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Understanding Mobile Application Usage Using Battery Status and Wi-Fi Network

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Abstract

Since the prevalence of smartphones, the smartphone application (app) industry has penetrated rapidly. Such growth encourages a deeper understanding of mobile user behavior. Using contextual information, previous studies have attempted to understand when users launch different types of app categories. However, most were limited to the number of apps and categories. This study aims to contribute to the general understanding of mobile app usage in a wider range of categories. We analyzed contextual information that influences smartphone users' anxiety, such as the battery state and Wi-Fi network. We empirically examined a distinctive data set that contains mobile log data across a panel of users. As a result, our findings demonstrate that contextual features such as battery charging duration and Wi-Fi connection are highly related to the choice probability of app category usage. It reveals the importance of dynamic conditions incurred from the battery state and Wi-Fi connection when users choose which app to launch. Our findings have practical implications for smartphone app companies who seek app-targeting strategies or marketers who use mobile apps as a means of advertising to interact with potential customers.

Keywords: mobile industry, battery state, choice model, mobile app usage

Introduction

Due to emerging techniques in computing and ubiquitous usage of mobile devices, the mobile application (app) industry has thrived with an increasing number of apps available in mobile markets. Smartphone users increase the amount of time they spend on apps. App Annie, an app data platform, found that users launched 30 apps each month and at least 9 apps per day (App Annie 2017). With the growth in app usage, people also install new apps at a high rate. Mobile apps are expected to generate up to \$189 billion in revenues by 2020 (Mobile app download and usage statistics 2019). Such a growth of smartphone and app industries requires a deeper understanding of mobile user behavior to develop new marketing strategies in related industries.

Academia has attempted to understand users' behavior in mobile environments, especially the contextual usage of mobile apps. Scholars have studied mobile data to understand the situations in which mobile phone apps are used. Some studies have explored contextual features that are related to app usage (Huang et al. 2012; Shin et al. 2012), while others have focused on techniques for app usage prediction and identification using specific smartphone devices (Xu et al. 2011; Tongaonkar et al. 2013). However, previous studies selected a limited number of apps and categories. Therefore, due to limited access to the data and its idiosyncrasy, little has been identified about the mobile industry.

Thus, this study aims to contribute to the general understanding of mobile app usage in a wide range of categories. In addition, we analyzed contextual information that increases smartphone users' anxiety, such as the battery state and Wi-Fi network. We conduct an empirical investigation using a distinctive data set that contains mobile log data across a panel of users. Our sample consists of individual-level mobile data records obtained from a market research company. Our study uses mobile environment data, including app activities, battery level data, taxonomy, and demographic information. Our findings demonstrate that contextual features such as battery charging duration and Wi-Fi connection are highly related to app usage. The results reveal the dynamic conditions that create anxiety and pressure toward smartphones and when users prefer to use certain apps.

The remainder of this paper is organized as follows. In the next section, we review related literature and describe our research question. Section 3 outlines our data and variables, and we introduce the empirical model in section 4. Our empirical findings are discussed in section 5. Finally, concluding remarks are presented in section 6.

Related literature

Around 3.5 billion people use smartphones worldwide; in other words, almost one in three people owns a smartphone (O'Dea 2020). This phenomenon has led to an increase in the number of studies that analyze mobile data to understand the mobile app usage behavior (Xu et al. 2011; Tongaonkar et al. 2013) because smartphones allow researchers to expand the spectrum of mobile behavior research. Previous literature has examined the dynamics of mobile behavior. Kim et al. (2017) studied mobile shopping behavior in terms of shopping app possession and mobile purchasing through such apps. Ghose and Han (2011) examined mobile Internet usage, specifically comparing mobile-phone-based content generation behavior and content usage behavior.

Some studies have explored contextual information such as location, time, and previously used apps to understand and predict when and where apps are used (Verkasalo 2009; Böhmer et al. 2011; Huang et al. 2012). Froehlich et al. (2007) presented a MyExperience framework that uses mobile computing activities to understand how users experience mobile technology. They found that while users are moving, they are more likely to use the SMS service. However, these studies were based on a similar set of contexts, such as location and time, with a limited number of apps. Shin et al. (2012) expanded the range of contextual information in a smartphone. They found that the battery state has relatively poor performance in app usage prediction.

