

Monetary Assessment of Battery Life on Smartphones

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ABSTRACT

Research claims that users value the battery life of their smartphones, but no study to date has attempted to quantify battery value and how this value changes according to users' current context and needs. Previous work has quantified the monetary value that smartphone users place on their data (e.g., location), but not on battery life. Here we present a field study and methodology for systematically measuring the monetary value of smartphone battery life, using a reverse second-price sealed-bid auction protocol. Our results show that the prices for the first and last 10% battery segments differ substantially. Our findings also quantify the tradeoffs that users consider in relation to battery, and provide a monetary model that can be used to measure the value of apps and enable fair ad-hoc sharing of smartphone resources.

Author Keywords

Smartphones; battery value; auction; user study; monetary model; resource sharing.

ACM Classification Keywords

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

INTRODUCTION

Research on smartphone battery life has typically focused on improving the energy efficiency of hardware, software and network protocols [31], or on understanding user strategies for battery management [10,11,33]. While the energy efficiency of smartphones is a priority for hardware and software providers [3], the increasing screen sizes and sensor capabilities have practically stagnated the perceived battery life available for end users [30]. For example, a large-scale longitudinal study exploring the charging habits

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of more than 4000 smartphone users found that they charge their devices frequently throughout the day [10], and showed that users perceive battery draining as a tradeoff against obtaining value from an application. Thus, a user may happily play games to kill time on full battery, but may stringently conserve battery when it is almost depleted, saving it for "valuable" use such as emergency calls or wayfinding.

Given these concerns, an important way to characterise smartphone use is to quantify the value that smartphone users place on their devices' battery. Doing so can be a first step towards systematically characterising individual applications based on the value that they provide to users (as measured through the battery-tradeoff), as well enabling fair ad-hoc resource sharing between devices [7].

Here, the research question we answer is: *how much value do smartphone users place on their battery life?* Previous studies have systematically quantified the monetary value of sensitive data, such as location, communication logs, or apps use (e.g. [6,34]), but surprisingly we are not able to find studies that measure the perceived value of smartphone battery life. We present our findings from a small-scale pilot study and a field trial where 22 participants auctioned their device's remaining battery life in exchange for monetary rewards. We also include results from semi-structured interviews and a concluding workshop.

We begin by demonstrating that the monetary value of battery is not constant, but inversely related to current battery level. Battery life is valued about 3 times more when it is near depletion than it is when fully charged. Second, we show that users may associate intrinsic value with battery life. For instance, they may be willing to donate battery to friends in exchange for social capital. Finally, we utilise a well-known methodology in a new context, and describe how context and the renewable nature of a mobile resource such as battery life pose obstacles to similar methodologies that use second-price auctions.

RELATED WORK

Value-driven frameworks

Previous work has attempted to quantify the overall value that users obtain when using smartphones. For instance, one

study identified 15 value elements that users consider, including convenience and pleasure, which both provide satisfaction and influence choice of product [29]. A similar study conducted on mobile internet usage specifically, identified four types of value: functional (defined as technical and practical benefits e.g., Internet, email), emotional (explained as emotion related benefits e.g., watching movie), social (to fulfil interaction purposes e.g., chatting), and monetary (benefits in terms of money) [38]. Such value assessment frameworks depend on users' age, personality, or demographic characteristics [29], as well as cultural factors [38]. In general, we find that monetary value is an important aspect of how users value their smartphones, and therefore could be considered in the context of battery life. A battery-value framework that encompasses an understanding of its value to users is needed.

Smartphone Resource Sharing and Use

Battery life is crucial to opportunistic sharing of smartphone resources, which in itself has the potential to reduce overall energy consumption, improve application responsiveness, and lead to new possibilities for mobile services and applications [36]. For instance, by sharing wireless connectivity across devices, it is possible to create highly scalable sensor networks [22,23]. These networks can be small in scale (personal sensing), include a group of people with a common background (group sensing), or consist of a larger user base (community sensing) [23]. Other opportunistic resource sharing studies involve sharing of GPS location [36] or processing power [27].

Consequently, an important aspect of resource sharing is power consumption, and understanding how owners of the devices value their battery life. Previous studies have quantified the value of mobile phone resources (albeit not of battery life) and have identified differences in how users value different types of personal data [26,34]. These valuations may nudge day-to-day smartphone use, since users constantly weigh various choices against each other: for example, giving up privacy in return for added value of an application. Furthermore, data collected through smartphone use is of high interest to both commercial and research entities, giving rise to studies on the monetisation of personal information (PI) [34]. While the proclaimed monetary value of PI differs across users, some general characteristics can be found. For example, the identity of a user (containing personal information) has been rated to have double the value compared to revealing usage history of social websites [6]. Hence, we can expect that while users may have distinct strategies at evaluating their battery life they may also exhibit similar overall trends.

Human-Battery Interaction

Smartphone battery life has been shown to be a major concern for users. A survey from as early as 2007 revealed that 80% of mobile phone users take measures to increase the lifetime of their mobile devices [32]. Research on

improving the battery life of mobile devices has since focused on improving energy efficiency of hardware and software, for example by reducing the amount of data being transmitted, increasing the capacity of the internal battery, or restricting the resources allocated for idle (background) applications [5]. Another approach being actively investigated is code offloading: migrating mobile code to be executed remotely in the cloud or on dedicated servers, leading to energy savings on the mobile devices [15]. The mentioned examples demonstrate how devices can be designed and optimised for energy savings.

