Moving Beyond Market Research: Demystifying Smartphone User Behavior in India

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Large-scale mobile data studies can reveal valuable insights into user behavior, which in turn can assist system designers to create better user experiences. After a careful review of existing mobile data literature, we found that there have been no large-scale studies to understand smartphone usage behavior in India – the second-largest and fastest growing smartphone market in the world. With the goal of understanding various facets of smartphone usage in India, we conducted a mixed-method longitudinal data collection study through an Android app released on Google Play. Our app was installed by 215 users, and logged 11.9 million data points from them over a period of 8 months. We analyzed this rich dataset along the lines of four broad facets of smartphone behavior – how users use different apps, interact with notifications, react to different contexts, and charge their smartphones – to paint a holistic picture of smartphone usage behavior of Indian users. This quantitative analysis was complemented by a survey with 55 users and semi-structured interviews with 26 users to deeply understand their smartphone usage behavior. While our first-of-its-kind study uncovered many interesting facts about Indian smartphone users, we also found striking differences in usage behavior compared to past studies in other geographical contexts. We observed that Indian users spend significant time with their smartphones after midnight, continuously check notifications without attending to them and are extremely conscious about their smartphones' battery. Perhaps the most dramatic finding is the nature of mobile consumerism of Indian users as shown by our results. Taken together, these and the rest of our findings demonstrate the unique characteristics that are shaping the smartphone usage behavior of Indian users.

CCS Concepts: •**Human-centered computing** →**Empirical studies in ubiquitous and mobile computing;**

General Terms: User Study, Usage Behavior, India, Smartphone Usage

Additional Key Words and Phrases: Smartphone Usage Patterns, User Behavior, India, Notifications, Battery Charging, Contextual Usage

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1 INTRODUCTION

Mobile phones have transformed from basic communication tools into powerful information, communication, sensing and entertainment devices. It is projected that by the year 2020, 5.4 billion people in the world will have

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a mobile phone – more than those projected to have electricity (5.3 billion), running water (3.5 billion) or cars (2.8 billion) [2]. This rapid growth in smartphone ownership, coupled with the emergence of app distribution channels such as Google Play and Apple's App Store, has made it possible for app developers to reach millions of users around the world with varying geographical, social, economic and cultural backgrounds.

To study smartphone usage patterns among users, ubicomp researchers have also leveraged the same app distribution channels and conducted various large scale, in-the-wild studies with real smartphone users. Falaki et al. [13] conducted a comprehensive study of smartphone usage to characterize the impact of user interactions with the device on network and energy consumption. Ferreira et al. [15] analyzed the contextual nature of application micro-usage, and found that social applications are the primary triggers for user-initiated micro-usage sessions. Other works have studied notification delivery on smartphones [29, 31, 37], mobile energy consumption [22], and prediction of next app use [39].

Despite the increased research activity in this space, we observe that there have been no mobile data studies aimed at understanding user behavior in one of the major smartphone markets in the world, namely *India.* Most of the existing mobile data studies (e.g., [13, 32]) were conducted with users in Western countries and thus their findings may not reflect the user behavior in India. A key reason for this major gap in mobile data literature is that the smartphone market in India has only matured in the last few years. Prior to that, the mobile phone market was dominated by low-end feature phones which had duly prompted a number of HCI studies [16, 25] on designing technology solutions for resource-constrained devices. Only in the last few years has there been massive smartphone adoption in India, making it currently the second largest smartphone market and the country with the highest Android device usage time in the world [5]. This suggests that smartphones have indeed become ubiquitous in India, and it is an opportune time to study how users in India are interacting with their smartphones.

In addition to the large user base, there is another reason that makes it interesting to study smartphone behavior in an Indian context: on one hand, India has a large urban English-speaking population, many of whom are employed in the global technology industry and whose smartphone usage patterns might overlap with global usage patterns. However, there are also major differences in terms of infrastructure availability (e.g., electricity supply, internet speeds) and everyday cultural and social norms, which might lead to unique variations in user behavior in this context. As such, we argue that it is critical for mobile developers and ubicomp researchers to obtain an in-depth understanding of how users in India interact with their smartphones, so as to design better mobile systems and experiences for the fastest growing smartphone market in the world.

In this paper, we present a mixed-method longitudinal study which provides a holistic view of the smartphone usage behavior of Indian users. Our 8-month study was conducted through an app released on Google Play. A total of 215 Android smartphone users from India participated in the study, generating nearly 11.9 million data points related to smartphone usage and context. This quantitative data logging was followed by an online survey of 55 users and in-depth interviews of 26 users from the original user pool to further understand their mobile usage behavior. As this is the first ever longitudinal ubicomp study in an Indian context, our goal in this paper is to paint a broad picture of the smartphone usage behavior of Indian users rather than understanding a particular micro-behavioral pattern about this group. To this end, our data analysis follows a highly exploratory approach, wherein we analyze the collected smartphone usage data through four broad lenses that are highly relevant for the ubicomp community:

- *Application Usage Analysis:* According to the market research firm App Annie [1], Indian users recorded the highest number of Android app downloads (6.2 billion apps) in the world in 2016. We explore the temporal variations in app usage of this user group, uncover the motivations behind installation, usage and uninstallation of certain apps, and analyze the relationship between usage of various app categories.
- *Notification Analysis:* In the modern smartphone usage paradigm, notifications serve the very crucial role of promoting content awareness by alerting users to newly available information. Therefore, we analyze

the receptivity of Indian users towards mobile notifications, and explore if notification delivery context has any impact on its receptivity.

- *Context Analysis:* A sound understanding of user behavior in different contexts can help practitioners in designing adaptable ubicomp systems. As such, we explore the role of personal context, device context, and socio-economic context in shaping the smartphone usage of Indian users.
- *Charging Behavior Analysis:* Human-battery interaction has been an important research topic in ubicomp research. By accurately understanding the battery charging preferences of users, mobile apps can intelligently schedule their energy-heavy operations. In this vein, we analyze the duration and temporal distribution of charging sessions for Indian users, as well as the impact of battery levels on users' decision to charge their phones.

While uncovering the smartphone usage patterns of users in India is the primary goal of this paper, our work also builds upon the recent mobile data research in the community. In a recent critique on mobile data studies, Church et al. [8] argued that ubicomp and HCI research communities should encourage "reproducing of mobile data studies in different parts of the world, with different user populations and at different points in time" as this will enable us to combine and contrast the findings from various contexts and geographies, and build a better and more complete understanding of user behavior. We fundamentally agree with this position and therefore, in this paper, in addition to thoroughly analyzing the smartphone behavior for users in India, we also contrast it against published mobile data studies which were conducted in other geographical settings. More specifically, we highlight the similarities and differences in user behavior across geographies, and show that if these nuances are not taken into account while designing data-driven mobile systems, the performance of these systems could significantly degrade in-the-wild.

Some of our most interesting findings are: a) users in India are extremely conscious about their smartphone's battery level – smartphones are charged very frequently in order to maintain a high battery level, and nearly 50% of the charging sessions happen within 80 minutes of the last session, b) while users are remarkably quick to glance at incoming notifications on their devices, the attendance rate of notifications remains very low, c) the temporal patterns of app usage among Indian users are in stark contrast with the findings of prior mobile data studies in Western contexts, and finally d) we found evidence in our data that the 'app-only' business model pitched by e-commerce providers in India goes against the behavioral patterns of the users.

In summary, this paper makes the following contributions to mobile data literature:

- We present the first ever longitudinal data collection study analyzing smartphone usage patterns in India, from the perspective of four key facets of smartphone usage.
- Our findings throw light on several previously unknown aspects of smartphone user behavior in India, and offer a holistic understanding of the fastest growing smartphone market in the world.
- We present a detailed analysis of the variations in smartphone usage patterns across multiple geographical regions, and discuss its implications for the ubicomp community.

2 RELATED WORK

Large-scale Mobile Data Studies and their Implications. In recent years, many mobile data studies have been conducted to assess smartphone usage patterns of various user groups. Bohmer et al. studied the application life-cycles on Android smartphones of 4,125 users, mainly across Europe and the US, over a 5-month period [7]. One of their key observations was the surprisingly short duration of app usage sessions. Ferreira et al. [15] built upon their work and found that 41.5% of all application sessions lasted less than 15 seconds. Falaki et al. [13] evaluated the impact of user interactions with the device on network and energy consumption. A similar 9-month-long study by Do et al. [12], involving 77 European participants, brings out locality-based application usage patterns. They found that users tend to use more synchronous communication modes (such as voice calls) over others in unknown or non-stationary locations. Comparable contextual results have also been observed by Rahmati and Zhong among 15- to 18-year-olds from below average income households in Houston, USA [35]. They found that participants also tend to spend more of their time - and record longer sessions - in areas with better WiFi connectivity. The influence of WiFi connectivity has been further discussed by Baumann et al. [6], whose results show that the probability of users generating data traffic on a WiFi network is twice that on a cellular connection. The implications of such results is enormous, and has thereby led to the development of comprehensive models of user behavior that can be utilized in order to improve usability and efficiency of smartphones. An exemplification of the same is the Markov state transition model of smartphone screen use that has been developed by Kostakos et al. as described in [20].

Behavior Analysis on Smartphones. Studies on smaller scale have also brought up other details of behavioral patterns of smartphone users. For instance, Jones et al. [18] explore app "revisitation patterns" using an application deployed on Google Play. By studying the revisitation curves showing how frequently users returned to an app, they were able to confirm several intuitive structures of usage. Van Berkel et al. [42] discovered and reported flaws with the prevailing approach of approximating sessions, finding that when users lock and unlock their smartphones within a short duration (e.g., less than a minute), they are more likely to be establishing a new session than continuing the previous one. This counterintuitive observation called for further research on smartphone session approximations, perhaps along the lines of the comprehensive quantification of smartwatch sessions presented by Visuri et al. in [43].

