Propensity to Use Smartphone Applications

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Abstract—This article studies the impact of contextual variables on smartphone usage with a dataset collected from 256 people with mobile audience measurements. Real-life smartphone usage was tracked over a period of 1-2 months, and contextual information of the usage was collected to complement behavioral data. This article seeks for statistical understanding regarding how context affects usage patterns and likelihood to use smartphone features and applications. Results of the analyses suggest that, odds of using voice and mobile browsing are approximately 100% and 240% higher in home country than abroad, respectively. On the other hand, messaging is found to be used more while out of home country. Voice service is preferred when handset battery status is low, than any other service. Odds of using calendar on weekdays are 42% higher and for maps 20% lower, than on weekdays. Music service is found to be used more during night hours (00:00-07:59) and higher battery status (2.6% higher odds with every single unit increase on a seven-bar battery scale).

Keywords—handset-based usage tracking; user experience research; context analysis; mobile audience measurements

I. INTRODUCTION

Smartphones, advanced devices running operating systems to which applications can be installed, are driving the growth of the mobile industry in developed markets. In these markets most of the new innovations are based on new applications and services, and carriers together with device vendors are seeking new growth from these areas. Due to the increasing number of mobile applications and device features, also the heterogeneity in the ways people use them is increasing. Some applications are geared for office use (like email and document viewers), some applications are clearly more hedonic by nature (for example music playback or gaming). Therefore a need exists to analyze how people use new smartphone applications and features in practice, and in particular how context affects usage [1]. For example, there is a valid hypothesis that international roaming tariffs have a significant negative effect on usage, or that low battery status discourages people to use multimedia applications. The difficulties to conduct such analysis earlier have mainly resulted from the lack of hard data on usage and contextual variables.

Usage of mobile services is typically studied through surveys and interviews. A research method that is based on in-device meters has been defined and used during the past few years at Helsinki University of Technology. The method involves setting up a panel population consisting of smartphone users, who install a research application to their mobile phones. The application collects information on device usage and contextual factors, and sends the information to centralized servers for analysis. Thus, usage data is complemented with web-based surveys that are conducted during the study. The advantages of the method include the objectivity and accurate nature of the data, and possibilities to arrange research projects on specific topics not easy to study with other methods (for example adoption research). The shortcomings include the cost of arranging the studies, early-adopter bias involved, and the generic lack of interactivity in the research process. [2] [3] [4]

The goal of this article is to use data obtained through in-device measurements in a Finnish panel study or smartphone users in analyzing the impact of context on usage. In this research, context is defined to mean mainly the day of the week, hour of the day, battery status and location of subscribers (home vs. abroad). The research problem of the paper is:

"How does context affect smartphone usage?"

This article uses a handset-based research method in collecting data from a sample of smartphone users (see [2] and [4]). The method provides statistics on the actual use of mobile services. End-users participating in the study install a research client on their smartphone devices. This client runs on the background of the device, invisible to end-users, observing user actions and storing collected data points into device memory. The collected data points give an accurate and objective view on smartphone usage. This research data is transmitted daily to centralized servers for the purposes of analysis. The method is deployed in controlled panel studies, to which approximately 500–700 Finnish smartphone users are recruited annually, sampled randomly from the databases of all Finnish operators. The annual Finnish smartphone study has been repeated four times (2005–2008). The panelists (end-users participating in the study) are provided with €20 vouchers as compensation for the potential data transfer costs they have to bear due to the research setting (automatic transmission of data to servers), and everybody are required to agree on the terms of the study (opt-in).

The combination of subjective survey and objective usage-level data obtained in a natural environment of end-

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users is the main advantage of the used research method, in comparison to surveys, laboratory tests, network-based measurements and interviews (see [3] and [4]). The main shortcoming of the method is the adverse selection of panelists. Typically, only certain kinds of people participate in the research panels (tech-savvy, open-minded, explorative). In addition, the smartphone device penetration is still well below 20% in the Finnish market [5], and most panelists are still early-adopter users, instead of mass-market consumers.