Related to our work, studies have shown how users perceive and attempt to manage smartphone battery. Rahmati *et al.* [32] investigated the interpretation of battery life information. Their study indicated that users generally have limited knowledge regarding the actual battery characteristics of their phone, which suggests that detailed wattage information may not be as useful to them as battery percentile or hours of battery life. Following this, the researchers state that current battery interfaces are too complex (both cognitively and technologically) for users to effectively interpret and configure battery-related settings. A study investigating charging behaviour over a large group of users has identified distinguishable patterns across them [10], showing distinct preferences and keeping-alive strategies. To facilitate battery life management, the Task-Centered Battery Interface (TCBI) [35] and the Interactive Battery Interface (IBI) [11] draw users' attention to a set of phone activities, or specific battery draining applications and their impact in their device's battery life, respectively, allowing users to make informed decisions on what to do in order to keep their device alive. Carat [1] turns battery management into collaborative effort, where the "crowd" provides application's battery impact estimations, generating post-hoc reports with suggestions to improve the device's battery life.

However, despite earlier studies providing a wide array of findings on user strategies and expectations on battery life, as well as automated battery management tools [40], they do not clearly quantify the value users associate to battery life. Users nowadays do know what to do to extend their battery life [11]. Having a better understanding on how battery is valued can help improve automated battery management, resource sharing, and quantify smartphone use.

EXPERIMENTAL DESIGN

We designed an experiment where participants could auction their smartphone battery on an hourly basis, and winners of each auction would collect monetary rewards in exchange for rapidly depleting their device's battery. Data transfer between participants' smartphones and our server was performed in real-time using network sockets to ensure that the auction winners were rewarded immediately. Actual battery depletion was managed by our smartphone software.

Auction Procedure

Each participant in our study was prompted by their smartphone using a notification to bid on an hourly basis, every day from 10:00 to 22:00 for the duration of the study. This meant that each day we had 13 auctions. At each auction participants bid their desired amount of money for giving up exactly 10% units from their currently remaining battery life. We decided to control this variable and keep it constant at 10% units to increase the power of our statistical analysis and make our results comparable across participants. Our smartphone software detected whether a participant charged their phone during these hours, and would subsequently exclude them from bidding for the rest of that particular day.

All auctions followed the same procedure: a reverse second-price closed-bid auction (i.e., a reverse *Vickrey auction*). This means that the bidder with the lowest bid wins, but receives the amount indicated in the second lowest bid. Bids of other participants are not revealed to bidders, i.e., it is a sealed-bid auction. The mechanism has been shown to be truth-telling, as the optimal strategy for the bidders is simply to be honest in their bids [25]. This auction model is also conceptually clean [9] and thus easy to understand and explain to participants [34]. Finally, the model has been used in auctioning personally identifiable information [34] and Web browsing behaviour [6].

The daily starting and ending hours of auctioning were chosen to ensure that most participants would be awake and alert to place bids simultaneously. It would be easy for participants to rig an auction where only 2 bidders are awake to place bids, e.g. in the very early hours such as 04:00 or 05:00. For each auction notification, participants were given a window of 10 minutes to place their bids. Participants could also choose to dismiss the notification and not place a bid at that particular auction. Once the bidding window closed, the notification on participants' smartphones who had not placed a bid was withdrawn.

The winner of each auction was determined 10 minutes after the bidding closed. The 10-minute threshold ensured that data was synchronized between participants and our servers. Shortly after a winner had been determined by the server, the winning device was notified and began draining 10% units of the remaining battery life. If a device was unreachable (e.g., offline) the notification appeared whenever the device was switched back on again. The money for the winning bid was released only after the smartphone's battery was depleted ceaselessly by 10% units, and the depletion verified by our software.

Smartphone Logger

The logger was responsible for collecting sensor data from smartphones, as well as the actual bids. It was implemented as a plugin to the open-source mobile sensing framework AWARE [12]. AWARE enables collecting sensor data from Android-powered smartphones, and runtime

synchronisation of the collected data to a server database. The following data was collected from each participant:

- Bids: user-indicated bids (in EUR) for draining 10 percent units of the currently remaining smartphone battery life.
- Battery level: battery level (percentage), power related events (phone shutting down, rebooting), and user-driven contexts (initiating a charge and unplugging the device).
- Location: coarse network-based location (i.e., no GPS), collected every 5 minutes.
- Application Usage: application launches (name of application and timestamp), starting and stopping of background services, notifications and crashes.
- Screen Status: the phone's screen status, such as turning the screen off and on, or locking the screen.

Battery bids from participants were collected using the Experience Sampling Method [24] provided by AWARE. Using an interval contingent trigger, participants received one alert every hour during the auction days. Figure 1 (left) depicts one of these alerts asking how much money the participant wants in exchange for exactly 10% units of their battery life. The popup was not triggered if the user had less than 10% units of battery left, as it would not be possible to "sell" as much battery at the time.

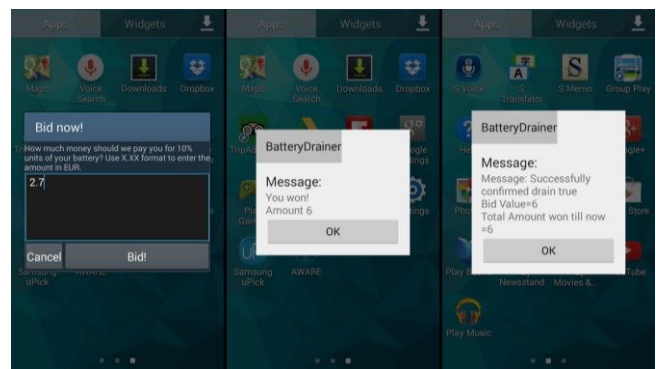


Figure 1. The user interface of the auction. From left: asking for a bid; notifying the participant about a win; notifying the participant about a successfully completed drain.