Notification preferences of smartphone users have also been explored in significant detail. Mehrotra et al. [27] designed smarter notification mechanisms by constructing association rules using combinations of text in the notification titles and the user's contextual aspects of activity, location and time. Mehrotra et al. [28] also designed classifiers to learn the most opportune moment to deliver notifications to users, based on content, social relationships, and application context. Additionally, a similar behavior analysis study aimed at youth in a Korean university was also conducted by Lee et al. [21]. This study, involving 95 students for a period of 67 days, sought to identify smartphone usage patterns of both "high/at-risk" and "non-risk" groups of users, who had been classified by pre-trial surveys. Sensor data from smartphones is also being utilized by researchers to study the behavior of users. Tsapeli et al. [41] detect the causal effects of several factors such as working, exercising and socializing on the stress levels of 48 students.

The dependency of user behavior on the context of the user has also been explored in prior research. The collection of quality contextual data has itself been an open challenge. Liu et al. [23] found that the perceived need for donation and the perceived organization reputation act as main motivators to encourage users to donate contextual data for studies. Numerous aspects of contextual dependence have been investigated in past studies. For instance, Karikoski et al. [19] studied the communication patterns of users based on parameters such as their location, mobile network cell ID, WLAN data etc. to determine their preference for length of voice calls, intensity of usage of email/SMS, IM or VoIP services etc. Liu et al. [24] questioned 267 users in China to build an adoption model of mobile gaming which indicated that context was the biggest influencer and predictor of mobile game adoption. The results of the above-mentioned works reiterate the need to examine the contextual factors driving user practices.

Another facet of user behavior that merits in-depth discussion is that of battery usage. Ferreira et al. in [14] investigate charging and battery usage patterns of over 4,000 users over 4 weeks. The study highlighted the energy wastage caused by users not unplugging their phones as soon as the charging cycle completed. Moreover, it asserts the value that users associate with the battery life of their devices, which is reiterated by the results of our independent survey. Hosio et al. [17] have attempted to systematically measure the monetary value of smartphone battery life and have found the prices of the first and last 10% battery segments to differ substantially.

Table 1. Facets of smartphone usage studied in the paper, along with the associated research questions

Facets of Smartphone Usage	Research Questions Addressed
Application Usage	How is the application usage distributed temporally? How long and how frequent are application usage sessions? What motivates the choice of applications among users? How does the usage of VoIP & IP messaging apps compare with traditional telephony apps? Why do users uninstall apps?
Notifications	How quickly do users respond to a notification? How effective are notifications in engaging the user? How does alert modality impact a notification's response time?
User Context	How does the user's physical activity context affect application usage? How are smartphone usage patterns impacted by the user's location? Can type of network connectivity have an effect on smartphone usage patterns? How does the broader socio-economic context affect smartphone usage of Indian users?
Charging Behavior	How does battery charging behavior vary temporally? How long and how frequent are the charging sessions?

Smartphone Usage Studies in India. As discussed previously, smartphone usage in India has been reaching new heights in the recent years. According to a 2016 report by business intelligence firm App Annie [1] , Indian users spent a staggering 150 billion hours on smartphones, a rise from around 100 billion hours in 2015. The report also predicts further growth in India's smartphone penetration. Another point to be noted from the report is that India leads markets such as China, South Korea, UK and the US in terms of the average number of shopping apps installed per user – pointing to the adaptivity of Indians towards mobile e-commerce as well as their tendency of comparing service providers before making a purchase. This is supported by Deshmukh et al. [10], who discuss the shift from e-commerce to m-commerce in India, and analyze the social factors that support this transition.

However, our understanding of Indian smartphone users is primarily restricted to marketing reports generated by business analyst firms. Usually the goal of such reports is to study the market opportunities and provide guidance to businesses, rather than looking into the nuances of user behavior that could be of interest to mobile researchers and developers. While there have been small-scale focused studies in the medical literature which have looked at addiction in mobile phone usage among Indian users [9, 11], to the best of our knowledge, no large-scale study has ever been done to develop a holistic understanding of smartphone usage behavior in India.

In this work, our goal is to gather large-scale smartphone usage data from Indian users, and systematically understand the various facets of smartphone use. We build upon prior mobile data research works, and also highlight unique aspects of smartphone usage among our target user group.

3 STUDY DESCRIPTION

In this section, we provide details of our user study to collect large-scale smartphone usage data from users in India. We begin by providing the study overview, which is followed by a description of our data collection system, study methodology, and participant demographics. Finally, we give a summary of the data logs collected in our study, and our analysis plan for the subsequent sections.

3.1 Overview

The domain of smartphone data analysis is clearly very broad, as is evident from the extensive and diverse research in this area as discussed in §2. In this paper, we focus our analysis on four broad facets of smartphone usage that are particularly relevant to the ubicomp community. These four facets along with the research questions explored within each facet are tabulated in Table 1 and explained below:

Application Usage Analysis: Mobile applications are at the core of the smartphone ecosystem – in 2016, a total of 90 billion apps were downloaded from Google Play and Apple App Store [1]. While a number of marketing surveys have been conducted on the growth and potential of the Indian app 'market', to the best of our knowledge, there has been no large-scale research study in the ubicomp and mobile systems community that provides detailed insights into the application usage behavior of this user group. In particular, we explore the *temporal patterns of app usage*, *distribution of app sessions*, *motivations behind installation, usage and uninstallation of certain apps*, and *relationship between the usage of various app categories.*

Notification Analysis: An in-depth understanding of the human-notification interaction can help mobile developers in creating intelligent notification delivery mechanisms that lead to higher user engagement. Our work specifically looks at the *receptivity and effectiveness of mobile notifications among Indian users*, and *the impact of alert modality on a notification's response time.*

Context Analysis: Prior ubicomp studies have shown that smartphone usage has a strong dependency on the user context [19]. An accurate inference of the user context, combined with a sound understanding of user behavior in that particular context, can help ubicomp practitioners design mobile systems that can better adapt to user needs. In this paper, we primarily look at four kinds of contexts that may influence smartphone usage behavior, namely *location context*, *physical activity context*, *connectivity context*, and *socio-economic context.*

Charging Behavior Analysis: Modern smartphone applications run sophisticated mobile sensing, inference and network connectivity operations which impose a major burden on the smartphone battery, and may require users to charge the phone batteries at regular intervals. By understanding the battery charging patterns of the end-users, mobile developers can schedule their energy-heavy operations to opportune moments – for example, when the battery level is high or when a user is likely to charge the phone. To this end, we analyze the *duration and temporal distribution of charging sessions*, as well as *the impact of battery levels on users' decision to charge their phones.*

While these four facets of smartphone usage have witnessed active research in the ubicomp community, it is important to acknowledge that there could be other interesting aspects of smartphone usage such as influence of the social network on usage, data traffic patterns, OS-specific variations in usage etc. which are out of scope of this paper, and can be explored in future work.

3.2 Methodology

In this section, we present our data collection system and provide details on our study methodology and participants.

Data Collection System: Our data collection exercise focused on users of Android OS – currently, Android has a 97% smartphone market share in India [5], making it a clear choice for a large-scale ubicomp study. We developed an Android application which runs on Android 5.0+ and distributed it to users via Google Play. The app is implemented to run as a background service on the user's device and passively records all usage sessions on the device along with various contextual information.

Table 2 details the five types of data points collected by the app. We used event-based Android APIs to collect application data, screen events, notification events and call data. Specifically, whenever a new data point

Table 2. List of data collected from user's phones. (*User's physical activity was obtained by querying the Android Activity Recognition APIs)

Data Type	Description
Application data	Package names of all apps installed on the phone, timestamps of app_open (an app coming into foreground) and app_close (an app going into background).
Screen events	Timestamps when the phone screen is turned on, off and unlocked.
Notification events	Timestamps of notification arrival, notification access or dismissal, name of application which sent the notification. The content inside the notification was not collected for privacy reasons.
Call events	Timestamps of calls, call medium (cellular/VOIP), type of call (incoming/outgoing/missed).
Sensor and Context	Battery level, cell tower ID, WifiDetails (isConnected, BSSID), isHeadphoneConnected, proximity to the phone, ambient light intensity, ambient sound level, user's physical activity*.

pertaining to these categories becomes available (e.g., a new notification is received), the Android OS fires an event which is caught by our background service and the required data points are logged. Further, sensor and context data items listed in the last row of Table 2 were collected by polling Android APIs at i) the start of each smartphone session (i.e., whenever the screen was turned on), and ii) once every 2 minutes. The periodic collection of sensor and context data was done to ensure that data is collected even during periods of inactivity. All data logs collected by the application are stored locally on the phone, and are periodically uploaded to a remote server.

System Deployment. We released our data collection app on Google Play Store, and solicited participation in the study by publicizing it on social forums and email lists. More specifically, we advertised the study in 6 university campuses through email lists and university forums, and in 7 industrial organizations (primarily software and business consulting companies) through employee forums. This resulted in a total geographical spread of more than 10 urban cities and 6 states in India. In addition, we also advertised the study through personal social networks, and participants were recruited through snowball sampling. While participant recruitment through social forums and email lists is widely done in mobile data literature [32–34, 42], there is nevertheless a possibility of sampling bias in this method of participant selection. In our study, as participant recruitment was done across multiple organizations in more than 10 urban cities, we argue that the problem of sampling bias is alleviated to a large extent. However, we do not claim that the sample is completely unbiased and representative for a country with a population of 1.3 billion. This is clearly a limitation of our study and with user studies in general, and as such we duly acknowledge it in the Limitations section in §6.

The data collection for our study was done in two phases – the first phase ran from December 2015 to July 2016 and the second from January 2017 to February 2017. The second phase was primarily motivated by a major socio-economic change in India – widely referred to as Demonetization [1] – that took place in November 2016. We wanted to understand how smartphone usage in India adapts to changes in broader socio-economic context (detailed in §4.3).

[1]The Indian government announced on November 8th, 2016 that the two highest-value currency notes in the country would cease to be legal tender with immediate effect. One of the intended goals of this decision was to encourage people to use digital payment mechanisms [3].

Participant Demographics. In total, the application was installed by 215 users, who were aged between 18 to 38 years. 63 of them identified themselves as females. For our analysis, however, we only included users contributing more than one month of data. This filtering step resulted in 160 users (41 females) aged between 18 and 38 years. While the age diversity in our participant group seem rather low, it is actually in line with prior research by Pew Research Center which found that only 9% of the population aged over 35 years owns a smartphone in India [4].