However, Banerjee et al. (2007) found that smartphone batteries have an impact on usability in mobile services, such as users mobile habits. The increasing dependency on mobile phones for daily life leads to battery reliance. A survey by LG revealed “Low Battery Anxiety,” which is anxiety regarding the battery level dropping, particularly when it is at a low level. (20 percent or lower) (LG 2016). A low battery may arouse great anxiety among people, and it may lead people to change their mobile behavior (Tang et al. 2020). Therefore, the smartphone battery state is a significant condition to be considered when studying mobile usage patterns in academia.

Understanding the relationship between smartphone battery level and users’ behavior is also critical in the industry. Considering the emerging mobile techniques such as mobile streaming services, advanced marketers have started to deliver mobile streaming ads on social media such as Facebook to interact with consumers. The view counts and time directly influence the company’s profits. However, according to a survey by Tang et al. (2020), users are more likely to turn a video off if they have low battery power. Following this, the battery level has a significant impact on leading users to watch streaming videos.

Wi-Fi network is also a key feature in the mobile world. Along with battery consumption anxiety, cellular data consumption may be another trigger that arouses anxiety. Compared to the 3G/LTE network, users could consume mobile data in a distinct way with a Wi-Fi network, especially for apps that users run for a long period, such as video streaming. Joe-Wong et al. (2015) compared the usage patterns of the most-used apps between 3G/LTE and Wi-Fi. Even though the same apps appear for cellular data and Wi-Fi, the results reveal the distributions of app usage are different. The usage percentage of social media apps, which stream videos, is relatively higher for Wi-Fi connection than for cellular data.

Despite the significance of both the smartphone battery state and Wi-Fi network, there is a lack of research on the mobile industry. These features were not focal in mobile data research but were rather considered as control variables. This study explores how mobile conditions in the context of battery state and Wi-Fi connection influence app usage behavior to demonstrate their importance in mobile behavior research.

Data

Our study is based on mobile panel data from an international market research company, TNS. TNS collected the mobile data of each phone using a mobile app. TNS Korea, a subsidiary of TNS, gathered information regarding smartphones from recruited Android smartphone users. They used a tracking app to collect not only phone-related information

such as smartphone brands and mobile service operators, but also log data, which refers to activities such as activated apps, duration, and battery level. We studied one-month mobile log data for 500 users, collected in December 2016.

Based on given information in each app, such as communication, social media, lifestyle/transportation, shopping, finance, reading, photo, media/video, entertainment/game, and audio/music, we segment the apps into ten representative groups for selection of alternatives.

We extract contextual information from mobile log data to understand a user’s situation or that of their environment. We derive the status of a user’s mobile phone and its surroundings from the environmental features in the data. Table 1 presents the variables and their descriptions. From the battery, we derive the current battery level and charging status. To represent the physical environment, the Wi-Fi status is included.

With the information from the battery charging status, we measure how long a user charges their phone between the period when they start to use a phone and when they start to run a particular app. Because the mobile log data is only available when a user activates their phone, we cannot estimate the status of the phone during the non-activated period. To use only actual values, we exclude the situation when a user does not use a phone. For example, if a user starts to use a phone when charging their phone battery at 11:00:30 a.m. and they run Facebook at 11:01:30 a.m., the charging session until using Facebook is one min. The battery charging duration is then recorded as sixty seconds for the Facebook app.

We include smartphone hardware information that is likely to influence mobile behavior. The smartphone brand is categorized with four values representing the top three brands in the data and one for the remaining brands. Smartphone display size represents the phone’s diagonal length in inches. Telecom represents three major mobile service operators based on categorical values.