Battery drainer

A key characteristic of our experiment is that participants did not bid hypothetically: we actually drained their smartphone's battery. To ensure the draining took place, we built a background service that ran on participants' smartphones. The server would notify our software of potential auction wins and inform the winner (Figure 1, middle). The software kept track of the device's battery level until 10% units were ceaselessly drained, and then notified the user (Figure 1, right) and the server of the successful battery draining.

To enable participants to potentially bid in every hourly auction, we had to ensure that draining of 10% battery units

could be achieved within one hour. We conducted a series of maximum battery draining tests to assess different methods of battery depletion. For our tests, we used a reference handset model: Motorola XT1032 (Moto G) with a Qualcomm MSM8226 Snapdragon 400 processor, 1 GHz RAM and Non-removable Li-Ion 2070 mAh battery. We tested multiple draining approaches (Figure 2) that rely on continuously activating commonly available hardware and performing computationally intensive tasks, as follows:

- Camera: activate the camera of the phone, without storing images;
- Microphone: activate audio listening on the microphone, without storing audio;
- Sensors (environment): activate all available environmental sensors, such as accelerometer, temperature sensor, gravity sensor, gyroscope, light sensor, linear accelerometer, magnetometer, pressure sensor, proximity sensor, relative humidity sensor, and rotation vector sensor. Sensors' availability may differ with handset models;
- GPS: activate GPS location requests;
- Flash: activate the flashlight of the phone. Due to the camera API, this also activates the camera;
- Computational processing: compute exponentiations with large integers;
- All of the above: all aforementioned battery draining approaches.

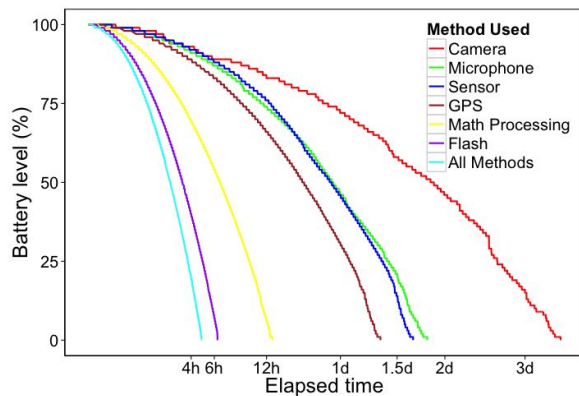


Figure 2. For each battery draining method we show how the battery level (y-axis) depletes over time (x-axis, logarithmic).

The tests were performed with the phone in an idle state, i.e., not running applications, and the display turned off. Our time-to-drain (TTD) results are therefore, upper bound since naturalistic device usage and any running application will accelerate the depletion of the battery. Our results found that the camera approach was the slowest, requiring 3.5 days to deplete the whole battery (or 8.4 hours for 10%), while all methods combined required 30 minutes for 10% units of battery. For our study we decided to use the flash method, which took about 35 minutes to deplete 10% battery units, and did not affect significantly normal device

usage – using all methods simultaneously had a noticeable effect on the device's performance. Our participants would have ample time to drain their battery between two consecutive auctions, without drawbacks in device performance.

STUDY

Pilot

We conducted a brief 3-day pilot with five colleagues. The participants were rewarded with a movie ticket plus any money they would win from the auction. To end the pilot, we conducted semi-structured interviews to discuss their bidding experience.

First, the lack of a persistent application interface was confusing to 2 participants, who felt unsure whether the auction actually was happening, and thus did not feel comfortable placing bids. As a result, in the main study we explained this more clearly in our instructions, and assured that our software was running in the background. We made a conscious decision against a constantly accessible and/or visible interface for bidding, as we wanted to minimise the disruption to participant's daily routine and usage patterns. Second, the bidding notifications were not disruptive enough, causing them to remain unnoticed and expire on their own. This led to not having enough bids in many of the auctions. To increase the popup's noticeability, we added an auditory cue to the notification (overriding the phone's current default notification, which could be vibrate-only or silent). After these changes we conducted our main study, which we will discuss next.

Participants and Rewards

Our main study had 22 participants (5 females, 17 males, average age 24.3, SD=3.0) recruited from University of Oulu in Finland, using email lists and posters placed at the campus. The requirements for participating were i) own an Internet-connected Android smartphone to use in the study – we wanted participants to use their own phones, ii) bid daily at least four times, and iii) participate in a workshop including a semi-structured interview at the end of the study. The mean hourly salary in Finland is above 18 EUR. Therefore, and to comply with the country's work guidelines, upon completing the study each of our participants was compensated with 50 EUR plus the money won in the auction. We estimated the 1-on-1 briefing, participating in the auction, and the post-study workshop together amounting to at least 3 hours per participant ($3 * 18 \text{ EUR} = 54 \text{ EUR}$).

