

Understanding the Role of Places and Activities on Mobile Phone Interaction and Usage Patterns

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User interaction patterns with mobile apps and notifications are generally complex due to the many factors involved. However a deep understanding of what influences them can lead to more acceptable applications that are able to deliver information at the right time. In this paper, we present for the first time an in-depth analysis of interaction behavior with notifications in relation to the location and activity of users. We conducted an in-situ study for a period of two weeks to collect more than 36,000 notifications, 17,000 instances of application usage, 77,000 location samples, and 487 days of daily activity entries from 26 students at a UK university.

Our results show that users' attention towards new notifications and willingness to accept them are strongly linked to the location they are in and in minor part to their current activity. We consider both users' receptivity and attentiveness, and we show that different response behaviors are associated to different locations. These findings are fundamental from a design perspective since they allow us to understand how certain types of places are linked to specific types of interaction behavior. This information can be used as a basis for the development of novel intelligent mobile applications and services.

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

Additional Key Words and Phrases: Mobile Sensing, Notifications, Application Usage, Context-aware Computing.

ACM Reference format:

Abhinav Mehrotra, Sandrine R. Müller, Gabriella M. Harari, Samuel D. Gosling, Cecilia Mascolo, Mirco Musolesi, and P. Jason Rentfrow. 2017. Understanding the Role of Places and Activities on Mobile Phone Interaction and Usage Patterns. *PACM Interact. Mob. Wearable Ubiquitous Technol.* 1, 1, Article 1 (July 2017), 22 pages.

DOI: 10.1145/nnnnnnn.nnnnnnn

1 INTRODUCTION

Mobile phones today have become an indispensable part of our daily lives. Far from being simple calling instruments, they are now advanced computing platforms with always-on connectivity, high-speed data processing and advanced sensing [21]. These affordances have opened the possibility of implementing novel context-aware and personalized applications that are able to assist us in a variety of day-to-day situations. At the same time, they

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DOI: 10.1145/nnnnnnn.nnnnnnn

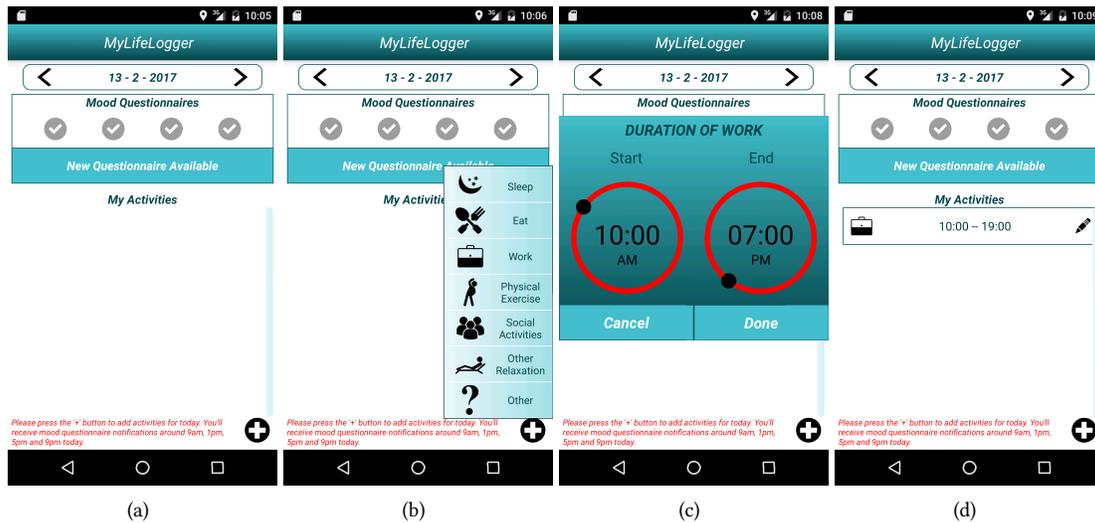


Fig. 1. The MyLifeLogger application.

represent a unique platform for real-time delivery of information about a variety of events ranging from emails to updates on online social networks, from advertisements to positive behavior change interventions [5, 20, 31].

The advent of mobile sensing has provided a great opportunity for researchers and practitioners to investigate users' mobile interaction behavior. Mobile apps are now capable of recording information about users' interactions with mobile phones and the surrounding context (e.g., location, activity, audio environment, and collocation with other devices). Thanks to the availability of this information, researchers have been able to conduct several studies on a variety of aspects of human-smartphone interaction. For example, studies have investigated the diversity in app usage behavior of individuals [14], the characterization of mobile usage in rural and urban societies [13] or in different socio-economic groups [32]. Others have focussed on the influence of personality [10, 11], the association between social context and app usage patterns [26], and users' motivations for using different types of apps [18]. Moreover, some studies have also focused on understanding users' app usage patterns for predicting their future interaction with apps [27, 38].

Another particular aspect that has attracted the attention of researchers given its practical importance is the characterization of the reaction of users to notifications and the design of mobile notification management systems. For example, some studies have investigated the factors that influence users' attentiveness and receptivity to notifications [24, 30] and how these are influenced by context [28], content [23], and the complexity of an ongoing task [24]. Other projects have aimed at anticipating users' attentiveness [30] and receptivity [22] to notifications by learning their behavioral patterns.

However, existing work has not considered the impact of the *external* factors, such as the type of locations users are in and the activities they are currently carrying out, on their interaction with notifications and app usage behavior. A deep understanding of these factors would enable us to improve users' experience and the effectiveness of notifications as well as applications (e.g., marketing and positive behavior intervention applications). Key challenges for such a study include data collection at a very fine granularity, which might require frequent inputs from users, and the extraction of high-level information from raw sensor data with the goal of assigning semantics to it.

To bridge this gap, in this paper we present the first in-situ study of the impact of location and activities on users' interaction with mobile notifications and applications. Over a period of two weeks, we collected more than 36,000 notifications, 17,000 instances of application usage, 77,000 location samples, and 487 days of daily activity entries (i.e., 2984 activity instances) from 26 students at a UK university. Using this data, we investigate users' interaction with mobile notifications and apps when they are performing different activities, when they visit different types of locations, and locations with different characteristics such as being boring vs. exciting, sad vs. happy, inactive vs. busy, lazy vs. productive, distressing vs. relaxing, and natural vs. urban.

The key contributions and findings of this work can be summarized as follows:

- We discuss an in-depth study of the relationships between users' activities and interaction with notifications and apps.
- We discuss a quantitative evaluation of users' interaction with notifications and apps when they are at different types of locations; this is important from a design perspective, since it allows us to understand how certain types of places are linked to specific types of interaction behavior as a basis of the development of intelligent applications.
- We present an extensive investigation of the impact of location characteristics on users' attentiveness and receptivity to notifications and app usage pattern. We consider different characterization of places (e.g., urban, productive and so on) in relation to users' interaction with notifications. Again, besides the inherent intellectual interest, the findings might be used in the design of personalized applications based only on the knowledge of the current location.