104 out of the 160 participants identified themselves as students, while the remaining were working professionals. Except for these basic demographics, we did not collect any personal information from the users. Due to the inherent anonymity in our study, we do not know the ethnicities of the participants, as such our findings should be interpreted as applicable to *smartphone users in an Indian context* rather than ethnic Indian users. However for brevity, we refer to our participants as *Indian smartphone users* in the paper. Finally, as an incentive for using the app, users were entered into a lottery (if they agreed to provide their email address) and two winners were each given a wearable fitness band.

Qualitative Data Collection In order to complement our quantitative data analysis with subjective perceptions of users, we conducted an online survey with the participants from our study. A total of 55 participants (10 females) completed the survey, which comprised of 30 questions revolving around the aforementioned four facets of smartphone usage analyzed in our study. Finally, we conducted a series of post-study interviews with 26 participants (10 females) from our quantitative study, aged between 18 to 30 years. The interviews were semi-structured, 30 minutes long, and aimed at uncovering the subjective reasons behind the quantitative findings of our study. Each interview was recorded and later partially transcribed to complete the observer's notes. No compensation was provided to the participants.

3.3 Data Logs and Analysis

The combined dataset collected in our study consists of 11.9 million data points, out of which there are 1.7 million application usage events, 433,900 notifications, and more than 6 million sensor and context data points. In total, we observed 620,194 smartphone usage sessions across all users (μ = 3875, σ = 2100) with a combined duration of 55,619 hours. We did not observe any significant difference in the participant demographics (age, gender, occupation) between the two phases of data collection. As such, we decided to combine the datasets from the two phases while presenting our findings, except for when we specifically analyze the effects of Demonetization on smartphone usage (detailed in §4.3). The results of the survey and the interview together with the quantitive data we extracted from the system logs are presented in the subsequent sections.

4 RESULTS

In this section, we present a detailed analysis of the rich dataset collected in our study. As discussed in § 3.1, we explore four broad facets of smartphone usage in India that are relevant for the ubicomp community, namely a) *Application Usage Patterns*, b) *Notification Attendance Behavior*, c) *Relationship between Context and Smartphone Usage*, and d) *Battery Charging Behavior*. Our analysis of each of these broad facets is presented in separate subsections, and is guided by the research questions outlined in § 3.1 and summarized in Table 1. As highlighted earlier, in addition to uncovering the smartphone usage behavior of Indian users, this paper also aims to contrast their behavior with prior mobile data studies conducted in different geographical regions. Therefore, after analyzing the Indian user data across the four facets, we present a comparison between findings from the Indian context vs. prior mobile data literature in § 5.

4.1 Understanding Application Usage

In this section, we study the application usage behavior of users in India. Our application logs consist of app usage information from 2931 unique apps, which were used nearly 1.7 million times, with a total usage duration of 51,800 hours. Additionally, we collected subjective data about app usage through a survey and semi-structured interviews. This rich dataset provides a unique opportunity to answer the following research questions regarding the app usage of Indian users. We also contrast the usage behavior of Indian users with prior literature on app usage from other geographical regions, and later in § 6, we explain the implications of these geographical variations for the ubicomp community.

- *How is the application usage distributed temporally?*: We seek to understand the temporal variations in usage of applications from various app categories – is app usage evenly distributed throughout the day or are there certain peak usage times?
- *How long and how frequent are application usage sessions?*: We explore if app usage happens in bursts of short and frequent sessions, or are users more inclined towards less frequent but longer sessions?
- *What motivates the choice of applications among users*: With the presence of both a booming local startup ecosystem and global e-commerce and transport companies, Indian users have multiple apps to choose from to avail any given service. We seek to understand how users manage this 'dilemma' of choice – what strategies do they adopt for choosing a service?
- *How does the usage of VoIP and IP messaging apps compare with traditional telephony apps?*: We explore user preferences with regards to communication apps – specifically, we aim to understand how VoIP and IP messaging apps co-exist with traditional telephony services like GSM calls and SMS.
- *Why do users uninstall apps?*: We study the underlying subjective reasons that cause users to uninstall apps from their phone. This information is particularly important for app developers, who may want to adapt their mobile systems to meet end-user expectations.

How is the application usage distributed temporally? In Figure 1, we plot the temporal distribution of *app usage* by category, i.e., when are apps from various categories launched. Quite surprisingly, we observe that the highest volume of app usage takes place between 12am - 4am for most of the app categories, which accounts for roughly 23.94% of all app usage. In particular, apps in Communication, Photography, Weather, and Food and Drinks categories have their peak usage at these times. Further, the hours between 8am - 12am see the least app usage in our dataset (2.62%). This observation is remarkably different from prior studies (e.g., [7] which found that for American users, morning hours between 8am - 12am contribute to a significant percentage of app usage (16.17%).

We further investigated the cause of these differences through our survey and interviews and found that users refrain from using their smartphones in the morning hours which tend to be the starting hours of work or school. Moreover, a majority of the participants ($n = 19$) mentioned that they typically sleep well after midnight, and spend a significant time on their phones during late night hours. One interviewee said,

> *"I often stay up till 2 am working, after which I scroll aimlessly through my social media feeds while lying in bed."*

We suspect that this behavior could be due to the age demographics of Indian smartphone users [4] (also reflected in our participants) which is skewed towards younger users.

Next, we analyze the co-occurrence probabilities of the top 20 app categories within a smartphone usage session (i.e., the time from screen unlock to screen off). The co-occurrence matrix in Figure 2 is best interpreted row-wise, with each row representing the probability of a category on the x-axis co-occurring with the row category on the y-axis in the same session. More formally, co-occurrence probability is computed as $P(x,y) = count(x,y)/count(x)$ where P is the co-occurrence probability of categories x and y, and $count(x,y)$ represents the number of usage

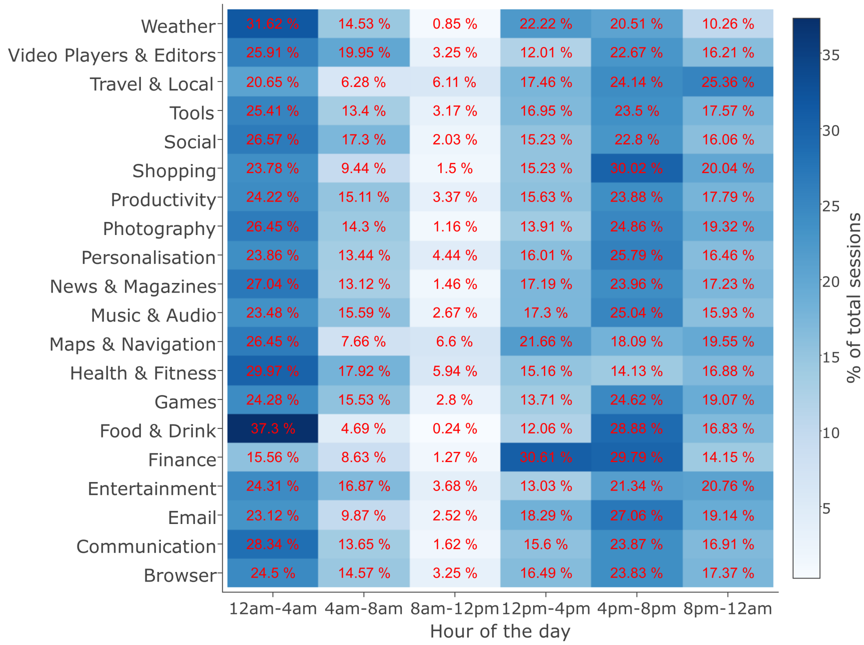


Fig. 1. Category-wise Diurnal Session Distribution

sessions where both x and y category apps were present. For example, when a Browser app is used on the phone, the chances of also using a Communication and a Social app in the same session are 0.42 and 0.22 respectively, and of using another Browser app (diagonal entry) is only 0.02. From Figure 2, we observe heavy usage of Communication apps along with other categories – for all app categories, there is nearly 30% chance that a Communication app will be used in the same session. User responses suggest that this is because they tend to engage in discussions with their friends or colleagues about their activities on other applications. For example, one of the respondents noted,

> *"I usually use WhatsApp to share screenshots of my social media feed with my friends if I come across something interesting".*

Participants (n = 9) also reported using Communication apps to get their friends' opinions when purchasing something, or to reach a consensus while ordering food or making plans for a group of people.

How long and how frequent are application usage sessions? In Figure 3, we plot the CDF of app usage durations for the top application categories by usage. As expected, apps under the Games category tend to have the longest usage time, with half of the usage sessions lasting for more than 90 seconds (mean duration = 195 seconds). This is followed by Shopping (mean = 101 seconds) and Social apps (mean = 95 seconds), while Email apps have the lowest mean session duration of 37 seconds. We also observe that Music apps have surprisingly low session durations (mean = 38.1 seconds), which can be attributed to the fact that Music apps are mostly used in the background and as such, their foreground times are rather short. Overall, the session durations were found to be significantly longer than those of American users reported by Church et al. in [8], where over 48% of all application usages were reported to last 15 seconds or less, and approximately 56% to last 22.5 seconds or less.