Participation

The study began with a 2-day enrolment phase, followed by 8 days of auctions. The participants were incrementally enrolled into the study during this 2-day enrolment phase, to allow us to individually explain the study details. During the enrolment phase, the auction system was not active, although participants could place non-winning bids to get acquainted with the system. The data collected during this period was excluded from analysis. All participants

participated simultaneously during the 8 days of auctions. Given 13 auctions on any full day (from 10:00 to 22:00), the study offered a total of 102 bid opportunities (on the first day, bidding began exceptionally at noon 12).

During the 8 days of auctions, we employed a motivational strategy to elicit sustained participation: we sent daily motivational messages to all bidders, using our software’s popup functionality. The messages leveraged two previously studied psychological motivators: perceived self-efficacy [2] (e.g., “*Your participation has been awesome so far! Please keep bidding whenever you can.*”) and causal importance [41] (e.g., “*Because of your help, we are able to conduct a much better study! Keep bidding!*”). Both of these motivation types have been found effective in eliciting sustained participation in a similar mobile data collection study [17].

Finally, we invited the participants to an open-ended discussion about the study and issues around the value they assign to battery life. We organised two workshops to accommodate everyone’s availability. Each participant took part in only one of the workshops. In the workshops, one researcher led the discussion and showed statistics from the experiment, focusing on issues such as auction and bidding strategies, themselves from data patterns, battery valuation contexts, and the mental models around smartphone battery in general. Two additional researchers scribed the discussions and collected further insights on the issues directly from the participants’ observations. A short data collection form was also distributed, containing questions on demographic data, self-perceived truthfulness of the bids, and a free textual feedback item.

RESULTS

Data

In the end, we had bidding data from 20/22 smartphones. Two participants’ data was discarded due to data quality issues (software-phone incompatibilities led to sporadic data collection). We expected to collect a maximum of 2040 bids if the 20 active participants responded to all bid notifications. Ultimately, we collected 1211 bids. In addition to these bids, participants cancelled the bid notification 120 times, i.e., they actively decided not to bid during that bidding round. Thus the total amount of user interactions to bid notifications was 1331. In addition, 342 bid requests expired on their own (i.e., no user interaction was registered). Finally, 367 bids are missing because participants’ phones were either disconnected or turned off.

During the 8 days of the study we recorded 795,374 state changes in the battery levels of our participants around the clock (i.e., 24-hours per day), and 480 charging events (i.e., participants charging their phones). We collected 14,852 location events, 34,231 screen state changes, and 221,808 application-related events. Finally, we summarised the key insights from the workshops. We defer our workshop findings to this paper’s discussion section.

Analysis

We analyse participants’ battery management patterns, bidding behaviour, and derive a model to observe human behaviour through their application use in different battery contexts. Our initial analysis of location and screen status data did not yield interesting insights in the scope of this paper.

Battery management

Figure 3 depicts the Probability Density Function (density plot) of participants’ battery levels during the study (right: auction hours only, left: 24-hour basis). On average, the aggregated battery level of smartphone users during any hour of the day is seldom less than 65%, also reported in [10]. Here we noticed that participants very frequently allowed their battery levels to deplete much lower than this, similar to what has been reported in [11]. This is not a surprise, but rather indicates the auction being successful in its purpose. We specifically instructed participants not to charge their phones during bidding hours, as they would not be allowed to bid otherwise.

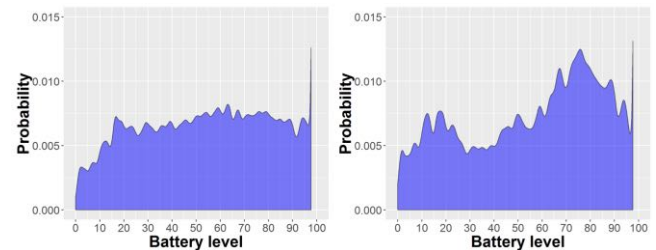


Figure 3. Left: battery level fluctuation during the entire study on a 24-hour basis. Right: battery levels during auction hours only (from 10:00 to 22:00).

To illustrate the diversity in participants’ battery management behaviour, we show the density plot for participants P1, P2, and P3 in Figure 4 (during auction hours). We notice that P1 seldom had low battery levels, indicating very frequent device charges. P1 did not win the auction even once, since participants that charged their device during auction hours were not eligible to win. In contrast, P2 and P3 spent considerable time on low battery levels, and for example P3 won 8 auctions.

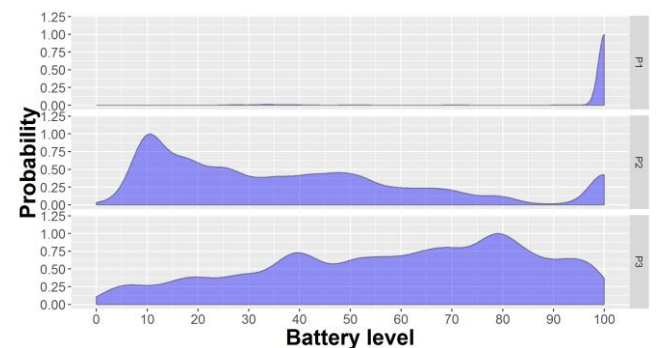


Figure 4. Different battery management behaviours by three different participants during the auction hours.

In Figure 5 we show for P1, P2, P3 the mean battery level per hour of day. We notice that P2 and P3 charged during the night and gradually discharged their battery during work hours [8h-16h]. On the other hand, P1 discharged their phone during the night, began charging during work hours, and in the afternoon began discharging again.