Through our analysis we uncover various new insights about the phone usage and notification interaction behaviors of users and also, quite importantly, confirm some findings of previous studies. More specifically, the main novel findings of our analysis are:

- Participants were more receptive to notifications while they were exercising and doing routine tasks.
- Overall communication apps were used the most, except while participants were going to sleep, which is when they mostly used lifestyle apps.
- Participants were more receptive to notifications when they were at college, in libraries, on streets, and they were least attentive while being at religious institutions.
- The app usage was highest while participants were at college or in libraries.
- Participants used mostly music and reading apps while waiting at bus stops and train stations.
- Participants were more attentive to notifications at productive places compared to lazy places.
- Participants were less receptive to notifications at natural places compared to urban places.
- While at lazy, distressing and natural places participants used their phones less compared to productive, relaxing and urban places respectively.

This study has led to many interesting insights that are discussed in detail in the following sections. First of all, people pay less attention to notifications when they are preparing to go to bed (or they are in bed before sleeping) and while exercising. People accept most notifications that are delivered while they are doing exercise and routine tasks. When people are on streets, or in college, university and residential areas, they not only pay more attention towards notifications but also accept most of them. Also, people are more attentive to notifications at places that are characterized as "productive". They accept more notifications at productive and urban places. Furthermore, overall phone usage duration as well as usage of specific apps vary when people visit specific types of places and while performing specific activities. Overall app usage is highest while people are relaxing, at college or in libraries, whereas it is lowest while people are doing exercise, routine tasks or going to sleep, and when they are at gyms, religious institutions or in parking places.

We believe that the potential applications of this work are many. First of all the findings of this paper can be used as a basis for the development of predictive applications that rely on the analysis of users' current

locations and not only on their past behavioral patterns. More specifically, this is particularly important in the bootstrapping phase of intelligent applications that are based on learning algorithms that require a large history of past interactions with the phones in order to make accurate prediction about users' behavior. Examples include notification management systems, and pre-caching and pre-launching mechanisms for mobile applications.

2 RELATED WORK

In this section we review the related work in two key areas, namely the studies about the characterization of users' interaction with notifications and those about users' app usage behavior.

2.1 Understanding Users' Interaction with Notifications

In recent years the area of mobile interruptibility has received increasing attention. Previous studies have explored various aspects of users' interaction with mobile notifications [4, 6, 7, 12, 24, 29, 35]. In particular, in [35] Sahami et al. show that users deal with around 60 notifications per day, and most of these are viewed within a few minutes of arrival. Additionally, by collecting the subjective feedback from mobile users, the authors demonstrate that users assign different importance to notifications triggered by application from different categories. At the same time, Pielot et al. [29] show that personal communication notifications are responded to quickest because of social pressure and the exchange of time critical information through communication applications (i.e., Whatsapp). On the other hand, as Iqbal et al. suggest in [19], users are willing to tolerate some disruption in return for receiving notifications that contain valuable information. Similarly, in [24] Mehrotra et al. show that notifications containing important or useful content are often accepted despite the disruption caused by them.

Moreover, other studies have also investigated how users' attentiveness and receptivity to notifications are influenced by their context [28, 30] and content [16, 22, 23]. In [28], the authors show that the attentiveness of users can be determined by contextual factors including activity, location and time of day. They propose a mechanism that relies on these context modalities to predict opportune moments for delivering notifications. In [30] Pielot et al. propose a model that can predict whether a user will view a notification within a few minutes with a precision of approximately 81%. On the other hand, in [16] the authors show that users' receptivity is influenced by their general interest in the notification content, entertainment value perceived in it and action required by it, but not the time of delivery. In [23] Mehrotra et al. suggest to use contextual information, sender-recipient relationship and application category that triggered the notification for determining the user's interruptibility. In another study [22], the authors demonstrate that users' receptivity to notifications is influenced by their location and the content of notifications delivered. The authors propose a system that relies on machine learning algorithms for the automatic extraction of rules that reflect user's preferences for receiving notifications in different situations.

2.2 Understanding Users' App Usage Behavior

Previous studies have investigated the association between users' app usage behavior and various socio-economic [13, 14, 32] and psychological [10, 11, 26] factors. Others have focussed on users' motivations for using different types of apps [8, 18].

More specifically, in [32], Rahmati et al. present a study that investigates how users with a certain socio-economic status install and use apps. Their findings confirm the influence of socio-economic status on phone usage. In [11], the authors show that there is a significant association between users' personality traits and phone usage. Furthermore, quite interestingly, in [18] Hiniker et al. provide evidence that users' motivations for engaging with technology can be divided into instrumental and ritualistic.

In [8], Bohmer et al. present a large-scale study with the goal of understanding users' app usage patterns based on their context. The findings of this study demonstrate that users spend around an hour every day using their phones, but their average session using an application lasts for a minute. Overall, communication apps get

Group	Feature	Description
Notification	Arrival time	Time at which a notification arrives in the notification bar.
	Removal time	Time at which a notification is removed from the notification bar.
	Sender application	Name and package of the application that triggers the notification.
Application Usage	App Name	Name of the application.
	Launch Time	Time at which the application is launched and appeared in the foreground.
	Background Time	Time at which the application use is ended and it is moved from foreground to background.
Phone Interaction	Lock/unlock event	Time at which the phone was locked and unlocked.
	Screen interaction	Type of interaction (i.e., single click, long click and scroll), time and the name of foreground applications (including home screen) with which the interaction happened.
Context	Location	Geo-location of the places visited.
	Daily Activity	Type and time duration of different activities performed in a day. These activities include sleep, eat, work, physical exercise, social activity and relaxation.

Table 1. Description of features from the dataset.

used most, except when users are traveling, in which case they are more likely to use multimedia apps. In [15], Ferreira et. al. conducted a study showing that app usage behavior of users is strongly influenced by their social and spatial context. Also, Xu et al. [37] exploit the network traffic from apps (based on HTTP signatures) to demonstrate that app usage is influenced by spatial and temporal factors including geographical areas and time of the day. Their findings also show that certain apps have a non negligible likelihood of co-occurrence.

An open question in this area remains the impact of locations and activities on users' interaction with notifications. The present study aims to bridge this gap by investigating the effects of these factors on users' attentiveness and receptivity to notifications as well as on their app usage behavior.

3 METHODOLOGY

In this section we present our approach for investigating the influence of daily activities, type and characteristics of visited locations on users' app usage, and notification interaction behavior.

3.1 LifeLogger App

Given the aims of the proposed investigation, we designed and carried out an *in-the-wild* study [34] to collect users' data. More specifically, we developed an Android app called *MyLifeLogger* (shown in Figure 1). The app performs continuous sensing in the background to log users' interaction with notifications, app usage, and context. Table 1 provides a description of the features captured by *MyLifeLogger*.