II. LITERATURE REVIEW

In order to create our research model, we first define *context* and its determinants in our scope. Context is a crucial concept, especially in the case of mobile services because of their ubiquitous nature, and is defined in the literature from different perspectives. Information defining context is very vast and in theory it is limitless [6]. Therefore it is imperative to define context in the study scope, prior exploring it.

Amongst many proposed elucidation of context, Shilit gave a categorical definition of context by dividing context into three categories [7]: computing context (e.g., network bandwidth, nearby resources), user context (e.g., user profile, location), and physical context (e.g., temperature, light). Chen and Kotz afterwards [8], extended it by adding a time context (e.g., time of a day, week). Dey intended a generalized and embracing definition of context as [9], "Context is any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves". Dey et al. also proposed a classification of context based on entities into people, places and things [10]. They also characterize contextual information as identity, location, status (or activity), and time. Whereas Lee et al. categorized context, in their mobile contexts framework, into personal and environmental context as depicted in Figure 1 [11].

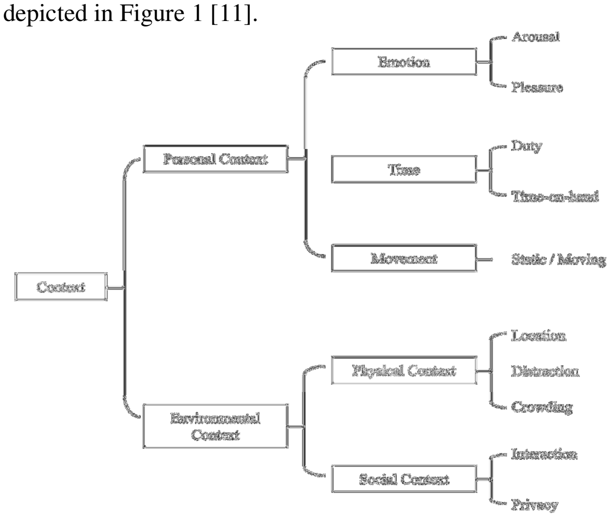

Figure 1. Framework of mobile contexts (adapted from [11])

The effect of context on specific mobile service usage has been studied by different researchers, through different research instruments (usually surveys). The studies typically define contextual variables, representing context, in different ways in order to study contextual determinants of the service(s) usage.

One classic study to explore effect of context (specifically time and location context) on the use of mobile internet was done by Sidel and Mayhew [12]. The location context was determined as home, work/school, commute and leisure, each of which was further detailed into micro-contexts (e.g., bedroom, kitchen, bathroom, etc. in home context). The study suggests that effect of time and location context on service usage is low.

Lee et al. study intended to identify contexts [11], where mobile internet services are likely to be used more frequently, through a longitudinal study. The study defined a framework (depicted in Figure 1) of mobile context centering the concept of *Use Context* which is defined as, "the full set of personal and environmental factors that may influence a person when he or she is using a mobile Internet service". Both environment and personal context were observed to affect internet usage and the service usage was clustered around few contexts.

Esbjörnsson and Weilenmann studied voice conversation over mobile phone in different contexts [13]. Contexts here were different environments (classroom, car and change room). The study finds that users find certain contexts felt inappropriate for such use (cloth change room and classrooms), while some context were preferred (driving a car). The study concludes that context has a significant impact in the mobile usage behavior and implies the need of context-aware applications.

Mallat et al. studied the effect of context on mobile service adoption taking mobile ticketing service for the analysis [14]. Her study was based on TAM and diffusion of innovations theory. It added a construct of use-context as a mediating construct for Perceived Usefulness (PU) and mobility, in effecting intentions of service usage. The context construct here was defined as, 'the conditions that users meet when they use mobile services in different places and times'. The study finds that the effect of PU and mobility was fully mediated by use-context and indeed PU had no significant direct effect on intentions.

Verkasalo defines a context identification algorithm (specifically location context) based on the handset-based measurement method and studied differences in service usage across observed contexts [1]. Location context was defined in terms of home, office and on-the-move context, and the study observed the difference in usage patterns of multimedia services across these contexts.