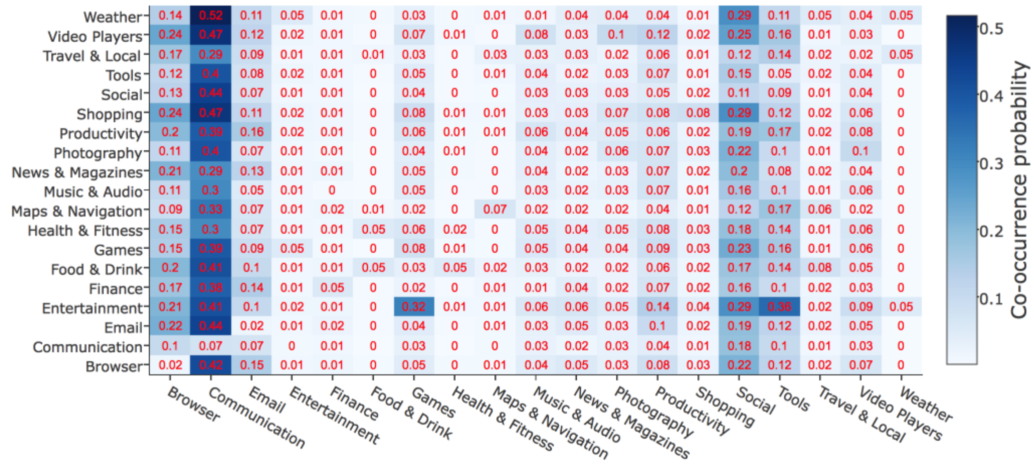


Fig. 2. Pairwise Category Co-occurrence Probabilities: each row represents the probability of an app from the category on the x-axis co-occurring with one from the category on the y-axis within the same session

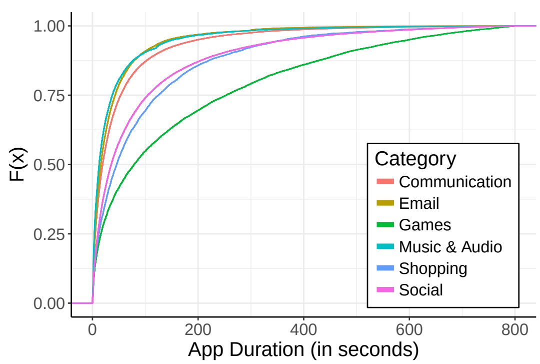


Fig. 3. CDF of app session durations

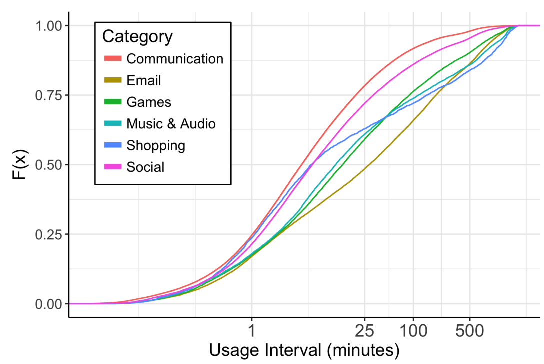


Fig. 4. CDF of app launch intervals (log-scale)

The CDF plot in Figure 4 depicts the time interval between two successive usage sessions of a given category. For all categories except Email, we see that half of the sessions happen within 15 minutes of the last session from the same category. This suggests the presence of a *clustering effect* in app usage – users tend to use multiple apps from the same category temporally close to each other. We found that Communication apps have the least average interval between usages (mean = 44 minutes) while Music and Shopping apps have the highest (mean = 7 hours). This finding on *clustered usage patterns* can provide a useful contextual cue to system designers for recommending similar apps – when apps from one category are being used, the system can prioritize notification delivery from other apps in the same category, or opportunistically re-arrange the home screen to show these apps prominently.

What motivates the choice of applications among users? We study how users choose between multiple applications installed on their phone which serve the same purpose. For example, users may have 2 or more ride-sharing apps installed – how do they decide which service to use? We focus our analysis on four prominent app categories where there are a growing number of competing service providers in India: transport (e.g., Uber), shopping (e.g., Amazon), food delivery (e.g., JustEat) and mobile wallet (e.g., Paytm). Our data logs reveal a remarkable user preference towards installing multiple competing apps on their phone – 84% of the users had at least 2 apps from each of the aforementioned categories installed on their phones, while 35% of the users had 3 or more competing apps installed.

Delving deeper into it, we analyze whether there is a temporal pattern visible in the usage of these competing apps. In our survey, nearly 50% of the respondents mentioned that "before availing any service, they **compare** various providers and opt for the one that has the best deal at the moment". To validate this subjective finding about the presence of a *comparison behavior* we evaluate whether competing apps from the same category are used temporally close to each other. We set the temporal search space for finding a competing app to (mean + standard deviation) of app usage time in the particular category.

However, our findings from the log analysis run contrary to the survey results – we found that users exhibit 'comparison behavior' in less than 8% of usage sessions. This suggests that while users prefer to do a 'service provider comparison' as they had mentioned in the survey, this comparison does **not** happen on the smartphone. As part of our interviews, many users ($n = 10$) highlighted that they prefer to compare various providers by opening their websites in multiple browser tabs on their laptops. One interviewee remarked,

> *Yes, I do it very often. I open tabs in Chrome for each (web)site and compare the price and features of the product I am looking for. It is easier to compare reviews and specifications side-by-side on a laptop.*

Interestingly, some users ($n = 7$) also mentioned that after comparing on a laptop, they eventually buy the product from their smartphone to avail app-only discounts offered by many service providers.

How does the usage of VoIP and IP messaging apps compare with traditional telephony apps? Here we investigate the impact of VoIP and IP messaging apps (e.g., WhatsApp, Skype etc.) on traditional telephony apps (i.e., cellular calls and SMS). We found a significant difference ($p < 0.0001$, $t = 5.3$) between the call durations on cellular and VoIP calls, with average duration of VoIP calls (median = 120 seconds) being nearly twice that of cellular calls (median = 58 seconds). However, the count of cellular calls per user was significantly higher than that of VoIP calls ($p < 0.0001$, $t = 13.9$). This behavior could be explained with our survey findings, wherein users mentioned that they use VoIP calls primarily for communicating with close social contacts (hence the higher call duration), while cellular calls are used for all other routine communication needs, e.g., calling a cab, ordering food. Interviewed users also claimed to make cellular calls if the nature of the call (or the callee) was relatively formal, urgent or important. These insights explain the higher call volume in case of cellular calls.

Next, we compare the usage of SMS apps against IP messaging apps. Users in our dataset exhibited a significant preference towards IP messaging apps ($p < 0.0001$, $t = 48.1$) – these apps accounted for 24 times more message exchanges than SMS. We also found that of all the SMS notifications received by the users, only 22% of them were attended. The low usage of SMS is further confirmed in our survey, with users reporting that only 24% of the received SMS messages are from personal contacts, and rest are either brand promotions or spam.

Why do users uninstall apps? Through our user survey, we studied the subjective reasons behind a user's decision to uninstall a certain app. 47.5% respondents pointed out that apps which put a major burden on system resources such as battery charge, memory and storage space are the most likely to be uninstalled. Interestingly, our interviews further revealed that if an app has low resource requirements (e.g., less storage space, minimal battery drain), some users ($n = 6$) would keep it on their phone *even if it is never used.* Around 20% users attributed their decision of uninstalling apps to frequent and unnecessary notifications.

4.2 Understanding Notification Attendance Behavior

In this section, we analyze the receptivity of Indian users towards mobile notifications. Mobile notifications have been a prominent topic in ubicomp research in the last few years – numerous studies have focused on understanding the interaction behavior of users with mobile notifications [29, 31]. However, many of these studies have been done on a small scale (15-20 users) and have either been limited to users in the US and Europe (e.g., [31, 32]), or have not considered geographic diversity in their analysis (e.g., [29]).

Below we present our analysis of notification-interaction behavior of Indian users from a large-scale dataset of 433,900 notification events collected in our study. As outlined in § 3.1, we aim to bring out the following aspects of notification-interaction behavior of Indian users: a) *the receptivity towards mobile notifications*, b) *the effectiveness of mobile notifications*, and c) *effect of contextual factors on notifications receptivity.*

How quickly do users respond to a notification? We first analyze the response time to a notification, which is the sum of: a) time from notification arrival until it is first viewed, and b) time from the notification's first viewing to the time the user either dismisses or reads it (by clicking on it or launching the notifying app). In order to maintain consistency with prior literature [29], we refer to these times as *'Seen Time'* and *'Decision Time'* respectively. We compute the Seen Time for a given notification by considering the first 'screen unlock' event after the notification's arrival and assuming that the user 'sees' the notification when he/she unlocks the screen. In cases where a notification arrives when the screen is already unlocked, the Seen Time of the notification is marked as 0.

Our analysis of Seen Times show that 71% of the notifications have a Seen Time of less than 1 minute, suggesting that Indian users are remarkably quick at 'viewing' majority of the notifications. This finding significantly differs from prior notification works (e.g., [29, 32]) where the reported seen times are at least three times higher than those in our dataset. Similarly, we found that the Decision Times for 76% of notifications were less than 1 minute, which means that after becoming aware of a notification's arrival, users either attend or dismiss 76% of them very quickly (i.e., within 1 minute).

In Figure 5, we plot the seen times and decision times for four application categories (viz. Communication, Email, Social, Shopping) which generated the most number of notifications. A one-way ANOVA showed that application category has a significant effect on both seen times ($F = 178.9, p < 0.0001$) and decision times ($F = 254.3, p < 0.0001$). We found that Communication and Shopping apps respectively have the lowest and highest mean Seen Times and Decision Times across all categories. This finding was also confirmed in the survey where 65% respondents mentioned that they attend Communication notifications within 1 minute, while only 4% said the same for Shopping notifications. Finally, we also found a significant effect of the hour of the day on both Seen Times ($F = 321.1, p < 0.0001$) and Decision Times ($F = 85.38, p < 0.0001$), both being lowest between 8pm - 12am.

How effective are notifications in engaging the user? To study the effectiveness of notifications, we analyze the overall attendance rate, i.e., the percentage of notifications attended by the user. We mark a notification as attended if a user launches its corresponding application either directly or by clicking on the notification. In Figure 6, we plot the hourly attendance rates for notifications in four app categories which generated the most number of notifications. We observe a rather low attendance rate for notifications among Indian users – in all categories, the attendance rate for notifications is always less than 40% even at peak hours. Social applications (e.g., Facebook) have the highest mean attendance rate (29%) while apps in the Shopping category (e.g., e-commerce apps) have a very low mean attendance rate of 7.5%. This finding for Indian users also differs from prior work [28, 29] which found more than 60% notification attendance rate among users in the UK.