The app relies on Android's Notification Listener Service [1] and Usage Stats Manager [2] to trace notifications and application usage. Moreover, the app allows users to provide their daily activity schedules, for which a reminder notification is triggered every night at 9pm (local time). As shown in Figure 1(b), users were given a list of six possible daily activities:

- Eat: time period when a user is having food.
- Sleep: time period for which a user slept. ¹
- Work: time period when a user is engaged in an activity involving mental or physical effort. Since our participants are students, this activity would mostly consist of or be related to studying.

¹It is worth noting that participants did not receive any standard definition of these activities before the study. Therefore, for example, some participants might have interpreted sleeping as being in bed.

- Exercise: time period when a user is performing health and fitness activities.
- Social: time period when a user is socializing with others.
- Relaxation: time period during which a user is being free from tension and anxiety.

It is worth noting that participants were able to select only one activity for a specific time interval. Moreover, they were allowed to enter other activities by selecting the *other* option, through which they could input an activity name as free text. Most activities registered through the *other* activity option were related to routine tasks such as laundry, cooking, getting ready, packing, supermarket and so on. Therefore, we created another category for *chores* and mapped the routine tasks entered through the *other* activity option to this new activity.

The MyLifeLogger app also collected additional data about other contextual features (such as movement, call and SMS logs) as well as mood-related questionnaires. However, we do not discuss those aspects of the data because they are not used for the analysis presented in this paper.

3.2 Recruitment of the Participants

MyLifeLogger was published on Google Play Store² and advertised to first-year undergraduate students at a UK University. It was installed by 28 students and 26 students completed the study by keeping the app running on their phone for a minimum of two weeks. These participants come from both sexes (16 males and 10 females), with the age span between 18 and 27 years (*mean* = 19.46 and *standard deviation* = 2.18). The students were enrolled in 15 different courses and 27% ($n=7$) were non-British. All participants who completed the study were given £25.

3.3 Ensuring Privacy Compliance

In order to allow the MyLifeLogger application to monitor notifications and app usage, the user has to give explicit permission as required by the Android operating system. Moreover, the application also shows a consent form detailing the information that is collected. This ensures that the user goes through a two-level user agreement and is completely aware of the type of information captured by the application.

It is worth noting that we received ethical approval for the study, including all procedures and materials, from the Psychology Research Ethics Committee at the University of Cambridge.

3.4 Dataset

We analyzed the data of 26 users who participated for a minimum period of two weeks. The dataset corresponding to these users includes 36,106 notifications, 17,680 instances of application usage, 77,306 location samples, and 487 days of daily activity entries (i.e., 2,984 activities).

3.4.1 Characterizing Locations. In order to perform our analysis on the impact of location on notification response and application usage, we cannot just rely on sensor (i.e., GPS) data as it only provides the coordinates of a place rather than its type and characteristics. Therefore, we manually categorized the locations by clustering them into significant places, and then characterized the significant places by having coders rate each place on several dimensions (e.g., the degree to which a place is inactive vs busy).

Identifying Significant Places. First of all, we discard the location samples with more than 50 meters accuracy so that the estimated location clusters are of better quality. We then find the location samples that were collected while users were moving and we also discard them. In order to infer such location points, we compute the speed of the user by using the distance and the time between the last and the current location points. If the speed is

²<https://play.google.com/store/apps/details?id=com.nsdsmystudentlife>

less than a certain threshold (i.e., 5 km per hour) we consider that location reading was collected when the user was not moving.

Now, we use the location clustering approach presented in [36] for grouping the filtered location samples. We iterate over all location samples and for each location point we create a new cluster only if the distance of this location from the centroid of each existing cluster is more than 200 meters. Otherwise, we add this location to the corresponding cluster and update its centroid. Finally, we consider all centroids as significant places.

Identifying Place Type and Characteristics. Places can be described in terms of objective information, such as whether a location is indoor or outdoor, or in a residential or industrial area, and also in terms of information that relates to users' affective appraisals of them. Despite people's experiences of course being subjective, they on average agree on a variety of characteristics such as liveliness, pleasantness, and naturalness, to name a few [17, 25]. At the same time, we recruited coders belonging to the same demographics of the participants (e.g., student status, average age, even gender distribution) to reduce the subjectiveness in place ratings. Moreover, we computed the similarity in the ratings to ensure that they are reliable.

On average, 53 significant places (per person) were identified in the two-week study period. For each participant we selected the top ten places in which they had spent most time. We recruited four independent coders who were undergraduate students themselves but not participants in the study. First, they were trained in person and provided with a detailed handbook on the location coding process. After their training, they were provided with a list of coordinates (i.e., longitude and latitude) of the respective places, and they were asked to categorize and evaluate these places for the given characteristics by looking at them using Google maps.

In order to categorize the place type, we rely on Google's Place Types [3] as the possible categories. Moreover, coders were provided with an option to enter an additional place type in case it was not present in the given list. In cases where a place type was unclear, coders used an "unclear" category to denote an ambiguous place. Finally, each place type that was classified by four coders was merged by one of the authors. It is worth noting that we filtered out the categories that appeared rarely or not at all. In order to perform this filtering, we ensured that places of each category were visited at least once by a minimum of 50% of the participants.

In order to identify the characteristics of significant places, these were also coded for 24 descriptive characteristics that captured the ambience of the place, and the types of people that would visit the place. In this work, we focused on the four characteristic ratings that describe the ambience of the place. Specifically, we focused on the degree to which the place was: *inactive-busy*, *lazy-productive*, *distressing-relaxing*, and *natural-urban*. These four characteristics were rated on a 7-point Likert scale. These ratings from the four coders were then merged by computing their mean. Finally, the merged ratings were centered and rescaled from a 1 to 7 scale to a -3 to 3 scale. We then transform these from a 7-point scale to a 3 points scale (-1 to 1) by using these ranges: -3 to -0.5 as -1, -0.5 to 0.5 as 0, and 0.5 to 3 as 1. This turned the continuous variable into a categorical one and makes it likely that we have enough data for all levels. Levels -1, 0, 1 represent the negative, neutral, and positive value of the location characteristic respectively. For instance, these ratings for *inactive-busy* characteristics would convert to *inactive*, *neutral* and *busy*.

3.4.2 App Categories. In order to investigate users' behavior for interacting with specific apps, we categorized all apps using the categories defined on the Google Play store. Overall, the apps belong to 11 categories, namely reading, fitness, business, photography, communication, game, lifestyle, music, social, tools, and travel applications. However, apps of certain categories are not used by all participants. Therefore, we consider the type of apps that were used by all participants. Consequently, we came up with the following six categories: *communication*, *lifestyle*, *music*, *reading*, *social*, and *travel* applications.

3.5 Quantitative Measures for Notification and Phone Usage

In this section we discuss the metrics used in this study for quantifying users' behavior in terms of their interactions with notifications and apps. We use two metrics for quantifying interaction with notifications – *Notification Receptivity* and *Notification Seen Time*, and one metric for interaction with app – *App Usage Time*. These are classic indicators widely adopted for this type of studies by the ubiquitous computing community (see for example [16, 30]). The definitions of these metrics are reported below.