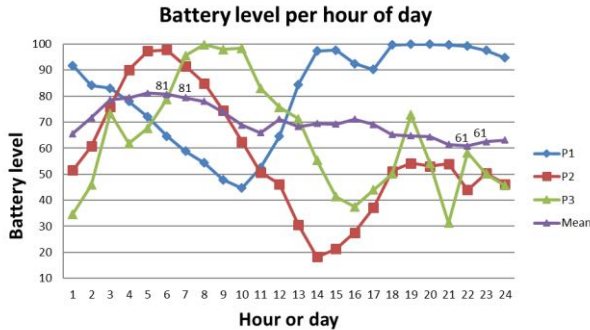


Figure 5. The aggregated battery level of all participants stays high throughout the day, but individual participants' battery levels vary a lot.

We also calculated the aggregated battery level across all participants (“mean” in Figure 5), which gradually declines during working hours. The peak hours when the battery level of the entire population is highest (81%) are between 05:00 and 07:00 while the lowest (61%) hours are at night: 22:00 - 24:00. These findings are in line with previous work [10], with few exceptions.

Bids

Based on our workshop findings (discussed later), we removed 9 bids above 50 EUR as evident outliers. The mean bid across all participants was 2.22 EUR (SD=4.3), and the median bid 0.70 EUR. The high standard deviation indicates participants altered their battery valuation, which in our experiment is desirable as it denotes price elasticity. In Figure 6 we show the density plot of all bids valued less than 20 EUR (upper limit 20 for a cleaner visualisation, there were not many bids over 20).

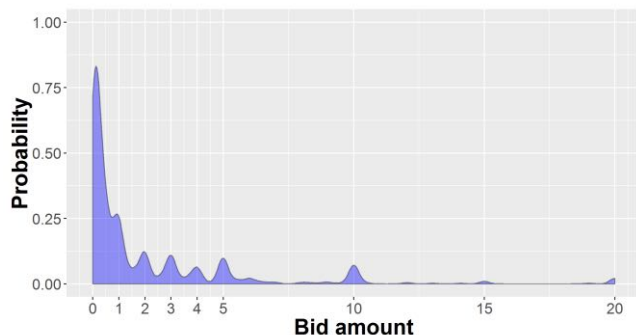


Figure 6. A density plot of the placed bids. Y-axis denotes probabilities, while x-axis represents bid values in EUR.

We find most bids were worth less than 1 EUR, with spikes at round values ranging between 1 to 5 EUR. During the study, 18/20 participants won at least one auction. On

average, participants won approximately 6 times (5.67, SD=5.36). And, as we expected, draining 10% units of battery took 23 minutes on average. Two participants constantly bid very low and thus won exceptionally many times – 18 and 19 wins, respectively. Finally, the winning bids summed up to 17.14 EUR, with a mean winning bid of 0.17 EUR (min=0.01 EUR, max=2.30 EUR).

For every bid we received from each participant, we had a record of the corresponding battery level at the bidding moment. Analysing the correlation between bids and battery levels, we found a weak reverse correlation (Pearson product-moment, $r=-.16$, $p<.05$). In other words, as the battery level decreases, the value increases. This finding suggests that participants valued battery higher as their devices' battery depleted.

Next, we binned battery levels into 9 bins, each representing a 10% unit range: 10-20, 20-30, 30-40, ..., and 90-100. For each battery level bin we can calculate the mean bid value (Figure 7). The trend is linear whereby bid values increase as battery level drops, and especially we observe a sharp increase in the final bin (20-10% battery). A post-hoc Tukey HSD test showed that the lowest battery level bin (20-10) differed significantly ($p<.05$) from bins 50-60 (diff = 2.25), 70-80 (diff = 3.05), 80-90 (diff = 3.00) and 90-100 (diff = 2.65).

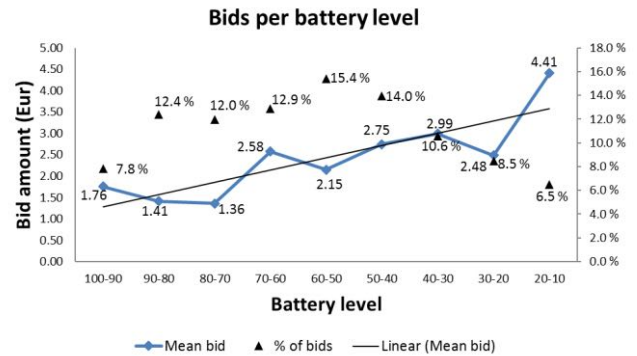


Figure 7. Mean, median, and the percentage of bids placed per battery level categories. As battery level decreases, bids increase.

The same graph also shows how often we received bids from each battery level bin (in percent). We observe that while participants mostly bid when battery levels were between 40% and 90% we still received a fair amount of bids even when battery levels were lower.

To illustrate the differences between participants' bidding strategies, we show the density plots for the bidding by P4, P5, and P6 in Figure 8. We observe that P4 tended to bid at integer values (2, 3, etc.), P5 tended to bid one order of magnitude higher (10, 20), while P6 bid one order of magnitude lower (0.1, 0.5). Finally, we examine the mean bid across all participants during the auction in Figure 9. The figure aggregates all bids from all auction days. The bidding value in general increases as the day progresses.

