2022 IEEE International Conferences on Internet of Things (iThings) and IEEE Green Computing & Communications (GreenCom) and IEEE Cyber, Physical & Social Computing (CPSCom) and IEEE Smart Data (SmartData) and IEEE Congress

2022 IEEE International Conferences on Internet of Things (iThings) and IEEE Green Computing & Communications (GreenCom) and IEEE Cyber, Physical & Social Computing (CPSCom) and IEEE Smart Data (SmartData) and IEEE Congress on Cybermatics (Cybermatics) | 978-1-6654-5417-9/22/$31.00 ©2022 IEEE | DOI: 10.1109/iThings-GreenCom-CPSCom-SmartData-Cybermatics55523.2022.00022

Investigating Low-Battery Anxiety of Mobile Users

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***Abstract*—With the continuous upgrading of mobile networks and highly popularization of mobile services, cellphones have taken an indispensable role in people's daily life. The intensive usage of cellphones usually leads to heavy dependence on the devices, and further triggers the pervasive low-battery anxiety (LBA) among mobile users. Although having been found that nearly 90% people more or less suffered from LBA, we are still not clear about the characteristics of those who are more prone to it and how to help them alleviate it. In this work, to better understand LBA susceptible populations, we conduct a questionnaire investigation over 2000+ mobile users, look into their feelings and reactions regarding LBA, and quantify their anxiety degree during the draining of battery power. Based on the numerical anxiety degree, we further divide the participated mobile users into four groups as per LBA severity and perform user profiling to learn the specific characteristics of each group. For the first time, this work reveals the potential characteristics of specific user groups with different LBA severeness and provides important references on alleviating LBA suffering. New angles on exploiting our findings for other mobile services/applications are also discussed.**

***Index Terms*—Low-battery anxiety, quality of experience, mobile user profiling, mobile services**

I. Introduction

"Have you ever ordered something at a bar just so you can ask to plug in your phone? Do you argue with loved ones because your phone died and you missed their calls or texts? Are you regularly accused of secretly 'borrowing' someone else's charger? If so, you might suffer from Low-Battery Anxiety.", according to a survey conducted by LG [1]. This survey investigated thousands of people and introduced the concept of "Low-Battery Anxiety" for the first time. It also revealed a shocking fact that nearly nine out of 10 people "felt panic" when their phone battery drops to 20 percent or lower [1], namely, about 90% of people suffered from the so-called low-battery anxiety (LBA). With the continuously expanding popularity of cellphone and mobile services, the impact of accompanying LBA could be profound.

To accommodate the low-battery anxiety, people could change their behaviors. For example, bearing in mind the dying battery, people may ask a total stranger to charge their smartphones, although it is awkward, or even secretly "borrow" someone else's charger [1]. What's more, chances are that low-battery anxiety might do harm to relationships as 60 percent of surveyed participants reported that they had blamed a dead phone for not speaking to a family member, friend, co-worker or significant other [1]. Apart from behavior changes, low-battery anxiety may also do harm to people's mental health as it becomes the major cause to "nomophobia" (a psychological disorder caused by being out of contact with a mobile phone or computer [2]). Based on our survey over 2000+ mobile users in 2019, about 92% of the participants are suffering from the LBA more or less, among which 6% are severe LBA sufferers (§ III-A). This raises deep concern about the psychological well-being of modern mobile users.

Meanwhile, understanding users' interactions with their low-battery smartphones also has business meanings. To begin with, for mobile OS designers, LBA study could provide valuable references and inspirations for more user-friendly human-battery interfaces (HBIs) [3]. Specifically, it is important to incorporate users' low-battery anxiety as a quality of experience (QoE) metric in designing the mobile OS and HBIs. As another vital observation , video streaming services at the mobile end are booming, triggered by the ubiquitous usage of mobile devices and emerging techniques in networking/computing [4]. According to our survey, mobile users are prone to abandon watching videos of interest when their battery power is lower than roughly 30%, and nearly half of them will abandon watching videos when the battery level drops to 10% (§ III-C). Thus, for mobile video streaming service providers, such as Instagram and ByteDance, LBA could impact the customer retention rate as well as the company's revenue.

A great deal of academic researches have been devoted to saving energy and prolonging the battery lifetime of mobile phones, e.g., targeted at the major components of CPU, communication and display. Particularly in pervasive and ubiquitous computing, energy efficient techniques have been developed for mobile sensing/crowdsensing [5], [6], wireless communication [7], [8], and battery management [9], [10]. Nevertheless, very few of them take low-battery anxiety into consideration and how effective are they at alleviating mobile users' LBA remains largely unanswered. Although there are relevant literature on the human-battery interaction [11], [12], [9], [13], they are usually subject to two pitfalls: i) the analysis was performed in a qualitative way over mobile users [1], [13], and thus the conclusions cannot be leveraged for quantitative evaluations; ii) the investigation was made for a specific and

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978-1-6654-5417-9/22/$31.00 ©2022 IEEE

DOI 10.1109/iThings-GreenCom-CPSCom-SmartData-Cybermatics55523.2022.00022

small user group [11], [12], [9], and thus the obtained findings have limited generalizability for a large population.