- **Notification Receptivity:** the user's willingness to receive a notification. This metric represents how willing a user is to receive interruptions. High receptivity (i.e., more clicks) indicates increase in the willingness of the user to be interrupted and vice versa. In order to infer the response to a notification, we check whether the corresponding app (which triggered the notification) was launched after the removal time of that notification. We are aware that our approach has limitations, because some notifications that do not require further action might not be clicked rather just seen and dismissed by the user.
- **Notification Seen Time (Notification Attentiveness):** the time from the notification arrival until the time the notification was seen by the user. This metric reflects the user's *attentiveness* towards new notifications. In order to detect the moment at which a notification is seen, we use the unlock event of the phone and assume that all newly available notifications in the notification bar are seen when the user unlocks the phone. In case a notification arrives when the user is already using the phone (i.e., the phone is unlocked), the seen time of this notification would be considered equal to zero. To detect the lock and unlock events we use the *Phone Interaction* data (discussed in Table 1). It is worth noting that we removed all notification instances that were not responded to within 2 hours. As a recent study [29] demonstrated that people receive notifications every hour (from morning to late night), which are handled within a few minutes. Therefore, we use 2-hour threshold for the maximum seen time to filter out notifications that arrived when the user was away from the phone or sleeping.
- **App Usage Time:** duration for which an application was in foreground. More specifically, it is the time interval between the launch of an application and the instant of time when it was sent to the background.

We compute these metrics for each user when they are performing specific activities and when they are at certain types of places. We then aggregate these metrics to compute their average values. Finally, we use statistical tests to compare the difference in users' interaction when performing different activities at different types of places.

It is worth noting that while computing *App Usage Time* for different activities, we normalize the app usage value by dividing it by the time spent by the user engaging in the corresponding activity. Similarly, to compute the *App Usage Time* for different types of places, we normalize the app usage value by dividing it by the time spent by the user at the corresponding place. This step is necessary in order to avoid biases due to the relative times spent in a given location or while engaging in a certain activity. Therefore, the use of a non-normalized *App Usage Time* metric could produce biased results.

3.6 Procedure

We want to investigate the influence of variables, including daily activities, type and characteristics of visited locations, on the notification and phone usage behavior of users, so we consider them as the independent variables. On the other hand, our dependent variables should represent the notification and phone usage behavior of users. Therefore, we use the three notification and phone usage metrics (*Notification Receptivity*, *Notification Seen Time*, and *App Usage Time*) as dependent variables. The analyses were performed for each pair of independent and dependent variables. We perform a one-way ANOVA for quantifying the differences in the dependent variables (i.e., *Notification Receptivity* and *Notification Seen Time*) that represents notification interaction behavior. However, for quantifying the variability in the dependent variable (i.e., *App Usage Time*) that represent app usage behavior,

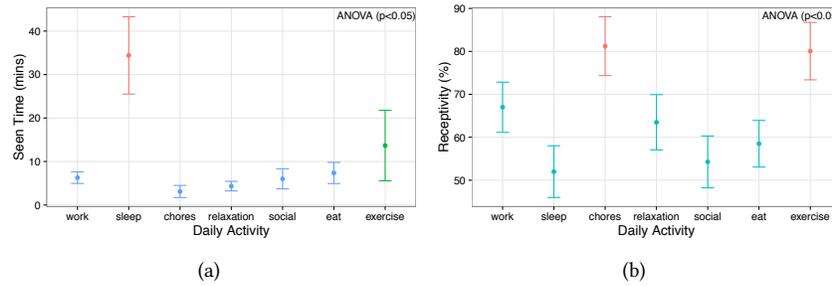


Fig. 2. Role of daily activity in influencing the user’s (a) attentiveness and (b) receptivity. Different color indicates statistically significant differences ($p < 0.05$). In these plots the dots represent the means and the bars represent the standard deviations.

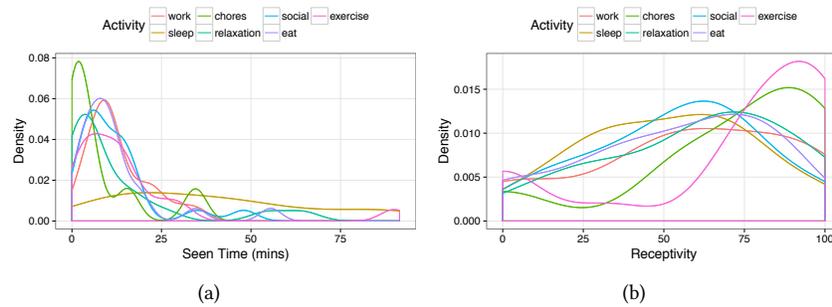


Fig. 3. Probability distributions of users’ average (a) attentiveness and (b) receptivity while performing different daily activities. Here, probabilities can be computed as multiplication of density with attentiveness and receptivity values respectively.

we perform a two-way ANOVA, because app category is considered as another independent variable apart from activity and location based independent variables. It is worth noting that we removed the levels of independent variables that did not have observations from at least 50% of the participants.

4 UNDERSTANDING THE ROLE OF DAILY ACTIVITY

In this section we provide a quantitative evaluation of the relationship between daily activity and the users’ behavior in terms of notification interaction and app usage.

The key findings of this section are:

- People are least attentive to notifications while they are preparing to go to bed (or using the phone in bed) and during the time they exercise.
- People are more receptive to notifications while they are exercising and doing chores (i.e., routine tasks).
- Overall app usage is highest while people are relaxing and lowest when they are engaged in chores, doing exercise and going to sleep.
- Usage of specific apps is associated to users’ daily activities.

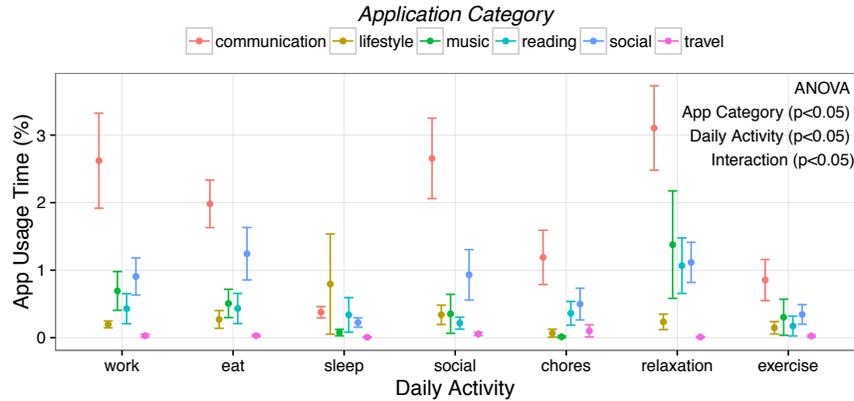


Fig. 4. Relation between daily activity and application usage. In this plot the dots represent the means and the bars represent the standard deviations..

