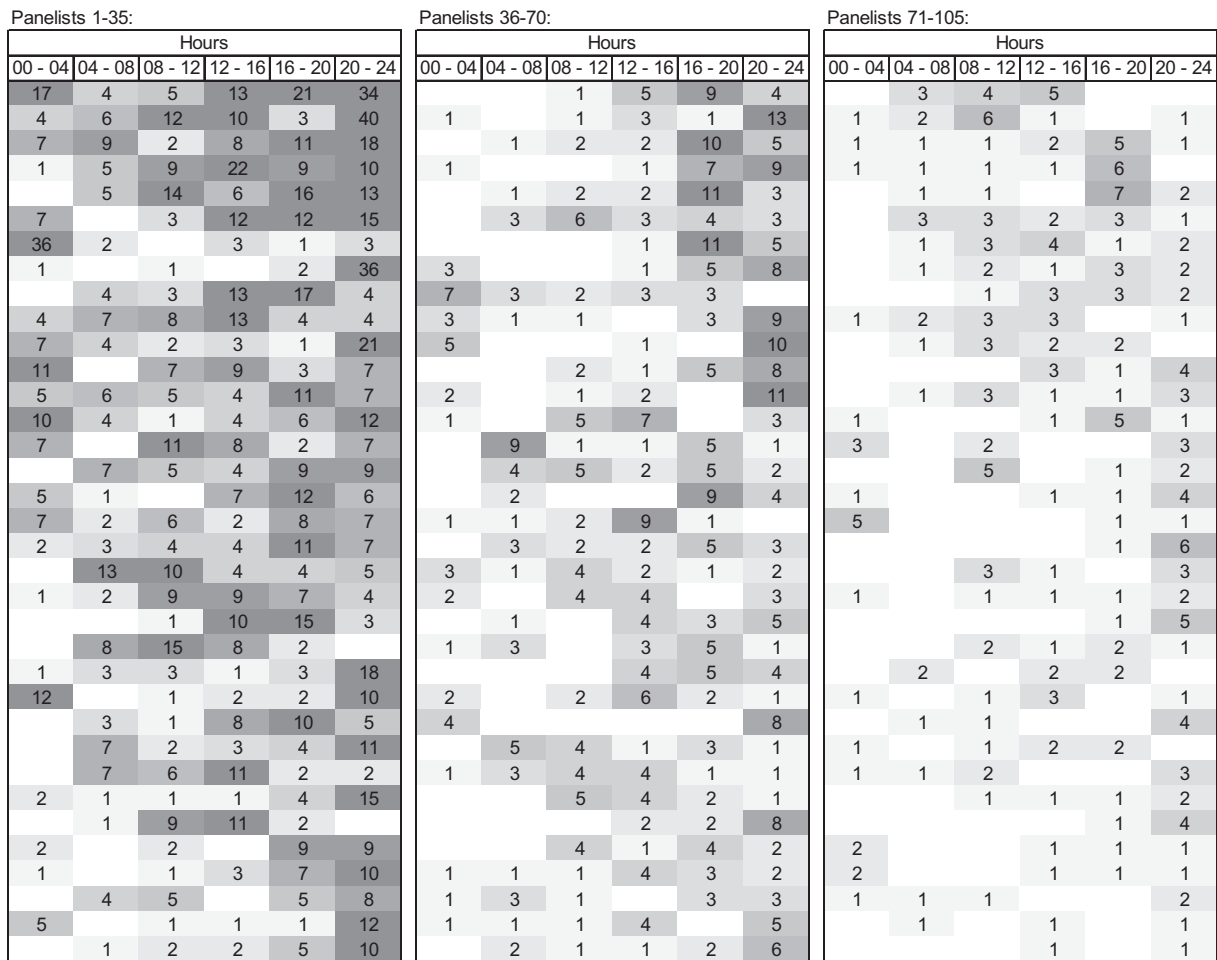


Fig. 3. Number of recharging events by hour per panelist in P08.

Table 4
Recharging durations.

	P07			P08		
	Total	Recharging	Idle	Total	Recharging	Idle
N	7264	3919	3576	1806	1026	965
Hours						
Sum	21,522	4718	11,916	5898	1315	3571
Average	3.0	1.2	3.3	3.3	1.3	3.7
Median	1.2	1.2	1.5	1.5	1.2	2.3
10th Percentile	0.1	0.4	0.1	0.2	0.5	0.2
90th Percentile	9.0	2.0	8.6	9.0	2.1	8.4

actual energy wasted on recharging is probably significantly higher than one would estimate based on these figures, as we are not able to measure how long chargers are plugged into the wall outlet without having a device to charge.