We argue that a better qualitative and quantitative profiling of LBA population's psychology and behavior could result in more efficient and even new solutions to LBA raised problems. Specifically, for personal users, quantitative metrics of LBA can be employed to evaluate the effectiveness of anxiety relieving approaches, e.g., energy saving approaches and HBI design. Also, for the mobile video streaming industry, with a quantitative model, the video service provider could introduce LBA into their optimization strategy to enhance users' QoE.

In this work, we not only conduct a large-scale investigation about the LBA issue, but also build LBA related quantitative models. Specifically, we set to answer three research questions: **RQ1:** How can we design the questionnaire in a user survey such that the LBA can be quantified by the (large-scale) feedback of mobile users? **RQ2:** How severe are modern mobile users suffering from the LBA and how can we group the population based on the suffered LBA severity? **RQ3:** For each of the user groups in different LBA severeness, what are their population characteristics and how do they behave to accommodate the LBA?

Through qualitative and quantitative analysis of the LBA survey data over 2000+ participants, we obtain abundant interesting and insightful **findings**, including:

- Nearly 92% of modern mobile users reported suffering from low-battery anxiety, and to accommodate the dying batteries, 80% of them ever use backup power.
- When the battery power drops below 30%, the anxiety degree of mobile users increases rapidly; when the battery power falls below 20%, most mobile users begin to abandon watching attractive videos just for power conserving.
- People with severer LBA are more likely to be female company workers, ageing 25-35 and using iPhone, while people without LBA tend to be male freelancers aged over 35, using Huawei mobile phones.
- Those with severer LBA charge their mobile phones and use portable charging more frequently, and abandon watching attractive videos at a higher battery level.
- Although suffering more from LBA, young college students show stronger retention to mobile videos than other mobile user groups.

Below, we summarize our **contributions**.

- We present a neat survey methodology to quantify the subjective low-battery anxiety degree from the feedback of mobile users. We also show that the methodology can be leveraged for quantifying the crowd's other emotion and behavior, e.g., the likelihood of people giving up watching videos, which leads to important findings on how people value its remaining battery power.
- Following the methodology of quantifying LBA, we conduct a user survey over 2000+ mobile users , and extract the anxiety degree and video abandoning likelihood of mobile users under various battery states. With a large number of user feedback, we also present a comprehensive study that reveals various aspects of the LBA issue.
- Based on the quantified anxiety degree, we divide all mobile users into four groups as per LBA severity, and for each group we perform fine-grained user profiling to learn their characteristics. As the new generation mobile users, we also look into the group of college students and find unique traits on how they assess battery power.

The rest of the paper is organized as follows. § II introduces the related work. § III presents an overview of the collected dataset as well as the quantified low-battery anxiety. In § IV, we partition mobile users into four groups based on LBA severity, profile their characteristics and analyze their behavior accordingly. Practical applications with our findings are presented in § V. The paper is concluded in § VI.

II. Related Work

In this section, we present the background of low-battery anxiety and review related work about mobile user profiling.

A. Low-battery Anxiety of Mobile Users

The concept of "Low-battery Anxiety" was first introduced in LG's survey to exemplify the behavior of people who are changing their everyday lives – just to accommodate the dying battery [1]. In this survey, LG surveyed $2,000$ smartphone users in the U.S. and concluded that "nearly nine out of 10 people 'felt panic' when their phone battery drops to 20% or lower". Meanwhile, they presented some signs of low-battery anxiety and mentioned that the LBA might lead to unhealthy choices and ruin relationships. Existing investigations related to battery use and recharge behavior of mobile users include *qualitative* study in large-scale[1] [1], [13] or *quantitative* study in small-scale [12], [9], [11]. However, not much attention has been paid to the emerging LBA issue. Our work makes a concrete first step to conduct a both *large-scale* and *quantitative* study specifically on LBA and its impacts.

Large-scale studies: A study of battery charging behaviors with $4,035$ participants was conducted in [13]. The battery information of participants was collected via an Android application. Some statistical values were computed with the collected data, e.g., charging duration, charging schedule and frequency, based on which the authors obtained some charging behaviors of participants, e.g., most users chose to interrupt the charging cycle which potentially reduces the battery life, and consistently overcharged their phones and tended to keep the battery levels above 30%. Nevertheless, neither quantitative models (beyond the statistical values) nor specific findings related to the LBA issue were provided.