4.1 Attentiveness and Receptivity

To investigate the relationship between daily activity and users' attentiveness and receptivity to notifications, we perform two separate one-way ANOVAs that quantify the differences in the user's (i) attentiveness and (ii) receptivity to notifications while they perform different activities. The results of the first analysis (i.e., effects on attentiveness) show that there is a significant effect of daily activities on the user's attentiveness, with $F = 4.788$, $p < 0.05$. In order to find which daily activities affect users' attentiveness, we perform a Tukey post-hoc test (by setting α equal to 0.05). As shown in Figure 2(a), the test reveals that the seen time is longest (i.e., low attentiveness) when notifications arrive while the user is sleeping. However, there is no significant difference in attentiveness of users while they are engaged in any other daily activity, except that they are slightly less attentive while exercising.

The results of the second analysis show that there is also a significant effect of daily activities on the users' receptivity to notifications, with $F = 2.947$, $p < 0.05$. As shown in Figure 2(b), a Tukey post-hoc test (by setting α equal to 0.05) reveals that users' are most receptive to notifications when they are performing chores or physical exercise compared to other activities.

Moreover, in order to investigate the diversity in users' attentiveness and receptivity, in Figure 3 we present the probability distribution of users' average attentiveness and receptivity while they are performing different daily activities. The results demonstrate that there is some variability in both attentiveness and receptivity between users. For instance, some users are considerably less attentive to notifications while exercising compared to other users. Users' receptivity varies across all activities.

4.2 App Usage Time

In order to investigate the relationship between daily activities and the app usage, we perform a two-way ANOVA by setting *app usage time* as dependent variable (DV), and *daily activity* and *app category* as independent variable (IVs). Here, we use two IVs as we can quantify both the effect of daily activity on overall app usage time and the effect of daily activity of the use of specific apps. The results demonstrate that all effects were statistically significant at the 0.05 significance level. The main effect for daily activity yielded $F = 7.45$ ($p < 0.05$), indicating a significant difference in the user's overall app usage time (all categories considered together) while performing

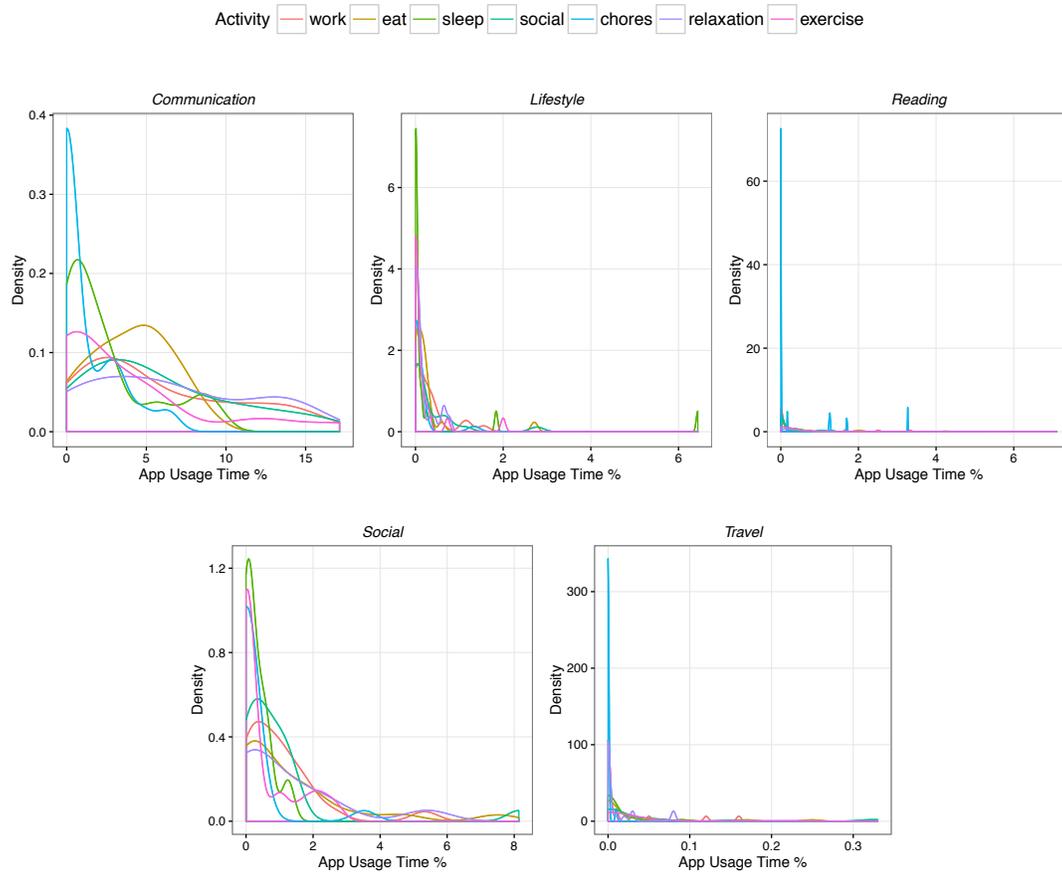


Fig. 5. Probability distribution of users' average app usage time percentage while performing different daily activities. Here, probability can be computed as multiplication of density and app usage values.

different activities. A Tukey post-hoc test (by setting α equal to 0.05) reveals that overall app usage time is highest while people are relaxing and lowest when they are engaged in chores, doing exercise and going to sleep.

The main effect for app category yielded $F = 20.22$ ($p < 0.05$), indicating a significant difference in the usage of different apps. A Tukey post-hoc test (by setting α equal to 0.05) reveals that people use communication apps the most and apps including lifestyle, music and travel are used the least. These findings are inline with some previous studies that show that communication apps are the most popular [8].

Also, there is a statistically significant interaction effect of daily activity and app category on app usage time, $F = 4.88$ ($p < 0.05$), which indicates that different apps are used while users are performing different activities. As shown in Figure 4, overall communication apps are used the most, except while people are going to sleep, which is when they tend to mostly use lifestyle apps. The usage of communication, reading, music and social apps is highest while people are relaxing.

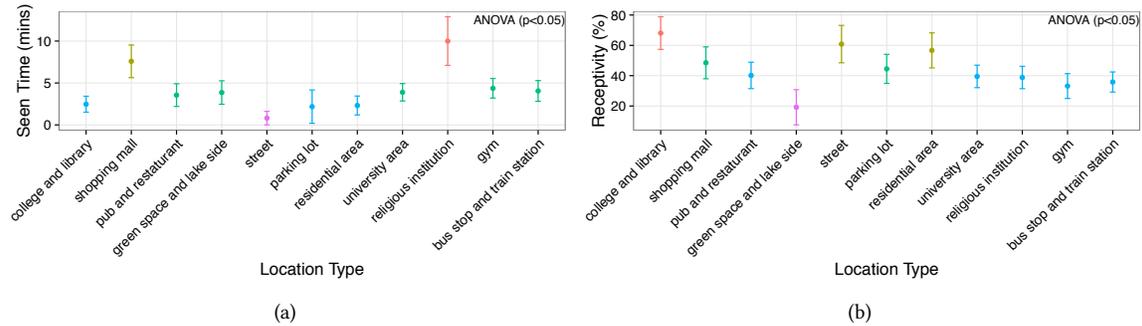


Fig. 6. Role of location type in influencing the user's (a) attentiveness and (b) receptivity. Different color indicates statistically significant differences ($p < 0.05$). In these plots the dots represent the means and the bars represent the standard deviations.