Another metric of notification effectiveness is the proportion of *reactive application usage* across all usage sessions of an app. Reactive application usage refers to those app sessions that are initiated by a notification. If an app has a larger proportion of reactive sessions, it could mean that its notifications are effective in driving user

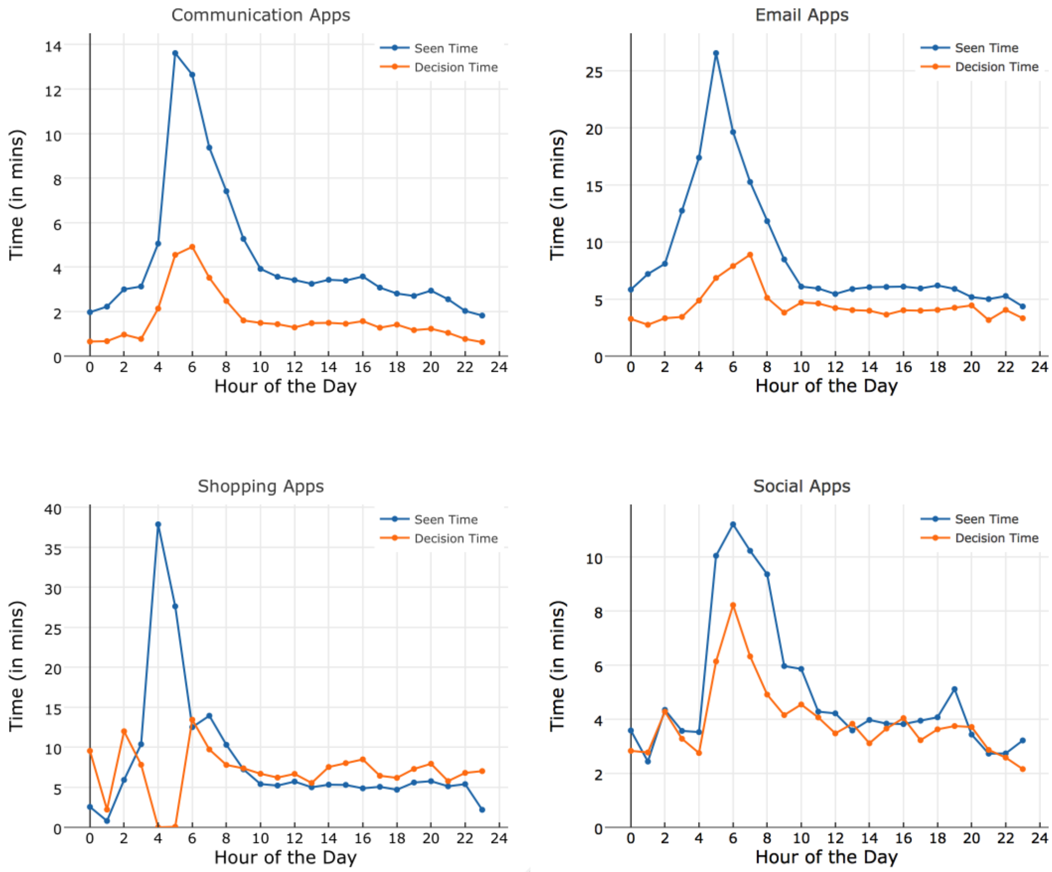


Fig. 5. Seen Time and Decision Time for Notifications from Various Categories of Apps

engagement. In order to mark reactive usage, we check for cases when the notifying app is launched by clicking on a notification, or if the notifying app is launched in the same smartphone session when the notification was first seen. In Figure 7, we plot the reactive application usage for the top 4 app categories that generated the most number of notifications. In general, we observe that notifications initiate less than 30% of the app usage for all categories – particularly, reactive app sessions are the lowest for Shopping (11%) and Social (12%) apps, which suggests that very few sessions for these app categories are initiated by notifications. Surprisingly, a prior study with Korean users shows a huge contrast from our results – Lee at al. [21] found that that nearly 79% of all usage sessions were reactive in nature (i.e., triggered by notifications). While they do not report per-app reactive sessions, their results do show a significant trend towards reactive usage among Korean users.

How does alert modality impact a notification's response time? A mobile notification can be programmed to alert the user through three modalities: vibration, sound and/or LED flashing. However, the ringer mode set by the user on the device (Silent/Vibrate/Normal) can override a notification's own choice of modality. Therefore, by taking into account each notification's modality along with the phone's current ringer state, we investigated the impact of various notification alerts on Seen Time, Decision Time and Response Rate.

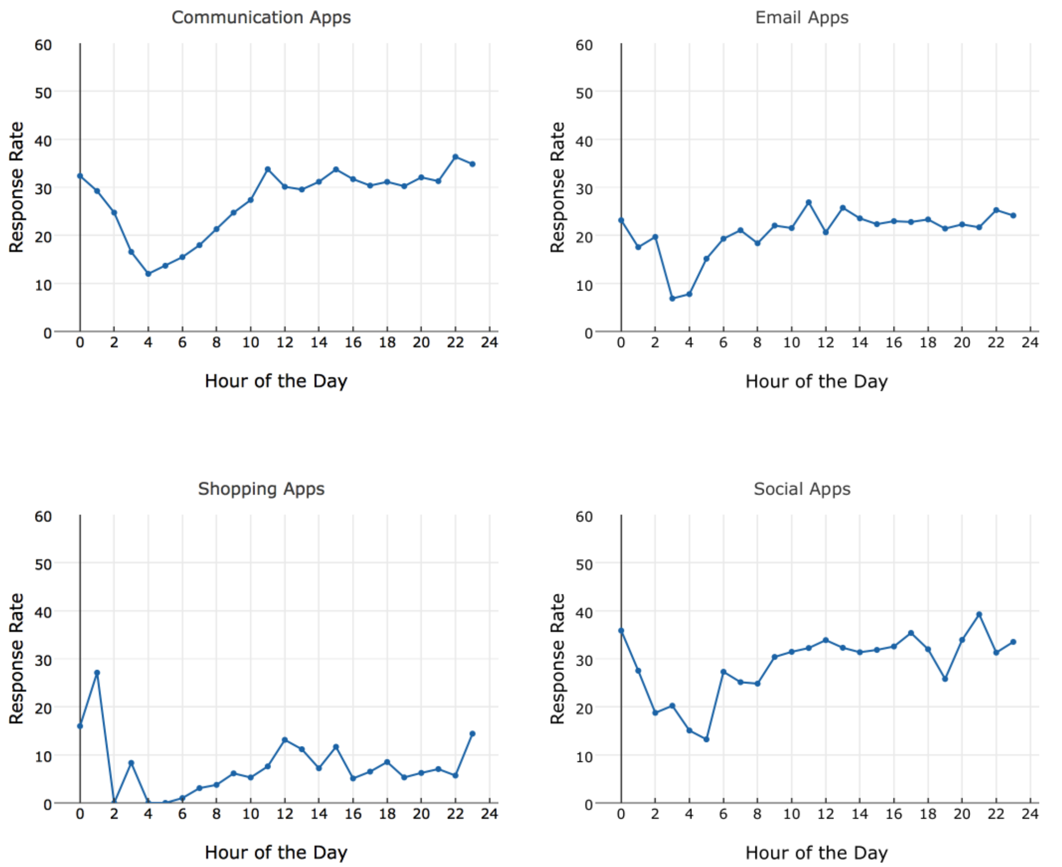


Fig. 6. Attendance Rate for Notifications from Various Categories of Apps

We found a significant effect of alert modality on both Seen Time ($F = 142.7$, $p < 0.001$) and Decision Time ($F = 165.0$, $p < 0.001$). Very surprisingly, we observe that when notifications are delivered in *Silent* mode, both Seen Times (mean = 3.32 mins) and Decision Times (mean = 2.23 mins) were the lowest. This was followed by vibrate-only (mean ST = 3.64 mins, mean DT = 2.68 mins), vibrate+sound (mean ST = 3.72 mins, mean DT = 2.72 mins), and sound-only (mean ST = 5.71 mins, mean DT = 4.92 mins).

This counter-intuitive result on low response times in Silent mode is significantly different from prior works (e.g., [29, 32] which found that notifications with vibrations take the least time to attend. Our post-study survey explains this finding to some extent: nearly 76% of the respondents mentioned that they put their phones in Silent mode only in formal social settings, such as during meetings/lectures, in a library etc. Interestingly, 85% of them also said that even when the phone is in Silent mode, they still actively use the device. A possible explanation of our finding is that in formal settings such as lectures or meetings, users have their phones closer to them and they are also actively using them. As such, if a notification arrives in this context, it is seen and attended faster than other contexts.

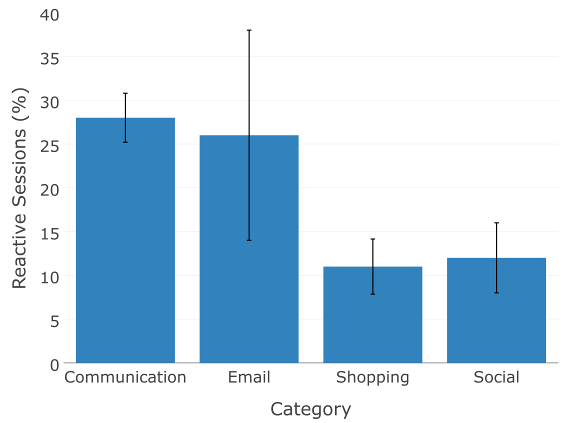


Fig. 7. Proportion of Reactive Sessions Across Different Categories

Table 3. Percentage-wise App Usage in Various Contexts (by App Category).

	Activity			Location		Connectivity	
Category	Stationary	Walking	Vehicle	Home	Work	Wi-Fi	3g
Games	52.3%	10.4%	37.3%	68.6%	31.4%	29.5%	70.5%
Social	68.6%	10.1%	21.3%	34%	66%	43.7%	56.3%
Communication	35.8%	21.3%	28.5%	34.5%	65.5%	40.7%	59.3%
Video Players	66.1%	5.4%	28.5%	73.4%	26.6%	78.9%	21.1%
Travel and Local	25%	29.1%	45.9%	52.1%	47.9%	37%	63%
Tools	56%	12.5%	31.5%	32.7%	67.3%	33.8%	66.2%
Email	66.1%	11.6%	22.3%	58%	42%	38.2%	61.8%
Shopping	65%	13.6%	21.4%	66.7%	33.3%	43.4%	56.6%
Productivity	71.4%	9.5%	19.1%	42.6%	57.4%	38.5%	61.5%
Entertainment	62%	11.6%	26.4%	73.1%	26.9%	65.2%	34.8%

In summary, we found that the notification receptivity of Indian users has significant differences from the findings in other geographical settings. Indian users tend to be fast at viewing the notification, but their attendance rate remains much lower than what was found in European and American contexts. Moreover, by analyzing the reactive usage proportions, we found that notifications are not the primary modality for initiating app sessions for this user group. All these findings have interesting implications for system developers, which we will discuss in § 6.