Small-scale studies: In [12], the authors conducted a small-scale questionnaire investigation among high school students, where only 41% of the participants were mobile phone users. In this survey, they conducted the qualitative analysis of LBA, based on participants' self-estimation. Although quantitative

[1]The scale of study is debatable, since there is no broadly-accepted threshold counting for the large scale. We consider a study of sample size greater than $1,000$ people as large scale.

analysis of users' charging behavior was given, it was obtained through structured interviews of twenty mobile phone users, neither massively nor methodologically. In [11], both questionnaire studies and handset monitoring were performed, on users' attitudes towards mobile devices' energy and their behavior on battery recharge. The studies involved up to 253 participants, whose charging behavior was quantitatively analysed. The anxiety caused by low-battery status, however, was not discussed in this work. In [9], the battery traces of 56 laptops and 10 mobile phones were collected and used to study the battery use and recharge behavior. Based on the user study, the authors designed a battery energy management system, called Llama, to enhance existing energy management policies. Nevertheless, the number of participants is too small to draw a reliable conclusion with respect to LBA.

B. Mobile User Profiling

Mobile user profiling aims to extract mobile user's interests and behavioral patterns from their behavioral data [14], thus providing references for campaigns [15], recommendation systems [16] and other applications. Specifically, in [15], the authors leveraged logistic-regression techniques to predict individual user preferences from past records, thus predicting the probability that a user would carry out specific crowdsensing tasks. In [17], both group partition and group profiling were conducted among $106,762$ Android users. This study aimed to discover different types of mobile users based on their application usage data and select the most distinct characteristics of each group. Through k-Means and Mean Shift clustering and a feature ranking approach, the authors obtained 382 user clusters as well as their features, which could be leveraged in the design of mobile applications.

Given existing mobile user profiling work, however, none of them are relevant to the emerging low-battery anxiety. This work is the first to profile mobile users from the perspective of LBA, e.g., partitioning mobile users based on LBA severity and extracting characteristics accordingly.

III. Dataset and LBA Quantification

From July 2019 to October 2019, we designed a survey questionnaire for low-battery anxiety investigation, distributed the questionnaire among mobile users through the WeChat platform, and eventually acquired $2,044$ effective answers. In this section, we provide an overview of the collected dataset (i.e., answers from the participants) and introduce the methodology to quantify the low-battery anxiety.

A. Dataset

1) Participants and Mobile Phones:

According to the metadata, the majority of participants came from 150 cities of 31 provincial-level administrative units in China. We also noticed a small number (70 out of $2,077$) of oversea participants, which were mainly from America, Canada, Singapore, Australia, and Japan. The demographic information is as follows.

- **Gender (Q1)**: It includes a total of $1,102$ male participants and 942 female participants, accounting for 53.9% and 46.1%, respectively. Generally speaking, this is a relatively balanced gender distribution.
- **Age (Q2)**: This question is not mandatory and $1,738$ participants answered it. From the feedback, nearly 80% of the participants are under the age of 35, with 51.4% aged 18-25 and 26.7% aged 25-35, indicating that our participants are mostly young people. Participants aged over 35 occupy about 20%, with 14.4% aged between 35 and 45 and 7.0% aged between 45 and 55.
- **Occupation (Q3)**: Half of our participants (50.44%) are students; participants from companies, institutions and governments account for 34.6%; 7.1% are freelancers.
- **Mobile phone manufacturer (Q4)**: Apple and Huawei are the top two mobile phone brands, occupying 36.1% and 33.6% respectively, followed by Xiaomi, occupying 11.3%, and other mobile phone brands, such as OPPO, VIVO and Samsung, occupying the last 19%.

2) User Charging Behavior:

- **Daily Charging Frequency (Q5)**: The majority of participants (86.3%) charge their phones twice or less a day, with people who charge twice a day occupying 49.0% and people who charge no more than once occupying 37.3%; only 4.4% of participants charge their phones more than three times a day.
- **Portable Charging Frequency (Q6)**: About 80% of our participants use portable charging (such as a power bank) as the backup power for their mobile phones, among which people who use power bank occasionally account for 70%. About two out of ten mobile uses never use portable charging.