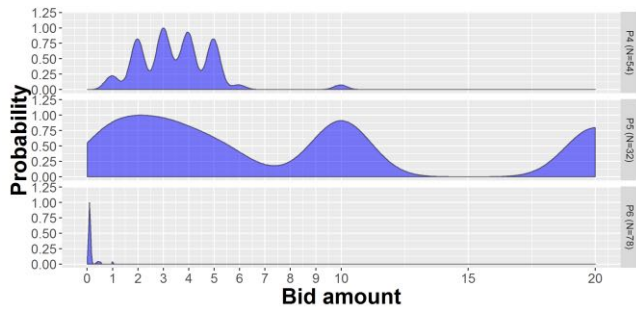


Figure 8. Different bidding behaviours by three different participants during the study.

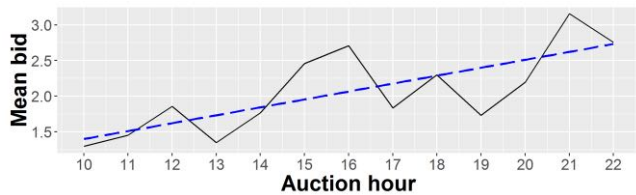


Figure 9. The mean bid per auction hour (continuous line) and the bid trend line (dashed line).

Using the monetary model: evaluating apps

We demonstrate the feasibility of using the monetary valuation of battery life as a lens to quantify user behaviour. We quantified the value that users place on individual applications by considering “when” participants run them, in terms of how much battery is left. Certain applications are more battery-intensive than others. Our findings and data on battery valuation demonstrate that users clearly take application-battery use into account, especially when battery is running low. This allows us to quantify the value that users place on specific applications with our monetary estimation for battery life.

We collected each application launch, and the amount of battery left at that moment on the device. We then generated a density plot for each individual app across all participants. The curve indicates the application’s launch frequency, or probability (y-axis) on a given battery level (x-axis, continuous from 0 to 100). This is a highly similar approach to what Jones *et al.* [21] use for analysing smartphone application patterns. Only in our case, the context variable is battery life. Here, this provides detailed insight into how frequently the participants used different applications at varying battery levels. In Table 1 we summarise the density curves for the most popular applications in our dataset.

Observing the curves, we notice how some apps are launched more often on high battery levels (e.g., YouTube), while other apps are launched regardless of the current battery left (e.g., Chrome), or on lower power levels (e.g., Instagram). Not surprising, regardless of the application, their use drops close to zero when battery levels are very low. This is indicative of the high value users associate with the last remaining battery on their phones.

Application	Frequency	EMV	Launch frequency per battery levels 0-100
Viber	992	2.54	
Chrome	904	2.39	
Instagram	271	2.36	
WhatsApp	2649	2.36	
Facebook	1552	2.33	
Spotify	254	2.31	
Twitter	212	2.11	
Gmail	279	2.09	
YouTube	106	2.03	

Table 1. For the most-often used applications in our study we calculate the number of times it was launched in our study (frequency), and the Expected Monetary Value (EMV) that the user population implicitly associates with that app. The axes of the density plots are probability (y-axis: [0,1]), and battery level (x-axis: [0,100]).

Next, for each application we consider its probability of being launched at the 90-100% battery level bin, 80-90%, and so on. For each such bin we have an associated monetary value extracted from Figure 7, which effectively places higher value on low-power bins.

Because we did not collect bids when battery level was less than 10%, we used the bid value from the second-lowest bin (10-20%) as the bid value of the lowest bin (0-10%). For each app we multiply the probability of each battery level bin with the monetary value of each bin. Summing those 10 products we obtain a measurement of “relative importance”. This metric is in EUR, and is typically called the Expected Monetary Value (EMV), shown in Table 1. This metric is used to evaluate the potential payoffs for a set of possible outcomes, and thus can be used to compare the relative value of different actions [28].

Workshops

We held two workshops after the 8 auction days were concluded. Prior to the workshops we generated anonymous

graphs and statistics regarding the study, which we used in slides to drive the discussion. The workshops revealed that the auctions were very successful in making participants think about battery value in new ways in their everyday context. Analysis of the (anonymous) questionnaires we collected during the workshops reveals that the self-assessed honesty of the bids for battery was high: 4.09/5.00 (SD = 0.67). Finally, although we use most of the workshop results in supporting the discussion, we note three key findings here:

1. Because chargers are ubiquitous in most environments, battery life is not really considered as a “real problem.” Only when battery level becomes very low, its perceived value increases rapidly.
2. The value judgement regarding battery is highly context-dependent.
3. While the auctions were determined to be truth-telling, the renewable nature of smartphone battery imposes challenges for conducting similar studies in the future.

We inquired about a handful of extremely high bids placed during the auction, such as 10,000 EUR. Our participants revealed that such bids were submitted to “*play with the system*” or as an attempt to get lucky, even if the participants seemed to be aware they would most likely not win with such bids. Based on the discussions, we set the upper cut-off limit in data analysis to 50 EUR, meaning that all higher bids were omitted from the analysis in this article.

On the other extreme, we discussed the reasons behind the extremely low bids (0.001 EUR and similar). The bids were placed either to test if the auction actually works, or to maximise the chances of winning a round, where participants reported not caring about battery life at all. However, typically after placing a very low bid and winning a round, participants started bidding honestly, as losing 10% units of battery for, say, 0.0001 EUR was perceived highly unpleasant. Participants also noted that “there was always someone bidding even lower”, so they just started bidding honestly.

We did not find out any of the participants knowing each other prior to the study, although we naturally cannot completely rule out this possibility. Further, the participants did not seem to collaborate in their bids during the study.