4.3 Understanding the Impact of Context

Prior ubicomp studies have shown that smartphone usage has a strong dependency on the user context [19]. Researchers have looked at understanding the effect of temporal and location context [40] on device usage and communication preferences of the user, effect of demographics [24] on app adoption, and impact of secondary activities (e.g., watching TV, eating) on the use of smart devices [30]. In this section, we explore the impact of following four types of user *contexts* on smartphone usage in an Indian context:

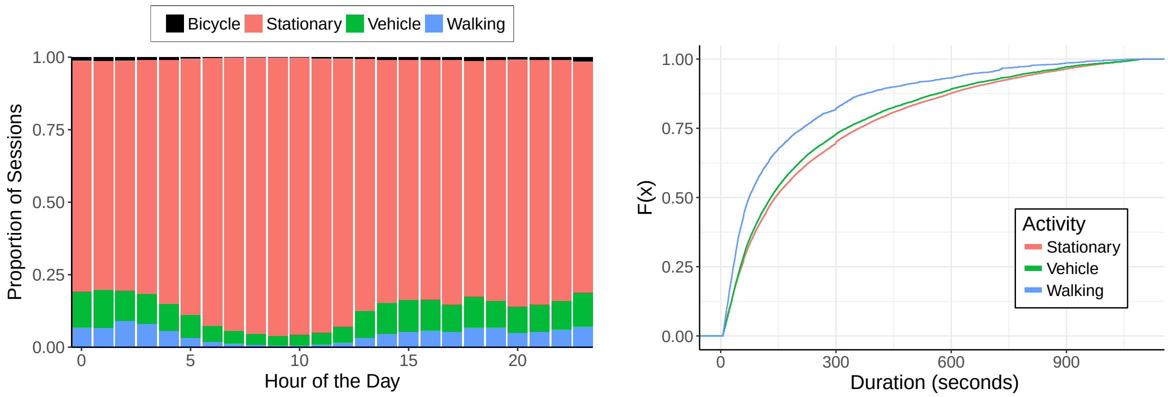
- Physical activity context: People use their smartphones throughout the day in various physical activity contexts (e.g., sitting, walking, running). Changes in activity contexts also lead to variations in the auditory and visual attentional resources that a user may possess. For example, during a morning run a user is likely to pay more attention to audio based content rather than visual content. Thus, we argue that smartphone apps need to adapt their interfaces to the changing physical activity contexts of a user. In addition, understanding the relationship between physical activities and smartphone usage could be particularly useful for the growing number of fitness and activity apps. As such, we present an in-depth analysis of this aspect.
- Connectivity context: We explore if the presence and nature of network connectivity (Wi-Fi, cellular data or none) has any impact on smartphone usage. Such analyses are particularly important for emerging data economies like India, where high speed cellular data plans are still quite expensive. We seek to understand if the availability of WiFi makes a significant difference to the application usage patterns.
- Location context: We explore if the location of a user has an effect on their smartphone usage. Particularly, we look at the usage patterns in 'home' and 'work' environments, and compare them against past studies on similar topics done in Finland and the UK [40].
- Socio-economic context: In addition to the personal and device contexts mentioned above, we explore whether the broader socio-economic context has any impact on smartphone usage. Specifically, we take the announcement of *demonetization* by the Indian government in November 2016 as an example of a major socio-economic contextual change for Indian users, and evaluate if this change led to any significant variations in the user behavior. As discussed in § 3.1, our study was conducted in two phases (2016 and 2017), putting us in a position to effectively compare smartphone usage pre- and post-*demonetization.*

Physical Activity Context: We begin by providing a descriptive analysis of our physical activity logs. In Figure 8a we plot the hour-wise activity proportion of four major activity classes (viz. 'Stationary', 'Walking', 'Bicycle' and 'Vehicle'). Firstly, as expected, most of the smartphone usage took place in the 'Stationary' activity. More interestingly, we found that users had $\leqslant$ 3% of the labels in the 'Walking' activity during morning hours. In our survey, however, nearly 50% of the users mentioned that they routinely go for a morning walk. This discrepancy about the 'walking' activity between our data logs and survey findings was explained through the semi-structured interviews, where participants (n = 11) mentioned that when they go for a morning walk, they prefer to not carry their smartphones with them. One respondent said,

> *"Even if I do go for a walk or a run, I find it a hassle to carry a phone in my hand. Since my active clothing doesn't usually have pockets, I just leave my phone in the room."*

Next, we analyze how long various *activity episodes* last, i.e. for how much time does a user stay in the same physical activity state. As expected, the mean episode duration was highest for 'Stationary' activities (mean = 29 minutes). Interestingly, we observe that nearly 80% of the episodes related to 'Walking' had a short duration of less than 5 minutes (90% episodes $\leqslant$ 9 minutes), which further adds to our previous finding that users may not be carrying their smartphones during long walking sessions. We discuss the implication of this finding in § 6.

Next, we look at the relationship between app usage and physical activity. In Figure 8b, we plot the CDF of app durations under different physical activity conditions. Through a one-way ANOVA analysis, we found a significant effect of physical activity type on app usage duration ($F = 39.1, p < 0.05$) – apps used while walking had the least mean usage duration (mean = 248 seconds), whereas apps in the stationary state had the highest mean usage duration (mean = 426 seconds). In Table 3, we show the effect of physical activity on usage of



(a)

(b)

Fig. 8. Understanding the impact of the physical activity context on smartphone usage - (a) Diurnal distribution of recorded activity fraction (by hour of the day), (b) CDF of session duration (in seconds, grouped by activity)

various app categories – it was found that Social apps are predominantly used when the user is Stationary, while Communication apps are used more when the user is in motion (e.g., walking or in vehicle)

Location Context. Now we turn our attention to studying the impact of location on smartphone usage. Studies in the past have approached location analysis from categorical perspectives of 'home use' and 'work use'. We adopt a similar approach of categorizing locations in our dataset as 'home' and 'work' based on the technique described in [40]. Our findings reveal similarities with previous studies done in Finland and the UK by Siokkeli et al. [40], which found that usage in 'home' context is on average 37% longer than that in the 'work' context, and Indian users. A one-way ANOVA on our data showed that there is a significant impact of location on app session duration ($F = 6.14$, $p < 0.01$) and the app sessions at 'home' are nearly 28% longer than at 'work'.

As shown in Table 3, we also observed a strong effect of location on a user's app preferences – while apps under Games, Email, and Shopping category tend to be used more in 'home' contexts, Communication and Social apps are likely to used more in the 'work' context.

Connectivity Context. Here we seek to answer our next research question – can the type of network connectivity (e.g., WiFi, cellular) have an effect on the usage patterns? Particularly in India, high speed cellular data plans are still quite expensive. Therefore, we seek to understand if the availability of WiFi makes a significant difference to smartphone usage patterns. We define a 'connectivity session' as the time period in which the smartphone is connected to a particular network. We first look at the mean duration of connectivity sessions for both cellular and WiFi networks. Our findings show that there is a significant difference between the session durations for cellular and WiFi networks ($F = 39.11, p < 0.03$), with WiFi sessions (mean = 120 minutes) lasting for 30% more time than cellular connections. Next, we evaluate the impact of network type on a smartphone usage session. We found a significant difference in usage durations ($F = 540$, $p < 0.0001$), with mean duration of usage sessions being 50 seconds on WiFi and 30 seconds on cellular connections.

In Table 3, we also show the impact of connectivity context on usage of various app categories. We found that data-heavy app categories such as Video and Entertainment are primarily used over WiFi, while apps belonging to categories which are less data-intensive and used in short bursts have higher total usage on cellular connections (e.g., Communication, Email, Productivity). This observation was supported by our interview findings, where participants ($n = 14$) mentioned that they are cautious with their app usage when using cellular data. One user interestingly remarked,

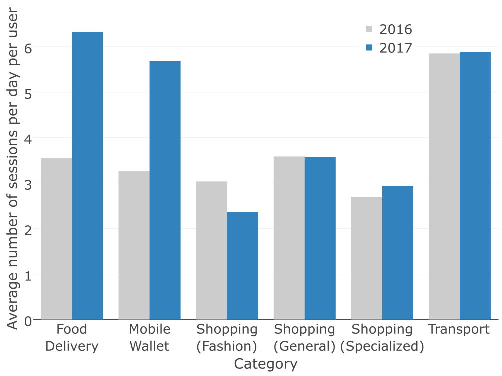


Fig. 9. Comparison of App Usage in 2016 and 2017

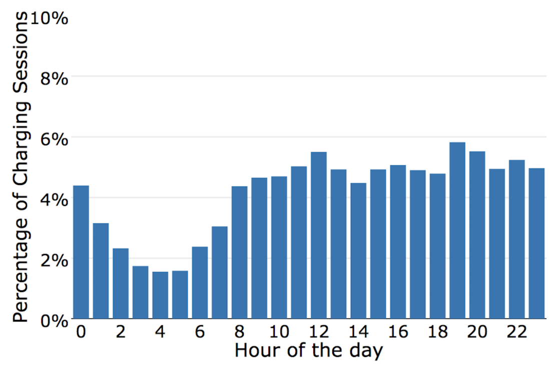


Fig. 10. Average Charging Schedule

> *"I keep my 3g off all the time. Only when I have to check something urgent or important like messages or emails, I turn it on....But I always turn it back off to prevent auto downloads by apps."*

Socio-Economic Context. We now turn our attention to study the effects of the broader socio-economic context on smartphone usage of Indian users. As mentioned earlier, the second phase of our study was motivated by a major socio-economic event in India, wherein the Indian government announced a decision to discontinue the legal tender status of the two highest-value currency notes overnight (commonly known as *demonetization*). This move resulted in a serious cash shortage for weeks, and was intended to motivate users towards adoption of electronic payment services.