3) Self-Assessed Severity of Low-Battery Anxiety:

Given the definition and "symptoms" of LBA, in the seventh question (**Q7**), participants were required to assess their own severity of LBA. To avoid ambiguity, we explicitly gave a general situation where charging is inconvenient. Based on the results, only 167 participants described themselves as having no low-battery anxiety, accounting for 8.2%, which is basically consistent with LG's survey. Meanwhile, 124 participants described themselves as severely suffering from low-battery anxiety, accounting for 6%. 573 participants confirmed having low-battery anxiety, accounting for 28%, and $1,180$ participants reported suffering from moderate low-battery anxiety, accounting for 57.7%. Thus, we can see that low-battery anxiety is a very common issue among modern mobile users.

These answers, however, are indeed coarse-grained self-assessments of LBA suffering and may not be accurate enough to reflect truth. In following section, we will show how fine-grained user profiling can be conducted with quantified LBA.

B. Quantify the Low-Battery Anxiety

Low-battery anxiety is essentially a kind of subjective feeling of people, so it is (methodologically) infeasible and (technically) inaccurate to ask a user to provide a real value

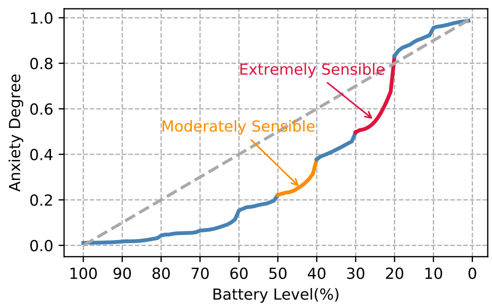


Fig. 1. LBA curve from the survey data of 2044 mobile users, where the anxiety sensible regions are highlighted by red and yellow.

representing her/his anxiety degree at each battery level. Thus, in our user survey, instead of directly asking for the anxiety degree, we turn to ask the battery level at which the user will charge the mobile phone, and then extract an LBA curve from the feedback of all participants.

Specifically, the ninth question (**Q8**) of our questionnaire is set as: *at what battery level (in percentage from* 0 *to* 100%*) will you charge your mobile phone, when it is possible?* The answer provides us with an angle to infer at which energy level the user begins to worry about the battery life, i.e., experience the low-battery anxiety. With all the answers from the $2,044$ participants, we are able to extract an empirical *LBA curve* by reversely accumulating over the histogram (showing the frequency at which users begin to experience the low-battery anxiety) and normalizing the cumulative numbers to $[0,1]$. The detailed procedure is as follows.

(1) **Initializing:** We first set 100 variables with an initial value of 0, labeling from 1-100, representing the battery level from almost 0 to 100%;
(2) **Counting:** For each answer, e.g., a (an integer in the region of $[1,100]$), we add one to the variables labeled from 1 to a;
(3) **Cumulating:** We conduct the above procedures for all answers and get the 100 variables with cumulative numbers, resulting in a declined (discrete) curve in the region of $[1,100]$;
(4) **Normalizing:** Through dividing each variable by 2044 (the number of all answers), we obtain the LBA curve: *battery level vs. anxiety degree*.

Note that although the LBA degree extraction process seems simple, it is the result of a reverse-engineering idea and its corresponding questionnaire design. Specifically, to learn the anxious degree curve of the mobile user with just one question, the question requires to make indications across different battery levels. By implicitly asking when a user begins to feel anxious about her/his battery power (i.e., the charging threshold), we are able to harvest the anxiety indications across all battery levels of the user, theoretically by a 0-1 binary vector with 0 indicating "not anxious" and 1 the opposite. Then, using a reversed accumulation approach among the 2000+ collected answers, the empirical LBA curve (anxious degree vs. battery level) can thus be derived.

The extracted LBA curve from the dataset is shown in Fig. 1, where we have the following observations.

- With the decrease of battery power level, the anxiety degree of mobile users continuously increases in a non-linear manner. As a comparison, we draw a straight dashed line in Fig. 1, representing the linear increase situation. More specifically, we find that the *LBA curve* is approximately convex to the battery level in [20%,100%], while approximately concave in [0,20%].
- There are two sensible regions of users' anxiety, namely, the *moderately sensible* and *extremely sensible* region as illustrated in Fig. 1, both corresponding to about 10% battery level drop. In the moderately sensible region [40%,50%], the 10% battery level dropping leads to 16% anxiety degree increases (from 0.22 to 0.38), while in the extremely sensible region [20%,30%] the anxiety degree climbs from 0.50 to 0.83.

The occurrence of the extremely sensible region is most possibly due to the HBI design of mobile OS. For example, when the battery level drops to 20% in iPhone or Huawei phones, the battery icon's color will turn to yellow and a low-battery warning message will pop up simultaneously.