Recently, Xu and Yuan highlighted the impact of context and incentives on the behavioral intentions to use mobile service (particularly m-commerce) [15]. Context in the study was defined in categories of personal and environmental context and the context variables concerned the observed service of GPS-based taxi dispatching system. The variables defining environmental context included location (rural or urban), weather (bad or normal), time (rush hour or normal hour) and personal context included mobility (user can easily move around or not) and urgency (taxi needed urgently or not). The study finds significant impact of context on the service usage.

Most of the studies in the literature review were found to be focused on a specific service, which limits the external validity of the analysis, especially when perceiving context as variable shaping behavior of mobile user in a holistic way. Therefore, this study intends to highlight the effect of contextual factors on the smartphone usage, not through a particular service but by analyzing complete handset usage. Also, existing studies typically observe the effect of context on behavioral intention to use a service, which can be different from the contextual factors which trigger the actual usage.

The context is also observed to be defined in different ways by researchers. Variables defining the contexts (even if it was labeled the same e.g., location) were diverse too. One possible reason could be the indefinite number of prospective contextual variables. We also choose different variables for defining context, which were observed accurately through the handset-based measurement method of the mobile user behavior. This provides a novel insight on the usage of smartphones, observed through a different set of contextual parameters.

III. RESEARCH MODEL AND HYPOTHESES

The literature about context gives an overview that context is a broader concept and can be elucidated from different perspectives. There can be numerous contextual parameters that effect handset usage (of different services), in different ways. Being able to capture all contextual information, of mobile service usage, is difficult. However, with our handset-based measurement methodology we are able to get part of it accurately. The contextual information we model here includes day of the week, time of the day, location (international roaming) and battery status of the device. From the categorical context description view, we have objective behavioral information pertaining to time context, computing context and user context, as depicted in Figure 2. However, it should be noted that this model represents *partial context* as per the availability of objective mobile usage-information. But, the model presented is extensible and cater for further contextual information if available.

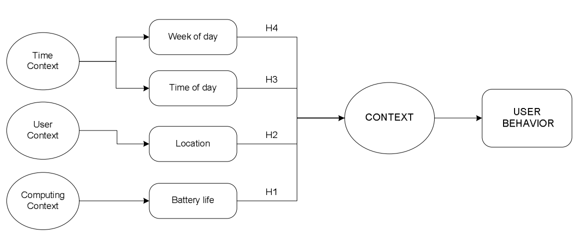

Figure 2. Research model

In order to form hypotheses, we take prior research work concerning these contextual factors as our starting point. For battery status, we use results from Rahmati and Zhong [19] study about *human-battery interaction* in user-centric perspective. The survey-based study provides insight about how people perceive battery indicators, their charging patterns, and their knowledge about power consumption from different services. Hypothesis regarding roaming is grounded on Europe wide study "Eurobarometer", commissioned by European Commission's Directorate-General Information Society and Media [20]. The study suggests that there is a clear difference observed in handset usage when roaming abroad and highlights the influencing factors. Hypotheses referring day of the week usage are based on the research on mobile internet usage by Sidel [12]. The study investigates whether context in which mobile internet is used, and specifically time and location context, differentiates mobile internet usage behavior. Day of the week hypothesis takes root in two separate studies (see [17]; [18]) which analyze mobile traffic at the web portal. Both the studies provide different insights about the weekend usage. Previously, the effect of context on all mobile services (and thus smartphone as a whole) has not been studied in detail except for voice and internet services. Therefore, in order to have a better understanding about the influence of context on the usage we do alongside exploratory research as well.

H1: Lower battery status increases likelihood of using basic voice service over other services

"Only 31% of the mobile users in our user survey correctly pointed out voice communication as a large power consumer. From the remaining 69%, 39% chose text messaging as a large power consumer while text messaging is usually much more energy-efficient than a voice call to convey the same message, as our measurement indicated." [19]

People consider smartphone as a communication device and voice as the most crucial mobile communication application. Moreover, they consider voice to be less power consuming application for communication, relatively, as shown in the study by Rahmati et al. [19].