DISCUSSION

A recent BBC article claims that permanently-powered smartphones are “*a necessity in a world where more of us suffer from nomophobia, also known as smartphone separation anxiety*” [20]. Researchers have also discussed how users experience even heavy anxiety when deprived of their smartphone [8]. So, it is no wonder that battery life – or rather the lack of it – has repeatedly been framed as a major challenge for smartphones: the culprit for smartphones dying on their loyal users. Even so, research

has overlooked the assessment of battery life from a value-driven perspective, and it has been assumed that battery is simply a valuable resource. Reflecting on our experiment, we discuss battery life, its perceived value in different contexts, and how the economic model we developed is useful in analysing user behaviour and smartphone applications. First, however, it is important to discuss the auction itself.

Reverse Second-price Auction for Measuring Battery Valuation

Previous studies have auctioned personal information [34] or web browsing habits [6] using reverse second-price auctions. This mechanism produces honest and truthful results, coinciding with the theoretical assessment for this mechanism: it “*makes sense to bid your true value even if other bidders are overbidding, underbidding, colluding, or behaving in other unpredictable ways*” [9]. The duration of our study (8 days) is admittedly shorter than in some of the most related previous studies (12 days in [4] and 6 weeks in [34]). However, in our auction the data collection frequency is higher (13 times per day vs. 1~4 times per day in [4,34]), overall yielding a higher number of entries per participant (average of 60.6 bids). Thus, we feel the shorter duration of our study is sufficiently balanced by the richer data collection.

While the collected data does show rationale and expected differences in battery valuation per different battery levels, we identified two key challenges with an auction: bid honesty, and bid strategy. For instance, although the best strategy in this type of auction is bidding honestly [9,25], in the workshops many respondents confessed bidding very low during the first rounds of auction. This was either to verify everything working correctly, or attempting to simply win without caring about bid honesty: “*I started by bidding really low, just to check that everything is working. And after that I started to bid more realistically...*” or “*Even before the study I was convinced there was no auction or at least real money involved*”. The latter was voiced by a participant bidding extremely low for a long time in the auction just to win many rounds, i.e., very similar behaviour to P6 in Figure 8.

Second, the bidding context had an impact on some of the participants: “*Time of day matters much more. Usually at night, closer at night, battery is cheaper because I know it is charging time*” and “*Time of the day has a big impact, much more than the battery level. Close to night, we know that we can charge it very soon and know that will be home, safe.*” Surprisingly, when aggregated across all participants, and depicted in Figure 9, bids did not significantly decline towards the end of the day, but in fact slightly increased. This suggests that personal bidding strategies were being employed by participants. Other real-world contexts could, in theory, affect bidding strategies and lead to adaptive behaviour right after winning a bid.

These comments reveal an inherent and fascinating challenge to studying battery value using an auction process: the renewable nature of battery life. Users charge their devices whenever convenient for them, however following a preferred charging schedule routine [11]. Despite participants indicating that they were truthful in their bidding (4.09 on 5-point Likert scale), in many cases battery was perceived as an endless resource due to ample charging possibilities: e.g., participants could bid low (to “game“ the auction) when they knew the next opportunity to charge is near, e.g., at the end of the day. In a sense they felt they would gain “*something for nothing*” if they won the round in such a context. This is a crucial difference with previous studies examining the value of data, such as location [18], personal information [34], or web browsing data [6]. By employing an auction to improve our understanding of battery value, we also learned more about how its value affects how the participants’ spend their device time, i.e., application usage.

Smartphone Battery Valuation

As expected, the battery value rose as battery level went down ($r=-.16$). However, only during the very lowest battery levels (below 20%) did this value substantially increase. Although we did not collect bids in the last battery level bin (below 10%), the workshops discussions revealed that the battery value becomes very high on those occasions. For example, one participant commented: “*I stopped bidding when the battery value became infinite!*” The density plots depicting launch trends per battery conditions in Table 1 show that users drastically reduce application usage as the battery level nears zero. In other words, the value of the last drops of battery is perceived much higher than the value a single application can deliver at the time.

Battery value is also dependent on location, and mobility context. When next to charging facilities, typically when someone is at home or at the office, battery loses its value: “*When I am next to a charger, I don't really care*”. The same was noted by many of our participants, indicating that the renewable nature of battery greatly deteriorates its monetary value when charging opportunities are near. On the other hand, mobility has the opposite effect on battery value, despite the current available level: “*When traveling, I did not know when I can charge, and when I need the phone. So I bid really high*” or “*In festivals or traveling, then it's a massive problem*”, in reference to the problem of battery potentially running out in the future. Indeed festivals were reported as a special case in the previously mentioned BBC article [20], and portable chargers for festivals is now a business case [37]. When at airports, it is now common to find travellers on the lookout for elusive power sockets [14]. The racks of power outlets for visitors are seen as a mechanism to offer highly sought value to customers in a situation where charging the device is not possible in the foreseeable near future. Based on our study, we find that smartphone battery becomes a real concern

only when the battery level is low, since that is when it seems to be valued the most.

Resource-sharing Applications

Our monetary assessment of battery value provides insight for fairer resource sharing amongst users. Several use cases for resource sharing or donating have been proposed in literature. For instance, Pering *et al.* [31] envision how a set of mobile devices, with no need for additional hardware, can form a local device conglomerate that shares radio interfaces in order to save battery life. They highlight significant energy savings introduced by such a scheme, and there can also be financial benefits for mobile users. An example is roaming abroad. Roaming is typically expensive, and a sharing scheme enables nearby devices to connect online via a local gateway device with fixed rate bandwidth -- either for free, for a small monetary fee, or even employing some other type of compensation scheme.