By comparing our datasets from before and after the demonetization event, we examine to what extent socio-economic factors impact smartphone usage. We focus our analysis on apps which are most likely to be affected by this change – e-commerce and electronic payment apps. The said apps were categorized into the following six classes - Mobile Wallets (e.g., PayTM), Transport (e.g., Uber), Shopping - General (e.g., Amazon), Shopping - Fashion (e.g., Myntra), Shopping - Specialized (e.g., LensKart) and Food Delivery (e.g., Justeat).

As evident in Figure 9, we observe a significant increase in the average number of sessions per day per user for digital payment apps ($p < 0.01$, $t = 8.17$), This is substantiated by the responses on our survey, where 92% people stated that they used Mobile Wallets for electronic transactions to a much greater extent post demonetization. Similarly, we observed a significant increase in adoption of food delivery apps – our subjective findings reveal that due to cash shortage, people could not pay for their food by cash, and hence relied heavily on online food delivery services. We did not see a significant difference in online-shopping app categories, likely because these apps had a much lower reliance on cash transactions previously.

4.4 Understanding Battery Charging Behavior

We begin by analyzing the temporal nature of smartphone charging sessions. A smartphone charging session starts when users plug-in their phone to an AC or USB power supply, and ends when the phone is plugged-out. To account for accidental or short-term disruptions in the charging process (for example, if the charger gets plugged-out and is immediately plugged back in), we merge all charging sessions that are 2 minutes or less apart into one session.

Figure 10 shows the proportion of charging session initiations by hour of the day. We observe that apart from the low number of charging sessions initiated between 1am - 7am (typical sleeping hours), users show no

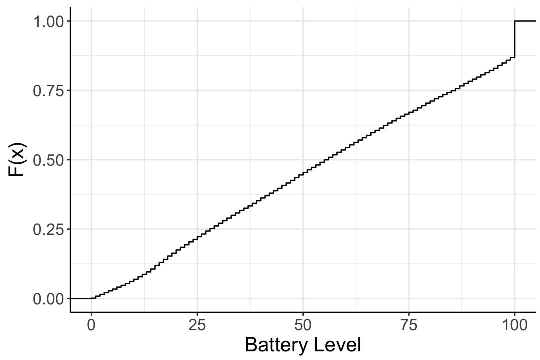


Fig. 11. CDF of battery levels at the start of charging sessions

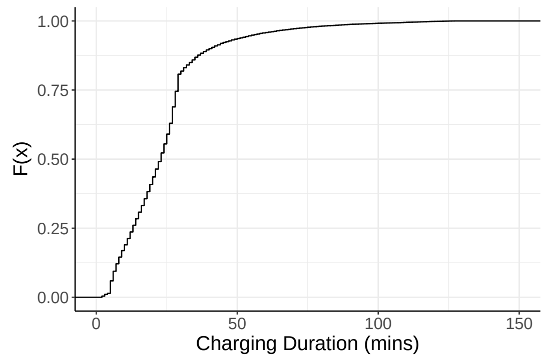


Fig. 12. CDF of durations of charging sessions

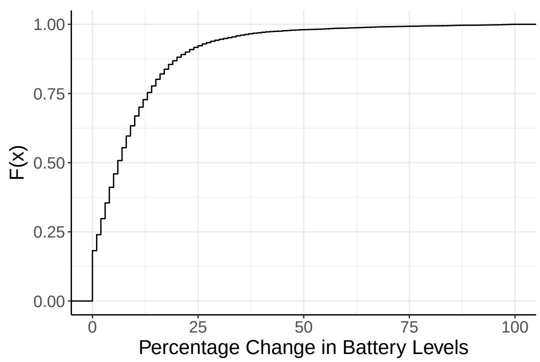


Fig. 13. CDF of battery gain from a charging session

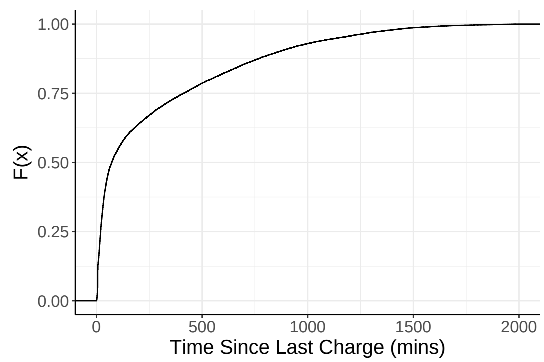


Fig. 14. CDF of charging intervals

significant difference in their temporal charging preferences. Next, Figure 11 shows the battery levels observed at the start of a charging session. We find that battery levels are also evenly distributed from 0 - 100% at the start of a charging session. Both these findings indicate that a user's decision to initiate a charging session does not depend on time of the day or their current battery level.

Next in Figure 12, we plot the CDF of charging session durations. Surprisingly, we observe that users tend to have very short charging sessions: 75% of the charging sessions lasted less than 30 minutes, and only 5% of the sessions lasted more than 90 minutes. This finding about the charging behavior of Indian users is in stark contrast to previous ubicomp studies (e.g., [14]) which concluded that more than 60% of charging sessions last for 2 hours or more. We observed similar patterns in Figure 13 where we plot the gain in battery levels after a charging session – our findings show that 75% of the charging sessions resulted in less than 15% battery gain.

Finally, in Figure 14 we plot the CDF of charging intervals, i.e., the time difference between two consecutive charging sessions. We find that the majority of charging intervals are remarkably short – about 50% of all charging sessions were started in less than 80 minutes of the previous session, and only 15% of the sessions were initiated after 12 hours (720 minutes) of the previous session.

In summary, our quantitative findings highlight that Indian smartphone users adopt a highly opportunistic and cautious approach towards battery charging. They prefer to charge their phones frequently irrespective of

Table 4. Comparison of patterns exhibited by Indian users with users from other geographical regions. (*) denotes the geographical identity of the majority of participants in the study.

Metric	Comparison Group	Comparison Group Results	Indian Users
Predominant App Usage Hours	American*	4pm - 8pm [7]	12am - 4am
Lowest App Usage Hours	American*	4am - 8am [7]	8am - 12pm
Mean inter-session duration for Communication apps	Korean	26.5 minutes [21]	44 minutes
Mean Notification Seen Time	UK*	> 3 minutes [29]	< 1 minute
Mean Notification Attendance Rate	UK*	> 60% [29]	20%
Reactive Usage Sessions	Korean	79% [21]	30%
Alert Modality for quickest notification attendance	European	Vibration [29, 32]	Silent
Number of sessions by location	Finnish*	56% more sessions at 'work' than 'home' [40]	12.3% more sessions at 'work' than at 'home'
Charging Session Duration	Global	60% sessions last at least 2 hours [14]	75% sessions are shorter than 30 minutes
Charging Frequency	NA	NA	< 80 minutes for 50% of the charging sessions

time of the day, and even for shorter charging durations. Our interview data reveal an interesting reason behind this behavior: a majority of participants ($n = 14$) told that smartphone is their primary source of connectivity and information access, and as such they are very mindful that it does not run out of battery. Therefore, they tend to charge their phones as and when they get a chance, even if it is for a short duration. The following user quotes are a good reflection of our interview findings:

> Student: *"I go to different lecture halls in the campus during the daytime. During my commute from one hall to other, I just connect my phone to my laptop (in the backpack) and let it charge so that my battery does not die during the day."*
>
> Professional: *"If I am in a long meeting and my phone is not charged, I get very frustrated. But it's not very polite to charge your phone during the meeting. To avoid this (scenario), I plug my phone for charging whenever I am at my (office) desk."*

5 CONTRAST WITH PRIOR RESEARCH

In this section, we compare the findings of our study with prior research on smartphone usage conducted in other geographical regions. Note that there is no single prior work which provides an in-depth and focused analysis of smartphone patterns in a geographical region. Therefore, we review multiple studies in the field and collect equivalent results from them. Table 4 summarizes the contrasts between our study and prior works.

We observed a significant divergence in the temporal usage patterns of Indian users from prior work by Bohmer et al. [7] with mostly American users. While they found evening hours (4pm - 8pm) to be the predominant usage hours, Indian users instead were most active during late night (12am - 4am). Similarly, morning hours between 8am - 12pm saw the least usage for Indian users which was again significantly different from the findings of Bohmer et al. [7]. The contrasts in notification receptivity were also very evident from our results. While Indian users tend to view a notification very quickly (in < 1minute), the overall attendance rate of notifications was very low (20%). On the contrary, the users in prior work by [29] were slow in viewing the notification (seen time: > 3 minutes), but their attendance rate was significantly higher (> 60%). In terms of the battery charging behavior, we found that charging session durations in our study were significantly shorter as compared to the work by Ferreira et al. [14]. Moreover, our findings on the high frequency of charging sessions in a day was unique to Indian users, with no prior study reporting such behavior.

The above findings clearly show that there are significant differences between smartphone usage behavior across geographically dispersed groups. We now present two exemplar case-studies that will highlight the importance of accounting for these geographical heterogeneities in mobile data research.

Efficacy of mobile notifications. Assume a scenario wherein a global mobile developer is evaluating whether to push relevant content to its end-users through mobile notifications. As shown in Table 4, Indian users have a low proportion of reactive usage sessions (30%) whereas the usage of Korean users is predominantly reactive (79%), i.e., triggered by notifications. Similarly, it is likely that users in other geographies (e.g., China, Germany) will have a different receptivity towards mobile notifications. Given this variability, if the mobile developer does not take this geographical diversity into account (if, for example, they simply average the reactive usage across various groups), they may reach an incorrect conclusion about the receptivity of mobile notifications among their target users.