H2: While roaming internationally, likelihood of using price-sensitive applications (e.g., voice, messaging and browsing) decrease significantly

"A clear majority of users limit their mobile communications when travelling abroad" AND *"The survey demonstrates clearly that excessive communication costs are by far (81%) the main reason why Europeans use their phone less often when travelling abroad"* [20]

The hypothesis is derived from Eurobarometer; the survey-based study is done in 25 member states of the EU, during that time, on 24,565 people (see [20]).

H3: Evening time (16:00-23:59) increases the likelihood of using mobile browsing

"Over half of respondents (54.8 percent), however, report that no day-part exceeds evening (18:00-24:00) in MobileNet usage." [12]

"Investigating whether heavy users have a particularly high proportion of their usage in any particular day-part, we find the strongest correlation between minutes per day and percentage of usage in the late night/early morning (0:00-6:00") [12]

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Hypothesis 3 is based on survey study by Sidel and Mayhew on the use of mobile internet by Japanese consumers [12]. It should be noted when interpreting results, that this study uses eight-hour time slot and divides day into three intervals referred as Morning, Evening and Night. Whereas, in Sidel study it is divided into four intervals of six-hour each. Also, Sidel study considers all services accessed on mobile internet, encompassing several services (e.g., browsing, email clients, instant messaging services, etc.)

H4: Weekend affects the use of browsing application on smart phones compared to weekdays.

"…Second, if you view the percentage of traffic over a weekly period, day by day, the weekdays are fairly regular and the peaks are found on the weekend days" [18]

"The relative importance of different categories did not change between weekdays and weekends (except stock quotes and sports). However, the amount of data accessed over the weekend drops by 45%." [17]

The hypothesis 4 is derived from a study on mobile internet by analysing traffic on mobile portal [18] and a study on wireless browsing patterns on popular web portal specifically designed for cell-phone and PDA users [17]. Halvey et al. study suggests a possibility of higher use on weekends, but Adya et al. study finds no significant difference in the weekend and weekday browsing use except for some application categories. However, both the studies are done during different time periods and it should be noted that increase in traffic could be a consequence of more intense data sessions and/or frequent application usage. Therefore, an open hypothesis is given regarding the browsing usage by day of the week context.

IV. ANALYSIS

A. Dataset

This article uses a dataset collected in fall 2007 of 579 users. Out of those, 255 active panelists (whose data has been consistently recorded) are included in the dataset. All of them had S60 3rd edition devices. Of the panelists, 31% have a GPS-enabled phone, and 52% have a WLAN-enabled phone; 81% are male, and 19% female. In addition, 77% of the panelists are less than 40 years old. This gender and age balance indicates that panelists are mostly early-adopters (typically tech-savvy younger men). Many (68%) of the panelists are in full-time work, and 20% are students. The panelists are recruited from the customer databases of all the major Finnish operators (TeliaSonera, Elisa and DNA), targeting only consumers. SMS invitations are sent to 27 000 consumers who own a smartphone, and do not resist operators' research oriented SMS messages. The panel study was arranged to collect data for better understanding market conditions and user behavior. All panelists were compensated with lump sum voucher of 20€ in the end of the study. Most people paid their bills themselves. The panel lasted for 1–2 months (depending on the time people signed up) between November 2007 and January 2008.

The following data points are used in the actual analysis:

- Application data
- Messaging data
- Location data (cellular tower ID codes)
- Time and date stamps of transactions
- Battery status data

B. Descriptive study

Descriptive statistics, in Figure 3, provides us with a summarized understanding about the behavioral dataset being analyzed. The statistical analysis further exhibits hard facts about the overall use of frequently-activated mobile services across different contexts.

In Figure 3, y-axis represents the average service-usage in terms of service launches normalized over *Active hours*. Active hours represent hours of the day where the device has been observed to be used at least once. Active hours along with different service launches are aggregated by different contexts, to present normalized launches per active hours.