C. Quantify the Value of Remaining Battery Power

Based on the quantification result in § III-B, we observe that with the decreasing of battery level, more and more people begin to "feel panic" about the dying battery power. Under this circumstance, people may start to abandon power-consuming mobile services/applications. We take mobile video playing as an example, as it accounts for a large proportion of battery consumption on a mobile phone [18]. Common sense informs us that when surfing the Internet, given enough battery power, most people will watch videos of interest. Nevertheless, when the battery power falls below a threshold, say 20%, the users may choose to give up video watching for battery power conservation. Therefore, in order to study how people assess the value of their mobile battery power, we analyze people's video abandoning behavior regarding different battery levels, namely, quantifying the value of remaining battery power.

Following the same way to extract *LBA curve*, we extract a *video abandoning likelihood* (VAL) curve, based on the feedback of **Q9**: *At what battery level (in percentage from 1% to 100%) will you give up watching a video you are interested in, when you are browsing the WeChat Moment or Weibo*[2]*?* This curve actually indicates the likelihood that a user may abandon video watching under different battery levels. It also indicates users' value of battery power at different levels through comparison with attractive videos. The extracted VAL curve is illustrated in Fig. 2, from which we observe that:

- Similar to the LBA curve, the video abandoning likelihood does not linearly increase with the dropping of battery level. For comparison, we draw a straight dashed

[2]The *WeChat Moment* and *Weibo* are currently the two biggest mobile social network platforms in China with billions of users. Tons of fresh and popular videos are shared there and updated by second.

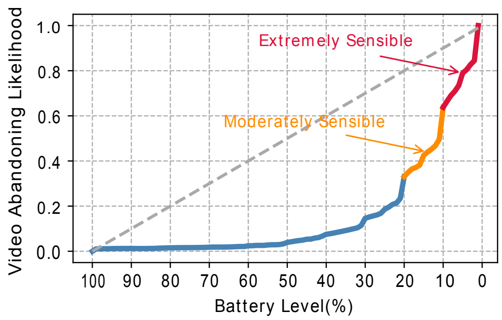
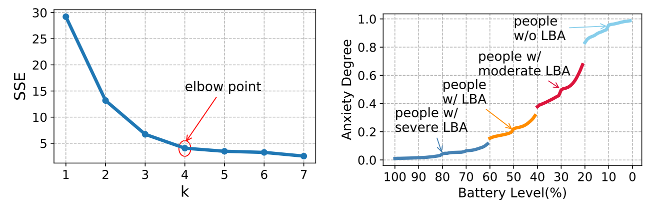


Fig. 2. VAL curve from the survey data of 2044 mobile users, where the sensible regions are highlighted by red and yellow.



(a) (b)

Fig. 3. (a) K-means SSE of different group numbers; (b) Four user groups inferred from the LBA curve stratification.

line in Fig. 2, representing the linear increase situation. What makes the VAL curve different from the LBA curve is, it is approximately convex to battery levels in the whole region [0%,100%].

- There are two sensible regions of users' video abandoning likelihood, namely, the *moderately sensible* and *extremely sensible* regions. In the moderately sensible region [10%, 20%], a drop of 10% battery power leads to the increase of 31% video abandoning likelihood (from 0.33 to 0.64), while in the extremely sensible region [0,10%], the video abandoning likelihood is enlarged from 0.64 to 1. In other words, in these two regions, people value their battery power significantly more than attractive videos.

IV. User Group Profiling

In this section, we profile the unique characteristics of multiple user groups. The first four groups discussed in § IV-A are classified by the severity of low-battery anxiety. Then, the behavior differences of the four groups are further discussed in § IV-B, including charging and video watching behaviors. As accounting for over half of the participants, the college students are also studied as a separated group in § IV-C.

A. *Characteristics of User Groups by LBA Severity*

1) Group Partition:

Based on the quantified LBA degree in § III-B, we find that the LBA curve shows a clear stratification determined by the gaps in LBA degree, as illustrated by Fig. 1. Interestingly, we observe that a gap usually occurs when the battery level is an integer, such as 20%, 40% and 60%. For example, when the battery level is 21%, the LBA degree is 0.68, and when the battery level drops to 20%, the LBA degree jumps to 0.83.

To further validate our observation, we make use of k-Means algorithm to cluster the LBA degree and determine the optimal group number via the elbow criterion [19]. More specifically, we leverage k-Means with a pre-specified cluster number (k) changing from one to seven in our case, and obtain the sum of squared error (SSE) under each cluster number. Based on the elbow criterion, with the increase of k, SSE would decrease rapidly before reaching the optimal cluster number. However, when exceeding the optimal number, the decreasing speed of SSE gets slowed down significantly and the curve would become flat as k continues to augment, forming an "elbow" shape during this process. We illustrate the variation of SSE corresponding to different k in Fig. 3(a), from which we observe that the optimal k (the elbow point of the curve) is 4 in our case. That is to say, the whole LBA curve can be optimally partitioned into four segments.