We also control for socio-demographic variables that are relevant in mobile behavior research (Ghose and Han 2011; Choi, Bell, and Lodish 2012; Kim et al. 2017). The variables included age, age squared, and gender. Gender is categorical, so it has a value of 1 for female and 0 otherwise. For time variables, we segment the time windows into four groups: 00:00 to 06:00, 06:00 to 12:00, 12:00 to 18:00, and 18:00 to 24:00, to control for app usage dependency on periods. To control for weekend versus weekday, we included a categorical variable, “day of week,” which equals 1 if a user uses a phone during the weekend and 0 otherwise. Finally, app duration is how long a user uses a particular app in seconds. Table 2 presents the descriptive results of the variables used in the analysis.

Table 1. Variable description

Contextual Information		Values
Independent variables		
Battery	Battery level	{0, ..., 100}
	Charging duration (log form)	{0, ...}
Wi-Fi	Wi-Fi status (Wi-Fi)	{on(1), off(0)}

Time	hour of day (Time interval)	{morning(1), afternoon(2), evening(3), night(0)}
	day of week (Time week)	{weekend(1), weekday(0)}
Demographic info	User ID	{user1, user2, ..., other}
	Gender	{woman(1), man(0)}
	Telecom	{SKT(0), KT(1), LG U+(2)}
	Age	{15, 16, ..., 59}
	Smartphone display size	{4.5, 4.7, ..., 29}
	Smartphone brands	{Samsung(1), LG(2), Pantech(3), etc(0)}
App	App duration	{0, ...}
Dependent variable		
App category	communication, social contents, lifestyle/traffic, shopping, finance, reading, photo, media/video, entertainment/game, music/audio	

Table 2. Descriptive results

Category	Freq.	Percent
Communication	2,609,925	32.12
Social media	1,203,624	14.81
Lifestyle/Transportation	1,722,296	21.2
Shopping	1,365,501	16.81
Finance	426,799	5.25
Reading	180,057	2.22
Photo	142,357	1.75
Media/Video	114,622	1.41
Entertainment/Game	228,684	2.81
Audio/Music	131,168	1.61

Independent variable	Mean	Std. Dev.
Battery level	61.497	25.273
Battery charging duration (log)	0.130	0.572
Age	31.875	10.522
Smartphone display size	18.371	5.403
Application duration	1.078	1.321

Model

To analyze the underlying usage behavior, we estimate individual-level panel data using a

multinomial logit model (MNL). The MNL choice model has been used to compute the probability of the different choices in categorically distributed data, such as product purchases in supermarket scanner data (Guadagni and Little 1983). MNL is an appropriate method for our data to classify which category of mobile app would be selected by users in different situations because our response variable is nominal.

Communication apps were used as the reference category for comparison with other app categories. The model estimated the choice probability of choosing alternative categories compared to the choice probability of choosing the reference category.

The app category, denoted by Y , is the dependent variable. Battery state, Wi-Fi state, and other control variables are the independent variables, denoted by $X_{i1}, X_{i2}, X_{i3}, \dots, X_{ik}$, where i refers to the observation and k refers to the number of independent variables.

When the dependent variable has M categories that are unordered, if we assume the communication category, the baseline category, as the first category (1) in M , then, for $m = 2, \dots, M$, the model is expressed as

$$\ln \frac{P(Y_i=m)}{P(Y_i=1)} = \alpha_m + \sum_{k=1}^K \beta_{mk} X_{ik} = Z_{mi} \quad (1)$$

β_{mk} refers to the coefficient vector for m^{th} the level of the response variable. β_{mk} can be interpreted as if there is a one-unit increase in the independent variable, there will be a change in the multinomial log-odds of the preferring category m to the reference category, holding other independent variables constant. For each case, the result will be $M - 1$ number of predicted log-odds.

For the non-reference categories, the choice probability P of choosing alternative m out of M can be calculated from Z as

$$P(Y_i = m) = \frac{\exp(Z_{mi})}{1 + \sum_{h=2}^M \exp(Z_{mi})} \quad (2)$$

For the reference category, the choice probability can be expressed as

$$P(Y_i = 1) = \frac{1}{1 + \sum_{h=2}^M \exp(Z_{mi})} \quad (3)$$

Any other category can be the reference group in this model, and the model fit would be unchanged. However, the interpretation should change because the baseline category and coefficients will be different. This study selected the category with the largest sample size as the baseline.