It can be observed from the descriptive statistics that time of the day and location context seem to impact all observed services. But day of the week usage segregation, by weekend and weekday, does not indicate any notable change in the voice, messaging and browsing service usage. Battery level descriptive, in the Figure 3, do show some variation in the different services usage but it is difficult to deduce any conclusive usage trends.

The descriptive analysis gives an overview of overall effect of context on the service usage pattern. But the results of the analysis are not interpreted in terms of trends about the user behavior in smartphone usage, because of the aggregate nature of the descriptive analysis.

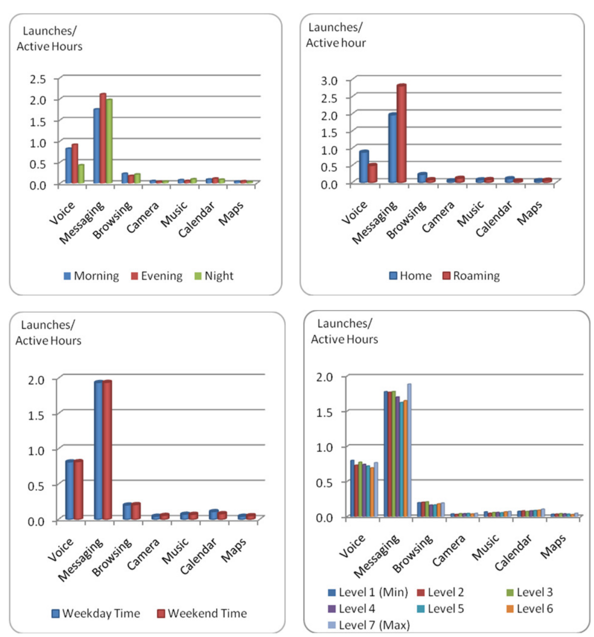

Figure 3. Contextual impact on smartphone usage

B.1.Statistical analysis

A logistic regression model is next deployed in analyzing smartphone user behavior. In exploring the likelihood of using the mobile service, the outcome is a dichotomous variable (service either used or not-used, for example) therefore logistic regression is a relevant method for the analysis. Use of this technique in related studies is studied in [22], [23] and [24].

The analysis is structured by the frequently used services on smartphones by the users. These services cumulatively account for more than 70% of the total handset usage, observed in the sample population. Observed smartphone services include: voice, messaging, browsing, camera, music, calendar and maps services. Regression analysis is run for each of the service using SPSS Statistics (v.16) software package. Typical output of logistic regression is odds ratio, but for easier interpretation output is presented in terms of *percent-change* in odds, of using a service. Having fitted the model, it is also required to assess the adequacy and significance of the model. Without assessing the fit of logistic model, consequences could be adverse [21]. Goodness-of-fit of all models is reported with both, the Hosmer–Lemeshow (H-L) and Omnibus tests of model coefficients. Coefficient of determination (R^2) is also checked in analysis.

An omnibus test of model coefficients test has positive response for all the models. Chi-squares listed under this column represents drop in deviance (-2Log likelihood) in model with variables included, compared to intercept-only model (model without variables). The chi-squares observed for all the models are statistically significant as well. Suggesting that model with predictors is significantly different from zero variable models.

H-L goodness-of-fit test divides the cases into deciles (referred as "deciles of risk") and computes a contingency table for H-L test, with predicted probabilities. It then uses observed and expected frequency to compute chi-square. *p* value then is calculated from the chi-square distribution with 8-degrees of freedom [25] and if it is greater than 0.05, research is unable reject the null hypothesis that there is no difference between model-predicted and observed values. Thus indicating that model fits the data at an acceptable level. The statistical analysis releveals that H-L test is statistically significant for all models except for Music service model. This suggests that (based on the difference between observed and predicted values) most of the models tend to favor alternate hypothesis, which means model prediction capability is not statistically sound (except Music service model).