TABLE I
Ratios in Four Groups

Group of People	Curve Partition Ratio (%)	Self-assessed Result Ratio (%)
People without LBA	16.8	8.2
People with moderate LBA	51.7	57.7
People with LBA	20.0	28.0
People with severe LBA	11.4	6.1

Accordingly, the entire LBA curve is divided into the following four segments: [0, 20%], (20%, 40%], (40%, 60%], (60%, 100%], as illustrated in Fig. 3(b). Given that the LBA degree virtually represents the proportion of people who choose to charge their phones at specific battery levels, we obtain the ratio of each part: 16.8% of participants choose to charge at battery level [0, 20%]; 51.7% of participants choose to charge at battery level (20%, 40%]; 20.0% of participants choose to charge at battery level (40%, 60%]; 11.4% of participants choose to charge at battery level (60%, 100%]. Meanwhile, we conclude that people who choose to charge at battery level (60%, 100%] suffer from severest low-battery anxiety since they begin to "feel panic" at the highest battery levels, and people who choose to charge at battery level [0, 20%] do not have low-battery anxiety as they seem not to worry about the battery power for most of the time. Overall, the four segments virtually indicate four groups of people who are undergoing different levels of LBA, from none to severe.

Recall that we asked the participants to self-assess their LBA severity in **Q8**, choosing from i) "Not at all", ii) "A little", iii) "Confirmed suffering" and iv) "Severely suffering". Based on the feedback, we also obtained four user groups. We now have two different versions of group partitions, which are obtained from different and unrelated answers to **Q8** and **Q9**. These two groups of ratios are calculated and shown in Table I. **From Table I, we can observe that the population distributions among the four user groups are roughly similar under the two different group partition methodologies.**

TABLE II
CORRELATIONS BETWEEN DEMOGRAPHICS AND FOUR LBA GROUPS

Demographic attributes	Chi-square value	p-value
Gender	17.43	$5.76 * e^{-4}$
Age	50.75	$1.03 * e^{-6}$
Occupation	61.40	$1.21 * e^{-6}$
Mobile phone brands	71.81	$2.21 * e^{-9}$

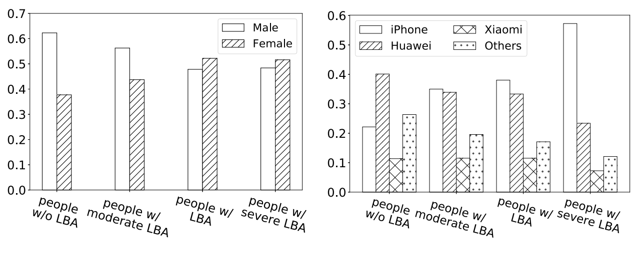


Fig. 4. (a) Gender distribution of four groups; (b) Mobile phone type distribution of four groups.

This, from the other side, validates the rationality of our group partition and reliability of our dataset.

2) Group Characteristics:

With the feedback from our user survey, we look into four demographic attributes: gender, age, occupation and mobile phone brands, and explore how they could correlate with the low-battery anxiety severeness. Specifically, we examine the correlation between these four attributes and four groups of people through *Contingency table analysis* and *Chi-square test*. For the *Chi-square test*, the null hypothesis is that there exists no correlation between each of the four demographics and four partitioned groups. By setting the significant level to 5%, we obtain the results in Table II. With the p-values much smaller than 0.05, we conclude that there exist significant correlations (i.e., $H = 1$) for the four attributes and partitioned groups, indicating the feasibility of leveraging these attributes for user group profiling.

Gender & Mobile Phone Share: The overall distributions of gender and phone type are relatively balanced. To be detailed, for gender, males account for 53.9% and females account for 46.1% of all participants. For mobile phone share, Apple and Huawei account for 36.1% and 33.6% respectively. Xiaomi occupies 11.3% and other mobile phone brands occupy the remaining 19.0%. Nevertheless, in each of the aforementioned four user groups, these two distributions vary more or less, which actually reflect unique characteristics of each group. The gender and mobile phone share distributions within the four groups are shown in Fig. 4(a) and Fig. 4(b), respectively. From the results we can learn that: i) as LBA severeness augments, the proportion of female increases while the male decreases, which indicates that **the female are more prone to LBA than the male**; ii) for the participants in our survey, **those with severe LBA are mostly iPhone users, while people without LBA are more likely to use Huawei cellphones**, potentially due to different battery capacity of

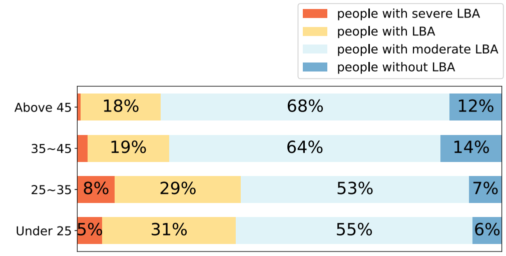


Fig. 5. Four groups distribution regarding age.