The introduced scenario naturally takes a toll on the gateway device’s battery life. In our vision the gateway can passively run in the background and offer sporadic connectivity for nearby sensors equipped with low-range, low energy consumption devices. The battery depletion experienced by the mobile user is compensable by a micro-payment scheme. The question is, then, how much should the users be paid for their battery, if at all, by whom, and under which circumstances?

Economic theory suggests that not all money is equal, or “*a dollar is not a dollar*”: people value and earmark money from different sources in different ways [39]. Similarly, in a crowdsourcing context it has been recently shown that some prefer receiving tangible goods rather than money for their work [16,19]. Using the resource sharing scenario to frame the discussion, we asked the workshop participants how they would feel about sharing or donating battery to friends, strangers, or institutions. Most participants indicated they would be willing to part from their battery for altruistic purposes, to share it with friends for free. Social charging infrastructures [13] are created symbiotically among friends, where phone chargers are placed, shared, and expected to be available during social events.

Moreover, some participants felt uncomfortable to ask for money for battery: “*I would rather say no for a friend then ask for money!*”. One participant also wished for “something else” than money in exchange for battery, similar to [19]: “*Not money from friends...give me battery, I give you lunch....So something tangible instead of money*”. This presents a welcome opportunity: while a micro-payment mechanism can be considered, there may also be potential for exchange of small goods.

The Economics of HCI and User Behaviour

Because the relationship between users and their smartphones is complex and evolving, quantifying the value that users place on these devices is challenging. For example, a recent study found smartphone users suffer from

severe psychological and physiological effects, such as elevated heart rate, when prevented from interacting with their devices [8]. That study suggests phones are an “*extension to self*,” meaning that when the phone is taken away, the user loses a very part of oneself. Park *et al.* [29] report that some of the aspects of smartphones’ value relate to their convenience (e.g., checking the weather, navigating) and pleasure (e.g., listening to music, watching movies).

As we show in our analysis, user interactions can be valued by considering the battery level at the given moments. The model we empirically derive places greater value on actions occurring when on low battery, and in this manner it enables us to estimate the expected value of other functions: maps, music, movies, and communication functions can be systematically valued in this manner.

Effectively, we can consider the battery-price plot (Figure 7) as a demand curve: price goes up as quantity goes down, due to battery scarcity. However, what is interesting in the case of smartphones is that users face intermittent scarcity, since while they charge their phone they effectively have an unlimited energy (i.e., value) supply, but to access that they need to give up their mobility [10]: one typically does not charge their device while they are moving. Due to these two constraints (intermittent scarcity and energy-mobility tradeoff) it may be possible to estimate how much value users place on their mobility, or to be more precise their potential for mobility. For instance, users who charge their phone when their battery is at 90% would be considered to value their mobility less than users who charge their battery only once it reaches very low levels. While this assessment is not profound, our work provides the tools to quantify such behaviour in a systematic manner, using our metric that reflects Expected Monetary Value [28].

More broadly, our work applies to HCI research in general. The early days of HCI focused on the benefits of usability by arguing that improved usability saved time, which in turn saved on salary costs. The archetypical example would be call-centres, where improved user interfaces would reduce operators’ time, and thus reduce costs. The metrics popularised in that era were largely linked to task completion time and error rate, and ultimately “time was money” on such desktop systems. However, on smartphones “battery is money”: without battery all functionality becomes unavailable. Thus, studying user behaviour from an energy aspect (rather than time & error performance) may present a fruitful avenue to explore for further research on smartphones. Because every user instance of interaction depletes battery, our approach can systematically quantify user behaviour by considering its energy impact.

Limitations

An economic model such as ours is always a simplified description of reality, designed to yield testable hypotheses about behaviour. An important feature of an economic model is that it is necessarily subjective in design because there are no objective measures of economic outcomes.

In our analysis we cannot reliably analyse certain factors like hour of day, as the experimental design is not suitable for this. Also, the fact that we asked individuals to avoid charging during bidding hours resulted in atypical behaviour. However, without such constraints it would have been very hard to gauge battery value low battery levels, since users naturally tend to avoid those [10].

Another limitation is that our software did not take into account the winning bidder’s current energy expenditure. For example, if a participant was watching a movie when winning, the amount drained was likely not 10% units of the entire battery, but slightly less. The software simply drained until the level was 10% units lower than at the time of starting the drain. Again, we argue that the high amount of bidding rounds compensates this.

Finally, we acknowledge that the results likely depend on cultural and societal backgrounds, demographic characteristics, and the personality of participants. Despite the limitations, the framework for measuring user value of smartphone resources is applicable to other populations.

CONCLUSION

One of the most prominent contextual elements of smartphones, battery life, has not been quantified from the perspective of perceived monetary value. In this paper, we presented the first auction-based study aiming to assess the value users assign to their remaining battery life in the context of daily life. We also discovered the renewable nature of battery to impose challenges for the de-facto auction protocol (reverse second-price auction). Overall, we observed that users place different values on battery depending on the current level of battery, and social and mobility contexts.

Our study provides a look into how monetary battery value can be quantified. It offers a replicable method to examine applications, features, and user behaviour, based on their use patterns across different battery levels. Future work may expand this assessment for other mobile resources, such as bandwidth or storage space.

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