Coefficients of determination (R^2) values, which indicate the proportion of variance explained by the predictive models, are also checked. For logistic regression R^2 is computed observing the difference between null and fitted model and are often referred as *Pseudo* R^2. We study two R^2 values, namely Cox and Snell and Nagelkerke, they both are computed using the concept of log likelihood differences between null-model and fitted-model. R^2 value ranges from 0 to 1, with 1 representing saturated model (model explaining full variance in the dataset). It can be seen that R^2 values are lower in the models, but as stated by Hosmer and Lemeshow [25] that R^2 are typically low even in well-fitted logistic regression models. Hence one should avoid its comparisons with other regression models.

B.1.1. Voice

Voice service includes both outgoing and incoming voice calls on the smartphone and accounts for 17.7 percent of total handset usage. Regression analysis reveals that time context has a substantial impact on the voice service usage followed by user and computing context. During Morning (08:00 – 15:59) and Evening (16:00-23:59) odds of using voice service increase by around 138 percent and 80 percent, respectively. Also, compared to travelling abroad when at home odds of using Voice are 99 percent higher approximately.

Battery status, denoting here computing context, brings out worth-noting paradigm of handset usage. It reads, with every unit increase in battery status odds of using Voice service decrease by roughly 3 percent. Thus, it can be argued that usage of voice increases when battery runs low. Therefore, hypothesis 1: '*Lower battery status increases likelihood of using basic voice service over other services'* is favored. Likelihood decrease in voice usage, also aligns with hypothesis 2.

B.1.2. Messaging

Messaging service here includes SMS, MMS, IM and other applications used through messaging application on Symbian S60 handsets. This service represents 43 percent of total handset usage.

Location seems to have deeper impact on the use of messaging service. It is likely to be used more when roaming abroad. Hypothesis 2: "*While roaming internationally, likelihood of using price-sensitive applications (e.g., voice and browsing) decrease significantly*" is not supported here. Messaging is more likely to be used during the usage of handset at nights. Also, greater battery status can enhance its usage.

B.1.3. Browsing

Browsing service refers to use of web browser from the handset and it corresponds to 4.1 percent of the cumulative mobile usage.

The study finds that location of the user has the most profound effect on its usage. Odds of using browsing service are around 242 percent higher when at home, compared to roaming internationally, thus supporting hypothesis 2. There is no significant difference between browsing use on weekend and weekday (in terms of service launches) therefore Hypothesis 4: *"Weekend affects the use of browsing application on smart phones compared to weekdays"* is rejected here.

Morning time is likely to lessen mobile web browsing usage, while the usage also decreases with increasing battery status. But no significant difference is found in

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usage difference during evening time and night time. This rejects hypothesis 3: *"Evening time (16:00-23:59) increases the likelihood of using mobile browsing"*.

B.1.4. Camera

Camera represents one percent of net smartphone usage. Although there is no hypothesis concerning camera usage, but it is essential to explore effect of context on this important service to model smartphone usage.

It can be observed that camera is more likely to be used on weekends. Besides, location-context has a high effect on its usage, with 55 percent (approximately) less odds of being used at home compared to abroad. Also its usage is likely to be more when battery level is high and during the evening time.

B.1.5. Music

Music applications on Symbian phones account for 1.5 percent of total handset usage.

Location context here appears to have no effect on music service usage. But time of the day and battery status has an impact. It is likely to be used more during the night hours and with battery levels on the upper side.

B.1.6. Calendar

Calendar is the mostly used application after Messaging, Voice and Browsing. It stands for 2.2 percent of the entire usage.

Calendar is more likely to be used on weekdays (around 42 percent higher odds than weekdays) and during the morning time (34 percent higher odds). Context of location has a significant impact, with approximately 130 percent more likely to be used at home (compared to abroad). Battery-life also has a deeper impact on Calendar usage compared to other services observed.

B.1.7. Maps

It represents use of different applications which activate GPS use on the device. Its use in the dataset is observed to be 0.9 percent of the total usage, with logistic regression analysis.

It is observed that Maps service is less likely to be used on weekdays but is more likely to be used during Morning time of the day. Also, usage is likely to increases with the increasing battery status.