Predictive Modeling for Smartphone Usage Data. The geographical variations in smartphone usage can also impact the accuracy of predictive inference models in-the-wild. While many works focus on building personalized inference models (e.g., [39, 44]), it is also common to develop models from composite data (e.g., [26, 34]) in order to avoid the user cold-start problem [38]. For such composite models, geographical heterogeneities could be a major obstacle in their wider applicability. For example, Pielot et al. [34] built a predictive model to detect boredom from smartphone usage data collected in European countries. Some of the important features considered for their classifier related to battery levels and SMS-sending behavior of users. However, our findings reveal that Indian users have remarkably different battery charging behavior from other groups, and the prevalence of SMS usage is very low in this user group. Consequently, if the composite models trained on usage data and features from one geographical area (e.g., Europe) are applied to a different one (e.g., India) without any fine-tuning, it is likely that the performance of the models would be very poor.

The above examples provide a strong intuition on why accounting for geographical diversities in mobile data in important for both developers and researchers. In § 6, we provide further reflection on tackling geographical heterogeneities in mobile data studies.

6 DISCUSSION

In this section we discuss several design implications emerging from our study findings, and also provide a reflection on the broader topic of large-scale mobile data research.

6.1 Key Findings on Smartphone Usage Behavior in India

Below we discuss some of our most interesting findings about smartphone usage behavior in India, and their possible implications on design of mobile systems:

The Urge to Compare. We uncovered a very interesting patten in the usage of 'competitor' apps among Indian users. The users exhibited a strong preference towards installing multiple competing apps on their phone (e.g., Uber and Ola as ride-hailing apps) – 84% of the users had at least 2 competing apps installed on their phones for major app categories. While installation of multiple apps itself may not be surprising, we found that before making any purchase decision, users prefer to compare the price of a product/service in each competing app and then choose the one with the best price or service availability. Moreover, we found that this *provider comparison* does not happen through smartphone apps, but instead through the desktop website of the service providers on a larger-screen device such as a laptop. Overall, this finding has a strong implication for the e-commerce ecosystem in India, wherein some service providers are exploring a transition to an app-only experience, i.e., to discontinue their desktop and mobile websites and push users towards an app-based shopping experience [36]. However, our findings caution that this approach may not be ideal for e-commerce providers, as it will prevent users from comparing their services on a desktop website, which in turn might lead to lower engagement with their services.

Uniqueness in temporal usage patterns. Our results show that smartphone usage among Indian users was most prominent during late night hours (12am - 4am), which significantly differs from prior work in other geographical regions where evening hours (4pm - 8pm) dominated smartphone usage. While it will require more focused qualitative research to understand the underlying reasons for the late night usage, our interviews suggested that it might be linked to the demographics and sleeping patterns of the participants. Nevertheless, this finding could have an interesting implication for crowdsourcing or experience sampling (ESM) systems commonly used in ubicomp research. Such systems rely on user responses and aim to maximize the user response rate. As such, they focus on sending ESM probes or questions at times when users are likely to be most engaged with their devices. For example, in a recently published study [29], the authors sent ESM probes between 8am to 8pm, and 'no probes were sent after 10pm to avoid annoyance for the users'. While this might be a reasonable assumption, our findings however show that the most active usage times for Indian users are after midnight – the ESM probes need to be scheduled accordingly for this user group to maximize user participation.

Notification Receptivity. Users in our study were remarkably fast at viewing a notification, but the attendance rate of notifications was very low. Nearly 75% of the notifications were viewed in less than 1 minute, however the average attendance rate was just around 20%, much lower than what was found in prior studies in European countries. This suggests that app developers focusing on Indian smartphone users should explore embedding more useful and richer content into the notification previews, which might lead to higher user engagement with their applications.

Battery Conscious Users. We found that Indian users are extremely battery conscious – the battery life of a phone plays a major role in their purchasing decision, and an app perceived as consuming too much energy is highly likely to be uninstalled. This behavior poses challenges for energy-heavy mobile apps (e.g., those performing periodic sensing or running expensive sensor inference algorithms), in requiring them to balance the sensing functionalities of the app with user preference for low energy consuming apps. Interestingly, our study also shows that users tend to charge their devices very frequently and multiple times in a day in order to maintain their battery charge at a high level. As such, one strategy for these apps could be to systematically spread their energy-heavy operations throughout the day, possibly aligning them with a user's charging sessions.

Lessons from Context Analysis: An interesting finding that emerged from our analysis of physical activity logs was the low prevalence of carrying a smartphone during long walking sessions. Users attributed this behavior to the discomfort of carrying smartphones while doing physically-intensive activities. This finding has an interesting implication on fitness or lifestyle apps which monitor a user's physical activity. For these apps, accurately capturing physical activity sessions is important to generate actionable insights for the user. In this regard, our findings show that in an Indian context, smartphones may not be the right device to gather fitness data as they are unlikely to reflect the true physical activity behavior of users. Instead, fitness apps could give higher weightage to data collected from other devices (e.g., smartwatches or fitness bands) owned by the users.

Finally, through our analysis of pre- and post-Demonetization app usage, we uncovered that smartphone usage patterns among Indian users rapidly adapt to changing socio-economic contexts. Therefore when designing smartphone systems for diverse user groups, ubicomp researchers and practitioners should pay special attention to the underlying socio-economic context, and remain prepared to adapt their systems should a significant change occur in the demography of interest.

6.2 Reflection on Mobile Data Studies

As ubicomp and HCI researchers, it is likely that we have all conducted small-scale studies to answer specific research questions. Indeed, there have been a number of such mobile data studies [18, 27, 28] which have shed light on previously unknown aspects of mobile use. However despite the scientific rigor, there are unavoidable biases in such studies due to the geographical location of researchers, demographics of users they have access to, and nature of devices and services available to the users. In order to make our research community's contributions more widely acceptable, we argue that researchers should be encouraged to reproduce prior small-scale studies with larger and diverse user groups. While this may not completely eliminate all biases, the scale of the study certainly helps in providing a more complete picture of smartphone usage among diverse users.

Indeed, this was a major motivation behind our work. We identified that despite having the second largest smartphone user base in the world, there were no large-scale research studies on understanding smartphone usage behavior in India. We collected data from hundreds of users over a long period of time and not only built upon the findings of prior small-scale works in ubicomp literature, but also explored *novel research questions* in an Indian context. We then analyzed the usage data from multiple viewpoints to build up a holistic picture of smartphone usage in India. In addition to their research contributions, large-scale studies in diverse geographical and social contexts are also beneficial to ubicomp practitioners. Although ubicomp practitioners and mobile app developers serve a global audience, they are unlikely to know the intricacies of user behavior in a social context different from their own. As a community of researchers scattered around the world, we can contribute by analyzing the usage behavior in diverse demographics, thereby widening the acceptability of our community's research findings.

6.3 Geographical Variations in Mobile Data

Our study clearly highlighted that smartphone usage in the Indian context exhibits significant differences from the usage in other geographical locations. We also showed the implications that such geographical variations may have on predictive modeling systems. This finding is however not unique to India – if a similar study is conducted in another geographical region (e.g., Kenya or Japan) with a different culture, socio-economic context, infrastructure availability or language, it is likely that the observed usage patterns would be different in that region. However, we note that many published studies on mobile data (e.g., [7, 37, 39]) do not account for such geographical variations even when analyzing the data or developing predictive models. Other studies have acknowledged the user diversity (e.g., [13]), but did not provide in-depth analysis of how it affects smartphone usage. The primary takeaway from our results is that as a research community, we should pay more attention to such demographic diversities when reporting our findings. This is particularly important for large-scale studies conducted using App Stores, in which users from across the globe might participate.

6.4 Thoughts on Generalizability

Generalizability of mobile data studies remains an important issue for ubicomp researchers. There are typically two threats to generalizability of such studies: a) *are the users representative*, and b) *is their usage representative*. Firstly, our study involved a large number of urban users spread across more than 10 cities in India, and with a demographical profile representative of Indian smartphone users [4]. We also had a large device diversity in our dataset - more than 25 types of Android smartphones were used by our participants. Secondly, our study was longitudinal in nature - it spanned 8 months, which should be sufficient to avoid any novelty biases in the data. Further, we only included users with at least one month of data in our analysis. Therefore, we believe that our findings present a good picture of smartphone usage among urban Indian users. At the same time, we are cognizant that India is a large and diverse country with a population of nearly 1.3 billion, and do not claim that our results generalize to the entire population. In particular, our findings do not apply to users in India who may have low-end features phones, or to those who may not use mobile internet, or live in rural areas with completely different usage needs.

6.5 Limitations and Future Work

We now highlight some other limitations of our study. Firstly, we did not explore the effect of social connections on smartphone usage behavior – this could be an interesting topic to explore in an Indian context in the future. We are also aware that smartphone usage patterns are constantly evolving with the rapid changes in the mobile hardware and software ecosystem. As such, a longer-term study spanning multiple years could throw light on these evolving patterns. Finally, an interesting topic of future research would be to explore how predictive models can be easily fine-tuned to support diverse geographical regions.

7 CONCLUSION

In this work, we undertake the first-ever longitudinal study to uncover smartphone usage behavior of urban Indian users. In doing so, we aim to fill a major gap in the mobile data literature which has until now not sufficiently explored the smartphone usage patterns in India – the fastest growing smartphone market in the world. Analyzing the behavior exhibited by Indian users over two phases of extensive data collection, we present insights into a variety of domains of user-smartphone interaction. Particularly, we show temporal application usage patterns and application co-usage that can be harnessed to develop anticipatory application systems for better user experience. We then understand the motivation behind users' choice of applications that would support app developers in catering better to the needs of target users. We also throw light on several interesting aspects of notification interaction behavior to further user engagement. Subsequently, we provide a detailed analysis on how various kinds of contextual factors influence smartphone usage among Indian users. Following this, we explore battery charging patterns of our target group in order to help enable adaptive battery-intensive task scheduling on smartphones.

More broadly, we build upon the theoretical assessment of Church et al. [8], and highlight the importance of doing mobile data studies at large-scale in diverse contexts, not just to reproduce prior work, but also to shed light on unique aspects of the target group. To this end, we provide a detailed comparison of our results with those of past studies aimed at dissimilar geographical user communities and present use-cases to emphasize the implications of these contrasting results. Lastly, we highlight characteristic aspects of smartphone usage behavior among Indian users and discuss their ramifications, and reflect on the future of mobile data studies and their generalizability. We hope that this work will pave the way for further large-scale smartphone usage studies in diverse contexts and make the findings of our research community more widely applicable.

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