Findings

Table 4 presents the estimated results from the multinomial logit model. The numbers represent the coefficients in terms of multinomial log-odds (logit) for each independent variable. The reference category in the model mentioned above is communication apps, referring mailing and messaging apps such as KakaoTalk, WeChat, LINE, Skype, and SMS messages.

We find that a longer battery charging period and Wi-Fi connection increases the probability of choosing lifestyle ($\beta_{charging_dura} = 0.040, p < 0.1; \beta_{wifi} = 0.482, p < 0.01$), shopping ($\beta_{charging_dura} = 0.083, p < 0.01; \beta_{wifi} = 0.595, p < 0.01$), and financial apps ($\beta_{charging_dura} = 0.076, p < 0.05; \beta_{wifi} = 0.390, p < 0.01$) over communication apps. For these categories, deliberate consideration is relatively important for making decisions. For example, people use lifestyle/transportation apps to reserve transportation or food delivery services, which require more time than sending a message through communication apps. In other cases, since shoppers spend more time using shopping apps rather than offline shops, they want to be in a comfortable condition in which there is no concern about the phone's status while shopping. If the battery is uncharged and Wi-Fi is not connected, they feel that there is only a limited amount of time on their phone, which likely leads to unusual choices or exiting the app. In contrast, a longer charging period ensures high battery power, which can reduce anxiety regarding low battery level. Therefore, both lengthy battery charging sessions and Wi-Fi connections encourage the use of these app categories without anxiety.

Mobile users prefer social media apps ($\beta_{charging_dura} = -0.054, p < 0.1; \beta_{wifi} = 0.392, p < 0.01$) to communication apps when the smartphone is charging only for a shorter period with Wi-Fi connection. Through social media apps, people not only frequently check their feeds to share and talk about content, but also watch videos. Habitual feed checkers, who need only a brief time on apps, may not need a lengthy charging period, but need Wi-Fi connection because it takes longer in app sessions than communication apps ($\beta_{app_dura} = 0.230, p < 0.001$). Video-watchers with social media apps may want to save battery power and data consumption, so they would start charging their phone and connect Wi-Fi before using the apps.

Wi-Fi status is positively correlated to the choice probability of media/video, entertainment/games, and reading apps over communication apps. Wi-Fi connection reduces anxiety toward data consumption, which leads users to use media/video, entertainment/game, and reading apps, which consume more mobile data than communication apps. However, battery charging duration has no significant effect on the usage of these categories.

The shorter battery charging duration is positively correlated with photo and audio/music apps. Users do not need to ensure high-level battery power when they use such apps because these categories do not usually waste the battery level.

Interestingly, the battery level itself has no significant direct impact on the app category decision. This suggests that, unlike charging patterns and Wi-Fi connections, the battery level does not reflect users' overall anxiety when using mobile apps.

We found that all time control variables significantly affect the usage of mobile apps in each category. Compared to communication apps, users are more likely to choose apps in all other categories during the morning period (6 a.m. to 12 p.m.). The day control variable that distinguishes between weekends and weekdays also has a significant impact on mobile app category choice in all cases.