V. DISCUSSION

The context, defined here by the variables: day of the week, time of the day, location (international roaming) and battery status of the device, is found to have an considerable impact on smartphone usage. It is observed that chances of using voice service are higher than other service in low battery status. This adds to the findings by Rahmati et al. [19], where people were observed to have an opinion that voice service consumes less power relatively, by confirming preference for voice service in case of low battery status. But this does not necessarily establish a potent causal relationship between low battery status and voice service usage, because of other factors (e.g., psychographic or motivational) which possibly can impact the usage as well, but are left outside the scope of this study. Other than browsing service which follows the same trend as voice, rest of the services are more likely to be used with higher battery power still in the handset.

Time of the day context, is observed to impact all the observed services and potentially music and maps service. Some services are more likely to be used during specific time periods. For example, voice, calendar and maps are preferred more during the morning (8:00-15:59) and camera in the evening (16:00-23:59) time. The study also finds no significant increase in mobile browsing likely-usage during evening time, thus finding an exception for mobile browsing use to Sidel [16] study's mobile internet findings.

Location context, defined here in terms of international roaming status, had a considerable impact on all service except music and maps. For voice and browsing the likelihood of using the services abroad is found to be reduced drastically, but for messaging the chances of using it abroad are found to be higher. This complements the findings by Eurobarometer study [20], but with an exception of messaging service. This has implications for price regulatory bodies in deciding fair charges for roaming consumers, backed by their usage behavior.

Day of the week context segregation by weekends versus weekdays is found to have less effect on smartphone usage, comparatively. More frequently used services including messaging, voice and browsing were found to be used evenly across defined day of the week context, while camera and maps are likely to be used more on weekends. Such a behavior can be fueled by several factors, analyzing those factors might help categorizing services from a different perspective (e.g., everyday services, weekend services, holiday services).

All the contextual variables analyzed were observed to influence smartphone usage, though to a varying degree. This is in-line with the reviewed existing literature in this research area. But some of the results provide different insights than the previous studies, as observed from the objective behavioral-data analysis.

VI. CONCLUSION

This research analyzed effect of context on smartphone usage, by first defining context in terms of variables (time, week, battery status and location). The novel method of analyzing context through handset-based measurement method is found to be empowering for analyzing use-context of smartphones.

The regression analysis revealed that time context, user context and computing context measured by time-of-the-day / day-of-the-week, user location and battery status of smartphone, significantly vary usage of most mobile services. It is also observed that, day-of-the-week time

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context does not seem to have much impact on most frequently used services (messaging, voice and browsing).

This analysis may have implications for designing of context-aware applications for smartphones. For example, making more likely-to-be-used services in a certain context quickly accessible to the users by dynamically adjusting user interfaces. Also, identifying usage context and analyzing contextual user behavior can open up new themes of mobile advertisement based revenue models for involved businesses. In particular, targeted advertising based on context is likely to be one of the future things that will transform the advertising business One a broader scale, the research about observing contextual information through smartphones, can also reveal valuable social and ethnographic information about people, and through "reality mining" new models explaining the behavior of people can be observed [16].

The study has certain limitations which should be considered when interpreting or using the direct findings:

- A small number of people from whom comprehensive datasets were collected
- Sample bias (e.g., male biased dataset) and problems with representativity (early-adopter smartphone users)
- Low level of variance explained by the dataset analyzed. One possible reason could be fewer contextual variables available in the dataset.
- Not enough data yet to confirm findings in a confirmatory study setting.
- Services which are used less frequently, each of which account for less than 0.9% of the total handset usage, are scoped out for simplicity reasons.

Future research should try to capture as many contextual variables as possible to have a more comprehensive analysis of context impact, on the smartphone use. Given the platform, future work should also focus on mobile services in the *long tail* of smartphone service usage. It should also analyze determinants of smartphone usage other than contextual factors simultaneously. This could help quantify impact of context in comparison to other factors, influencing mobile user behavior. This also highlights mediating effect of contextual factors.

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