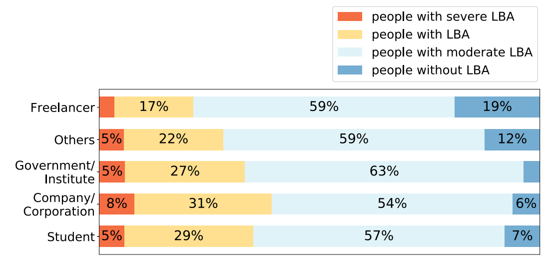


Fig. 6. Four groups distribution regarding occupation.

these two brands (e.g., the Huawei model Mate 30 Pro is with a 4500 mAh battery, versus iPhone 11 Pro 3046 mAh).

Age and Occupation: The distributions of age and occupation are virtually uneven, as more participants age between 18 and 25 and are college students. Thus, instead of analyzing the metric distribution of four groups as the gender or phone brand, we choose to investigate the ratio of each group under specific answers of age and occupation. The distribution of four groups regarding age is shown in Fig. 5 and that of occupation is shown in Fig. 6. From the results we can conclude that: i) **young people aged under 35 suffer severer LBA significantly than elderly aged above 35 ($p <$ 0.05, *t-test*)**, probably because modern young people are generally under more pressure of working and living, thus giving rise to heavier dependency on mobile phones; ii) **company/corporation workers suffer from severer LBA than those with other occupations, and freelancers are with the lightest LBA** partly due to their specific working environment or atmosphere.

We summarize our findings about the characteristics of four user groups in Table III.

B. Behavior Differences of Four Groups

In this section, we further analyze the behaviors of four user groups, including charging behavior and video watching behavior, and investigate the differences among these groups.

1) Charging Behavior Differences:

In our questionnaire, we set **Q6** and **Q7** to obtain participants' daily charging frequency and power bank charging frequency. Through comparing these two frequencies, we are able to learn the main charging behavior of each group. The daily cellphone charging frequency and power bank usage

TABLE III
POTENTIAL CHARACTERISTICS OF FOUR USER GROUPS

Group of People	Potential Characteristics
Without LBA	Male, Huawei user, aged over 35, freelancer
With Moderate LBA	Male, aged over 35, government or institute worker
With LBA	Female, iPhone user, aged under 35, company worker or students
With Severe LBA	Female, iPhone user, aged 25-35, company worker

TABLE IV
MEAN, MEDIAN AND MODE OF VIDEO ABANDONING BATTERY LEVEL IN FOUR GROUPS

Group of People	Mean	Median	Mode
People without LBA	28.5	21	20
People with moderate LBA	32.6	24	20
People with LBA	37.4	36	20
People with severe LBA	44.6	40	20

frequency of the four groups are illustrated in Fig. 7(a) and Fig. 7(b), respectively.

With the results we can find that: i) **with the increase of LBA severity, people tend to charge more times a day**, where those without LBA mostly charge no more than once, while the majority of those with severe LBA charge ≥ 2 times; ii) **as the LBA level augments, people tend to use portable charger more frequently**, and those with severest LBA have the largest ratio of using portable charging frequently.

2) Video Watching Behavior Differences:

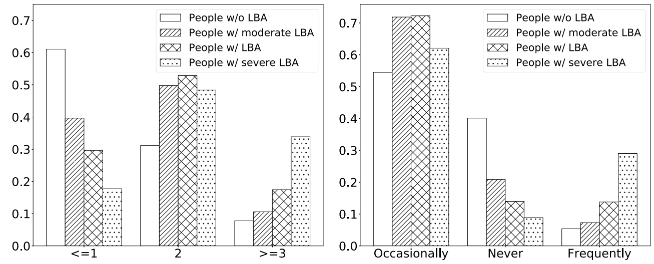
Different from the qualitative answers of charging behavior, the feedback regarding video watching behavior are exact battery levels at which people begin to give up watching videos of interest. Therefore, we select mean, median and mode to reflect the characteristics of each user group at video watching. The results are summarized in Table IV.

According to the results in TableIV, we can observe that with the increasing of LBA severity, the mean value of battery level for video abandoning increases, so does the median, while the mode remains the same. Namely, **the severer LBA people suffer from, the higher battery level at which they will abandon watching attractive videos**. For example, when battery level falls to 40%, only people with severe LBA would care about the battery power and start to give up watching videos of interest; however, **when the battery level falls below 20%, most mobile users begin to abandon watching videos for power conserving**.