Table 3. Estimate results

	App Categories								
	social	lifestyle/ transportation	shopping	finance	reading	photo	media	enter/ game	audio
Battery level	-0.002	0.003***	0.001	0.000	0.002	0.000	0.000	0.004	0.002
Battery charging duration	-0.054*	0.040*	0.083***	0.076**	-0.067	-0.102***	0.040	0.064	-0.065**
Wi-Fi: On	0.392***	0.482***	0.595***	0.390***	0.330**	0.048	0.535***	0.378**	-0.156
Gender: Female	0.829***	-0.147	0.726***	0.175	0.041	0.294*	-0.665***	-0.021	0.355
Age	-0.196***	0.300***	0.305***	0.376***	-0.069	-0.017	-0.011	0.129	-0.209**
Age Squared	0.003***	-0.003***	-0.003***	-0.005***	0.001	0.000	0.000	-0.002	0.002
Smartphone display size	-0.008	-0.016	-0.031*	-0.005	0.027	-0.027	0.002	0.064**	-0.049
Telecom: KT	0.029	-0.038	0.132	-0.105	0.548**	0.029	0.309	-0.246	0.023
Telecom: LG U+	0.084	-0.462**	-0.215	-0.462*	-0.050	-0.118	0.197	-0.370	0.232
Smartphone brands: Samsung	-0.209	-0.092	-1.002**	0.094	0.567	0.405	-0.328	1.115**	1.392
Smartphone brands: LG	-0.477	-0.312	-1.291**	-0.128	0.372	0.426	-0.551	1.476**	1.035
Smartphone brands: Pantech	-0.340	-0.183	-0.454	0.094	0.416	0.394	-0.915	0.806	0.485
Time interval: Morning (6am - 12pm)	0.236**	0.292***	0.457***	0.204*	0.534***	0.138*	0.375**	0.422***	0.302***
Time interval: Afternoon (12pm - 6pm)	-0.180***	0.127***	0.162**	0.178***	-0.071	-0.131***	-0.345***	-0.339***	0.178*
Time interval: Evening (6pm - 12am)	-0.245***	-0.137***	-0.230***	-0.063	-0.347***	-0.017	-0.401***	-0.329***	-0.047
Time week: Weekend	0.114***	0.121***	0.084**	-0.075*	0.110***	0.203***	0.237***	0.146***	0.152***
Application duration	0.230***	-0.119***	-0.004	-0.061*	0.281***	0.376***	0.458***	0.390***	-0.004
Intercept	1.984	-6.462***	-6.439***	-8.930***	-3.179***	-3.430***	-3.332***	-7.725***	0.021

The reference category is Communication (1)

Significance level: * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Conclusion

Rapid growth of the mobile app industry encourages users to use diverse app categories. Following this trend, scholars have examined extensive contextual information to understand the situation when a user runs a particular app. However, little is known about battery and Wi-Fi status and how they are associated with mobile app usage. This study empirically analyzed mobile panel data to examine the unexplored features of smartphones and explain the relationships with mobile app usage behavior across the app categories.

Our results indicate that the preference for app category choice depends on condition variations of battery charging duration and Wi-Fi status. For example, users are likely to use lifestyle/transportation, shopping, and financial apps over communication apps when they have both longer charging duration and Wi-Fi, while they decide to use social media apps in shorter charging durations. These features help understand app usage behavior while they exert different degrees of influence across app categories. The pressure and anxiety from the smartphone battery state and Wi-Fi connection could predict decision-making in the mobile environment. Our findings on mobile app usage behavior cannot be inferred from previous studies on mobile data, and thus, we offer a significant contribution to the mobile environment literature.

Practitioners can use our findings to allow real-time analysis to implement app-targeting strategies across multiple categories. App companies can increase installation and usage of apps by focusing on marketing efforts under certain smartphone conditions that make users willing to use a specific app category. For example, to increase the usage and installation of shopping apps, marketers can target heavy battery chargers who always bring a phone charger with them. Marketers using mobile streaming advertisement through social media can target users who frequently connect to Wi-Fi networks and do not charge their phones relatively often.

The mobile app environment is growing rapidly; thus, there are tremendous opportunities for researchers and practitioners to build new findings. Our research made efforts to provide significant contributions to this area. However, this study has several limitations. First, due to data limitations, we could not include contextual information that was analyzed in previous literature, such as location. Second, future research can conduct an in-depth examination of what contextual information derives specific app activities (e.g., whether a user is taking a photo or looking for photos in an album). Third, mobile data tracking requires consent from users to monitor their mobile log data because of privacy issues. Thus, it is difficult to examine contextual information without the need for consent.

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