This gives a clear indication that there is a need for chargers that are able to switch off automatically on completion of recharging. Of course it is possible to influence human behavior, but there is a limit: very few users are likely to get up from bed at night to plug off the charger from the wall socket to save energy.

3.3. Application usage

3.3.1. Propensity to launch applications depends slightly on battery level

Table 5 depicts user-initiated application events, time spent, and events-per-time ratio, at each battery level. The events-per-time ratio is simply the proportion of events divided by the proportion of time at each battery level. A ratio higher than

Table 5

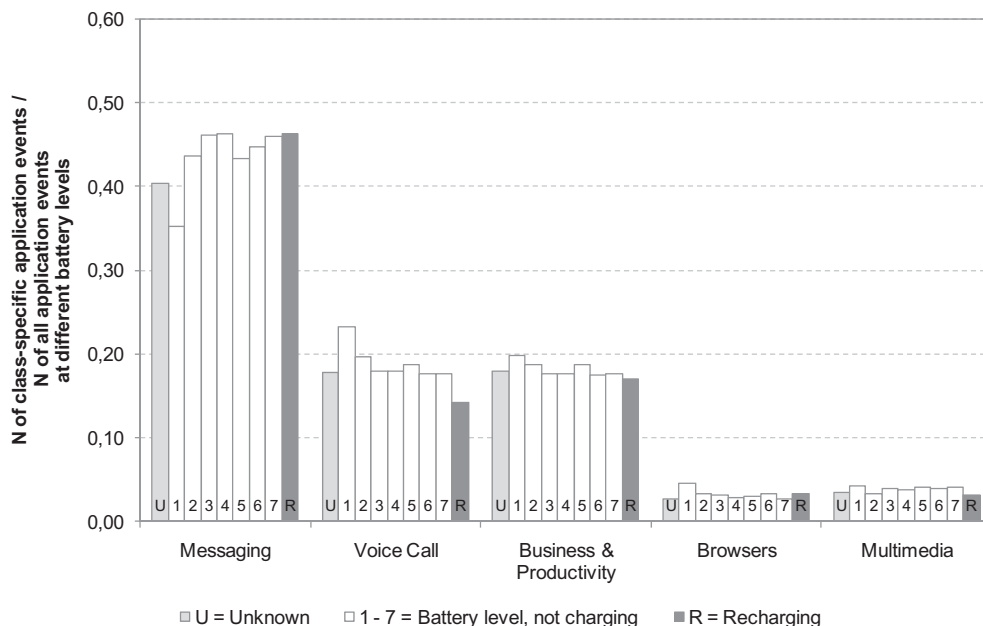
User-initiated application events, time spent, and events-per-time ratio, at each battery level.

Level	P07			P08		
	Events (%)	Time (%)	Events/time	Events (%)	Time (%)	Events/time
Unknown	2.1	N/A	N/A	4.8	N/A	N/A
1	0.3	0.1	3.44	0.3	0.1	2.52
2	5.0	3.8	1.33	4.0	3.8	1.06
3	7.5	6.6	1.14	5.7	5.9	0.97
4	10.0	9.2	1.09	9.0	8.7	1.04
5	10.1	9.9	1.02	10.2	10.5	0.97
6	9.9	9.6	1.03	11.1	10.6	1.05
7	47.9	41.8	1.15	49.6	47.9	1.04
Recharging	7.0	19.1	0.37	5.3	12.4	0.42

one suggests over-usage, whereas a ratio less than one suggests under-usage. Handsets are most of the time on the highest battery level (41.8% in P07, and 47.9% in P08). On the other hand, most user-initiated application events also occur at the highest battery level (47.9% in P07, and 49.6% in P08). Notably, the proportion of time spent at each battery level roughly corresponds to the proportion of user-initiated application events at each battery level, i.e., the propensity to launch applications is primarily evenly distributed over waking hours (when user is awake and battery is not recharging), and depends less on the battery level. The main exception is the statistically relevant above average usage at the highest battery level. This is particularly important when taking into account that most users (see Fig. 3) recharge in the evening, and thus have the highest battery level during night when little application usage takes place. This implies that application over-usage on the highest battery level during waking hours must be significant. Interestingly, when we look at the events-per-time ratio, the lowest battery level gets the highest ratio. This indicates potential inclination towards taking all benefit out of the lowest level (for example, carrying out important tasks before the battery runs out), although this observation should be taken with caution because of the high error margin due to low number of application events on the lowest battery level. Finally, the under-usage during recharging can be intuitively explained by voluntary inactivity (i.e., recharging while driving a car or sleeping), and by poorer usability during recharging (i.e., having the handset connected to a wall socket).