C. Student Group Analysis

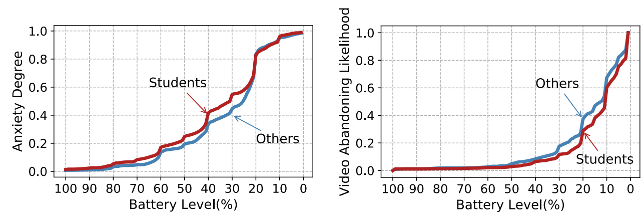
As over half of our participants are college students, we also conduct a specific analysis for this user group, comparing its LBA and VAL curves with all the other groups. The LBA curve comparison is illustrated in Fig. 8(a), from which we can observe that:

- The trends of *Students LBA curve* and *Others LBA curve* are generally similar. Especially, when the battery level is higher than 90% or lower than 20%, the two curves almost coincide.
- When battery level falls in the region [20%, 90%], the *Students LBA curve* stays above the *Overall LBA curve*. In other words, for battery levels in [20%, 90%], college students usually suffer more from LBA than others.



(a) (b)

Fig. 7. (a) Daily charging frequency of four groups; (b) Portable charging frequency of four groups.



(a) (b)

Fig. 8. (a) Overall LBA curve versus students LBA curve; (b) Overall VAL curve versus students VAL curve.

Also, from the VAL curve comparison in Fig. 8(b), we can observe:

- The trends of *Students VAL curve* and *Overall VAL curve* are also similar. When battery level is higher than 90% or lower than 60%, these two curves almost coincide.
- When battery level falls in the region [0, 60%], the *Overall VAL curve* stays above the *Students VAL curve*, which means for battery levels in [0, 60%], students are more likely to stick to watching videos of interest.

Interestingly, by combining the outcomes from Fig. 8(a) and Fig. 8(b), we can find that **college students generally suffer from severer LBA than others, while they are less likely to abandon attractive videos under the same battery levels.** This result seems contradictory with that obtained in § IV-B that people suffering severer LBA are more likely to abandon video watching. Actually, such a contradiction on the other hand indicates that **college students are usually with stronger retention to mobile video services than others, stressed under the same LBA.**

V. DISCUSSION: APPLICATIONS OF OUR FINDINGS

The findings in this work not only reflect the states on how modern people are suffering from the low-battery anxiety, but also provide useful instructions and references in several relevant fields.

Power charging facility deployment: One of the most effective ways to alleviate people's low-battery anxiety is to provide convenient-access charging facilities, including fixed charging equipments like electrical outlets and portable charging devices like power banks. For example, based on our findings that college students and youngsters suffer from severer LBA, we could allocate more (shared) power banks in places where these people frequently appear, such as classrooms, libraries, gyms, etc.

Pricing policy making in crowdsourcing: Crowdsourcing has become a popular organizational model to harness the advantage of a "virtual crowd" to achieve specific tasks. As crowdsourcing consumes mobile battery power, given the same payment, people without LBA would be more willing to participate than those with severe LBA. In other words, the pricing strategy should be distinguished for different users by referring to their LBA severity. Otherwise, the quality of crowdsourcing outcomes may not be reliable and consistent.

Mobile user QoE enhancement: QoE enhancement is a critical problem in ubiquitous computing. Our LBA quantification work could be leveraged in providing better mobile services. Specifically, the LBA measurements in this work can be a powerful knob in the QoE-aware design and enhancement of mobile services/applications in social IoTs [20] and cyber-physical-social systems [21]. For example, the quantified LBA model can be used for mobile user QoE optimization in mobile video streaming services, including reducing users' anxiety and increasing their retention [22], [23].

VI. Conclusions

In this paper, we conducted a questionnaire survey over 2000+ mobile users, quantified their low-battery anxiety degree and investigated users' assessment to remaining battery power. Based on the extracted LBA curve, we were able to divide the whole participants into four groups: people without LBA, people with moderate LBA, people with LBA and people with severe LBA. Then we performed user profiling for each group and obtained some interesting and insightful findings. As a case study, we studied the group of college students and revealed their own unique characteristics. At last, we provided some practical usages with the findings in this work.

VII. Acknowledgement

This work was partially supported by the National Key Research and Development Program of China (2020YFB1806400), the National Natural Science Foundation of China (62002150), the Major Key Project of Peng Cheng Laboratory (PCL2021A08), and Guangdong Basic and Applied Basic Research Foundation (2019B1515120031).

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