Moreover, in order to investigate the diversity in users' app usage while performing different daily activities, in Figure 5 we present the probability distribution of users' app usage time for five app categories. The results demonstrate that there is more variability in users' app usage time for communication apps compared to other app categories. On the other hand, there is almost negligible variation in users' app usage time for lifestyle, reading, and travel apps.

5 UNDERSTANDING THE ROLE OF LOCATION TYPE

In this section we provide a quantitative evaluation of the relationship between location type and users' behavior in terms of notification interaction and app usage.

The key findings of this section are:

- People are least attentive to notifications at religious institutions.
- People are more receptive to notifications when they are at college, in libraries, on streets or residential areas.
- Overall app usage is highest while people are at college or in libraries, and lowest when they are at gym, at religious institutions, or in parking places.
- Usage of specific apps is associated with users' location.

5.1 Attentiveness and Receptivity

To investigate the relationship between location type and users' attentiveness and receptivity to notifications, we perform two separate one-way ANOVAs that quantify the differences in users' (i) attentiveness and (ii) receptivity to notifications when they are at different locations. The results of the first analysis (i.e., effects on attentiveness) show that there is a significant effect of location type on users' attentiveness, with $F = 19.71$, $p < 0.05$. In order to find which location types affect the user's attentiveness, we perform a Tukey post-hoc test (by setting α equal to 0.05). As shown in Figure 6(a), the test reveals that the seen time is longest (i.e., low attentiveness) when notifications arrive while the user is at religious institutions. On the other hand, they are most attentive to notifications where they are outside in a street.

The results of the second analysis show that there is also a significant effect of location types on users' receptivity to notifications, with $F = 8.80$, $p < 0.05$. As shown in Figure 6(b), a Tukey post-hoc test (by setting

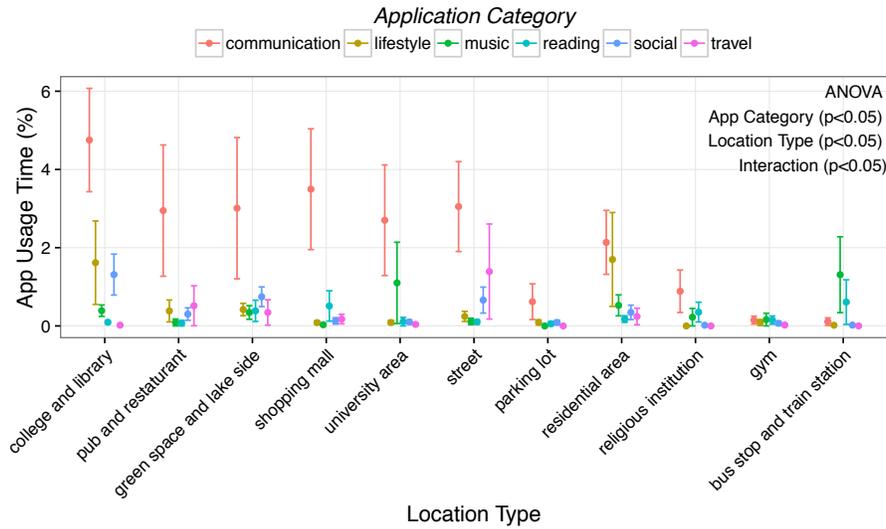


Fig. 7. Relation between location type and application usage. In this plot the dots represent the means and the bars represent the standard deviations.

α equal to 0.05) reveals that users’ are most receptive to notifications when they are at college, in libraries, on streets or in residential areas. Whereas, their receptivity to notifications is least when they are at green spaces and lakes side areas.

5.2 App Usage Time

In order to investigate the relationship between location type and the app usage, we perform a two-way ANOVA by setting *app usage time* as dependent variable (DV), and *location type* and *app category* as independent variables (IVs). Here, we use two IVs as we can quantify both the effect of location type on overall app usage time and the effect of location type of the use of specific apps. The results demonstrate that all effects were statistically significant at 0.05 significance level. The main effect for daily activity yielded $F = 6.85$ ($p < 0.05$), indicating a significant difference in the user’s overall app usage time (all categories considered together) when they are at different types of locations. A Tukey post-hoc test (by setting α equal to 0.05) reveals that overall app usage time is highest while people are at college or in libraries, and it is the least when they are at gyms, at religious institutions or in parking spaces.

Also, there is a statistically significant interaction effect of location type and app category on app usage time, $F = 4.56$ ($p < 0.05$), which indicates that different apps are used while users are at different types of locations. As shown in Figure 7, overall communication apps are used the most, except while people are at gyms, religious institutions or bus stops. Interestingly, our results show that people tend to use mostly music and reading apps while waiting at bus stops and train stations. Similarly, another study has demonstrated that while traveling (in vehicle) people tend to use mostly music apps [8]. On the other hand, our results show that travel apps are used mostly when users are outside on the streets. In a sense, this is in-line with the findings of [8] in which the authors show that when people are commuting at peak hours they tend to use travel apps.

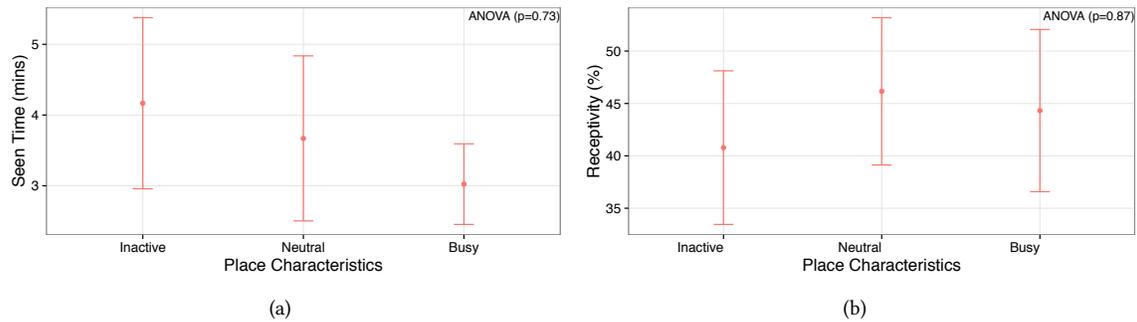


Fig. 8. Role of inactive and busy nature of places in influencing users' (a) attentiveness and (b) receptivity. In these plots the dots represent the means and the bars represent the standard deviations.