3.3.2. No significant difference on launch patterns between application classes at different battery levels

We are also interested whether there would be differences between application classes. When we scale the number of events of an application class at a level by dividing it by the total of number of events of all application classes at that level, we notice no significant difference on launch patterns between application classes at different battery levels; see Fig. 4 for P07. The results from P08 are similar to those from P07. It seems that users consider the energy question as part of the initial pros and cons analysis that determines whether they start using a new application or not and how much they will use it. The

**Fig. 4.** User-initiated application events by battery level in P07 (scaled by dividing class-specific events by all events at each battery level).

actual usage of all application classes, however, seems to spread over battery levels in quite a similar way. We do not report application classes with a low number of events leading to potential bias.

4. Conclusions

Our results indicate that users are interested in optimizing the energy consumption of advanced mobile handsets. Users demand more detailed and accurate battery level indicators and power saving settings. They want to understand and control the energy consumption of their advanced mobile handsets. Users vary in their battery usage and recharge behavior. Application usage is mostly independent of battery level.

The on-going trend of tackling the battery bottleneck by moving computing load from devices to servers (i.e., the proliferation of “cloud computing”) is relevant as long as users remain insensitive to the server-side energy issues. This insensitivity may change due to the rapid increase in server-side energy consumption, and the pressure to charge the increasing variable costs from users with metered service prices. Metered pricing decreases usage of communication services (Hämmäinen et al., 2009; Odlyzko, 2011), possibly leading to savings in their energy consumption. Users may also become more sensitive environmentally, and exploit the increasingly accurate service-specific energy consumption information to prioritize their usage of services. However, measuring the energy consumption of a “cloud” server infrastructure, and communicating it to its users is complex (Yu and Bhatti, 2010). If the trend of moving services into the “cloud” continues to be predominant, significant energy efficiency optimization of the “cloud” infrastructure is required to constrain its environmental impact within reasonable limits (Preist and Shabajee, 2010). One possible path of achieving significant energy savings in both network infrastructure and end-user devices is to adopt mobile information-centric networking, which takes into account energy efficiency in its design from the outset (Pentikousis, 2010).

A limitation of our study is that we cannot completely eliminate the effect of context in the handset measurement panels. We are interested in measuring the direct relationship of battery level affecting the behavior of the user, but context, such as mindset and location of a user, and time of the day, affects both battery level and behavior of the user. For example, some users could have the habit of recharging their phones during the night, and on the other hand carrying out certain tasks during the morning hours, which would result in relative overuse of some applications at high battery levels. We believe that even in highly controlled studies the effect of context cannot be completely eliminated but it could be partially observed. On the other hand, raising the level of control too high, for example in laboratory conditions, induces unnatural behavior.

Sample composition is a significant source of bias in panel and questionnaire studies. The differences in samples are probably the main reason for the differences in results between this and the previous studies (Banerjee et al., 2007; Rahmati and Zhong, 2008). Our purposeful sampling leads to an over-emphasis of young males interested in new technologies. The previous studies sampled student populations. However, we argue that some questions of interest in this study could not have been successfully verified among a general population due to their inherent technical complexity. Nevertheless, when advanced mobile devices become commonplace among the general population, conducting studies on a sample statistically representative of the general population will become feasible.

We can notice only slight differences between the datasets in our longitudinal study, which consists of the monitoring panels done in 2007 and 2008. We assume the main reasons for the low number of differences are the similar sampling process, and the relatively short time interval between the panels. Our questionnaire studies reinforce some findings from the monitoring panels, but mostly we designed the questionnaires to measure aspects the panels cannot. In summary, we can assert the results are consistent both in monitoring panels and questionnaire studies.

We believe our results can be generalized over other mobile software platforms (e.g., Apple iOS and Google Android), because the basic mechanisms of power storage and consumption in different mobile handsets are similar. The battery capacities and the energy consumptions do not have large variations, and the battery feedback mechanisms of the main mobile software platforms do not show major differences.

In the future, we are planning to enhance the monitoring panels by real-time questionnaires intended to partially record the context of and reasons for particular behavior. Also, conducting studies with larger samples on other mobile software platforms would be of interest. Finally, examining holistically the distribution of energy consumption of the whole mobile communications infrastructure (networks, servers, devices, etc.) using actual usage data instead of usage estimates could be beneficial. We invite mobile application and service developers, and device manufacturers to pay more attention to energy consumption of their products and services.

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