6 UNDERSTANDING THE ROLE OF LOCATION CHARACTERISTICS

In this section we discuss the effects of psychological features of a place (i.e., location characteristics) on users' interaction with notifications and apps. Our approach is adapted from a framework for studying the psychological meaning of situations (e.g., [33]). As shown in those studies [33], these psychological features of a location are important because they reflect the way people perceive the environment, which could effect their phone usage behavior.

Therefore, in this section we analyze the effects of location characteristics firstly on users' attentiveness and receptivity to notifications and then on app usage time. In order to investigate the former, two separate one-way ANOVAs are conducted to quantify the effect of location characteristics on users' (i) attentiveness and (ii) receptivity to notifications. For the latter, we conduct a two-way ANOVA to quantify the association of daily activity and app category on the app usage time.

The key findings of this section are:

- People's attentiveness is associated with the lazy-productive dimension of location characteristics. They are more attentive to notifications at productive places compared to lazy places.
- People's receptivity is associated with the lazy-productive, and urban-natural dimensions of location characteristics. They are more receptive to notifications at productive and urban places compared to lazy and natural places.
- Overall app usage is less at lazy, distressing and natural places compared to productive, relaxing and urban places respectively.

6.1 Inactive vs Busy Places

In this sub-section we compare users' interaction with notifications and apps at inactive and busy places. Places that were coded as inactive include green spaces, lakes side areas, residential and industrial areas. Places such as gyms, religious institutions, college and university areas are considered as neutral, whereas places such as shopping malls, pubs and restaurants are rated as busy places.

6.1.1 Effects on Attentiveness and Receptivity. As shown in Figure 8, our results demonstrate that there is no significant difference in both attentiveness and receptivity of users when they are at inactive, neutral and busy

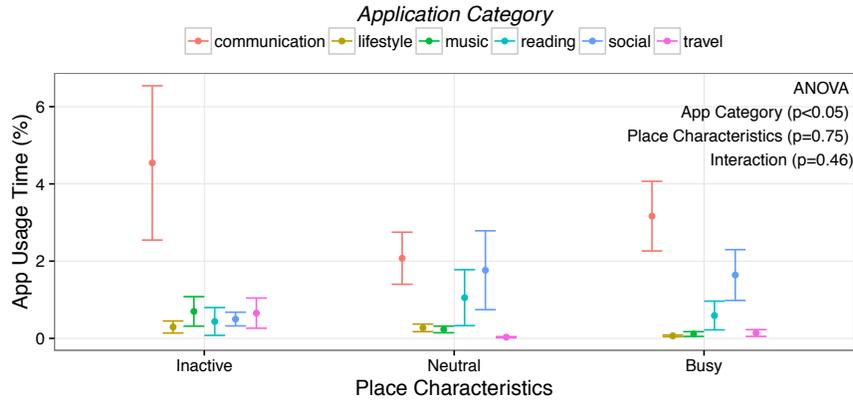


Fig. 9. Role of inactive and busy nature of places in influencing users’ application usage behavior. In this plot the dots represent the means and the bars represent the standard deviations.

place. In other words, this indicates that the inactive-busy dimension of the place characteristics have no effect on users’ attentiveness and receptivity to notifications.

6.1.2 Effects on App Usage Time. As shown in Figure 9, our results demonstrate that the main effect of place characteristics (for inactive-busy dimension) is not statistically significant, indicating no significant difference in users’ overall app usage time (all categories considered together) for inactive, neutral and busy places.

Also, there is no statistically significant interaction between the effects of place characteristics (for inactive-busy dimension) and app category on app usage time. This demonstrates that also users’ behavior in terms of their interaction specific apps does not vary with the inactive-busy dimension of place characteristics.

6.2 Lazy vs Productive Places

In this sub-section we compare users’ interaction with notifications and apps at lazy, neutral and productive places. Places that were coded as lazy include green spaces, lakes side areas, pubs and residential areas. Places such as religious institutions, shopping malls are considered as neutral, whereas places such as libraries, college and university areas are rated as productive.

6.2.1 Effects on Attentiveness and Receptivity. The results of our analysis show that there is a significant difference in users’ attentiveness to notifications when they are at lazy, neutral and productive places, $F = 5.43$ ($p < 0.05$). As shown in Figure 10(a), a Tukey post-hoc test (by setting α equal to 0.05) reveals that users are more attentive (i.e., seen time is shortest) to notifications at lazy places compared to productive places. Interestingly, these findings go inline with one of our recent study [24] in which we have shown that people become more attentive to notifications when they are engage in complicated tasks. People’s attentiveness is high at productive places could be explain with the fact that they are engaged in more complicated tasks at such places compared to the tasks they perform at other places.

Similarly, our results demonstrate that there is a significant difference in users’ receptivity at lazy, neutral and productive places, $F = 5.77$ ($p < 0.05$). As shown in Figure 10(b), a Tukey post-hoc test (by setting α equal to 0.05) reveals that users are least receptive to notifications at lazy places, and they are most receptive at productive places. These findings indicate that people are not only paying more attention but also accepting more mobile notifications at productive places compared to other places. This could be due to the fact that they receive

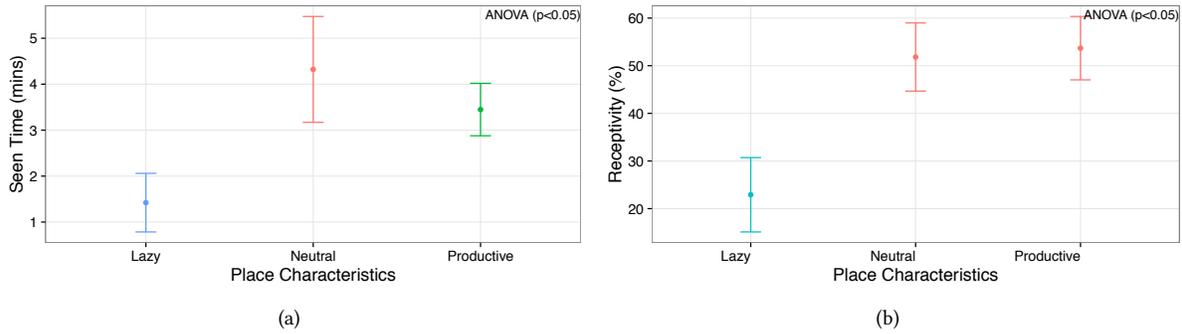


Fig. 10. Results for role of lazy and productive nature of places in influencing users’ (a) attentiveness and (b) receptivity. Different color indicates statistically significant differences ($p < 0.05$). In these plots the dots represent the means and the bars represent the standard deviations.

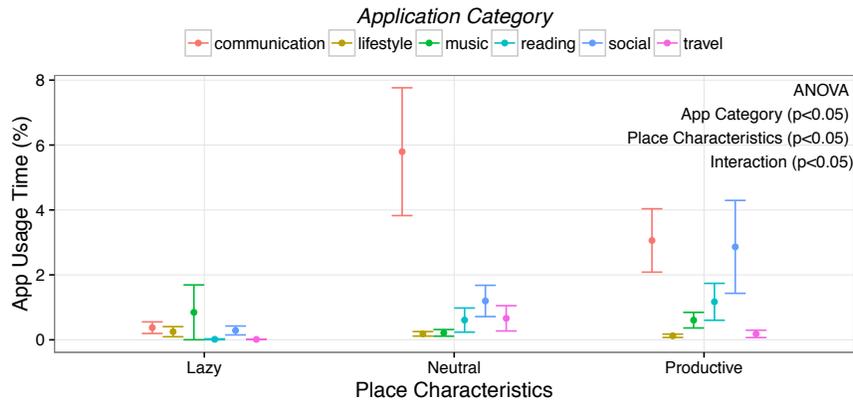


Fig. 11. Results for role of lazy and productive nature of places in influencing users’ application usage behavior. In this plot the dots represent the means and the bars represent the standard deviations.

important notifications (for example, while communicating with their colleagues), which they do not want to miss at such place.

6.2.2 Effects on App Usage Time. The analysis for measuring the effects of place characteristics (for lazy-productive dimension) and app category on app usage time reveals that all effects are statistically significant at the 0.05 significance level. As shown in Figure 11, our results demonstrate that the main effect of place characteristics (for lazy-productive dimension) yields $F = 6.38$ ($p < 0.05$), indicating a significant difference in users’ overall app usage time (all categories considered together) for lazy, neutral and productive places. A Tukey post-hoc test (by setting α equal to 0.05) reveals that users’ overall app usage time is less at lazy places compared to other places.

Moreover, there is also a statistically significant interaction between the effects of place characteristics (for lazy-productive dimension) and app category on app usage time, $F = 1.91$ ($p < 0.05$). This indicates that people use different apps at lazy, neutral and productive places. For instance, our results show that people tend to use

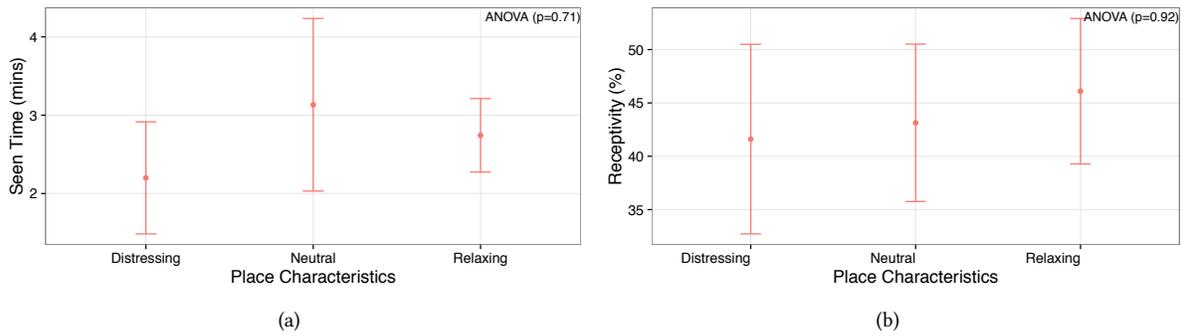


Fig. 12. Results for role of distressing and relaxing nature of places in influencing users’ (a) attentiveness and (b) receptivity. In these plots the dots represent the means and the bars represent the standard deviations.

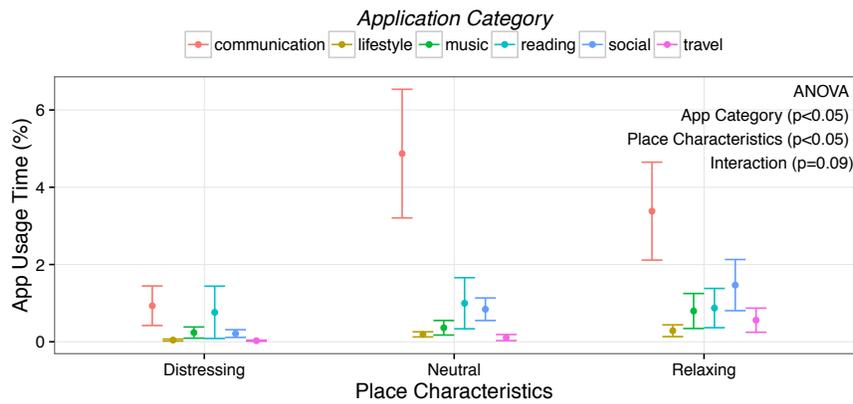


Fig. 13. Results for role of distressing and relaxing nature of places in influencing users’ application usage behavior. In this plot the dots represent the means and the bars represent the standard deviations.

music apps the most at lazy places, whereas social and reading apps are used the most at productive places. Interestingly, communication and travel apps are used mostly at neutral (neither lazy nor productive) places.

6.3 Distressing vs Relaxing Places

In this sub-section we investigate users’ interaction with notifications and apps at distressing and relaxing places. Places that were coded as distressing include shopping mall and train stations. Places such as restaurants, colleges and university areas are considered as neutral, whereas places such as green spaces, lakeside areas and pubs are rated as relaxing places.

6.3.1 Effects on Attentiveness and Receptivity. As shown in Figure 12, our results demonstrate that there is no significant difference in users’ attentiveness to notifications when they are at distressing, neutral and relaxing places. Similarly, their receptivity to notifications shows no significant difference at these places.

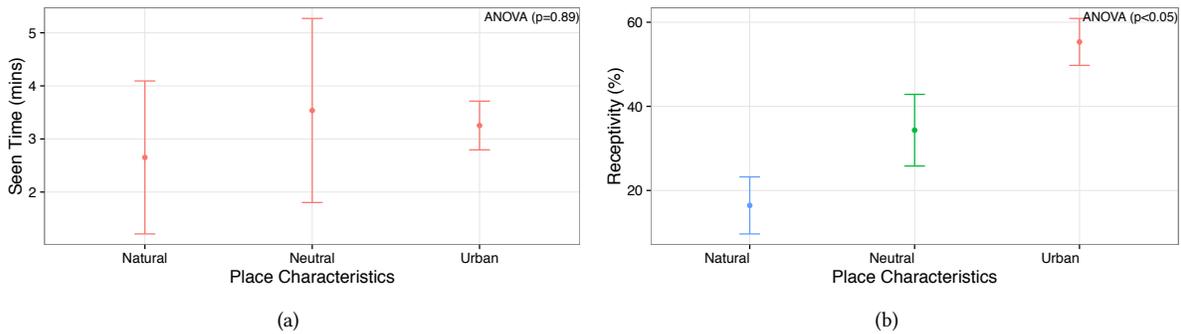


Fig. 14. Results for role of urban and natural nature of places in influencing users’ (a) attentiveness and (b) receptivity. Different color indicates statistically significant differences ($p < 0.05$). In these plots the dots represent the means and the bars represent the standard deviations.

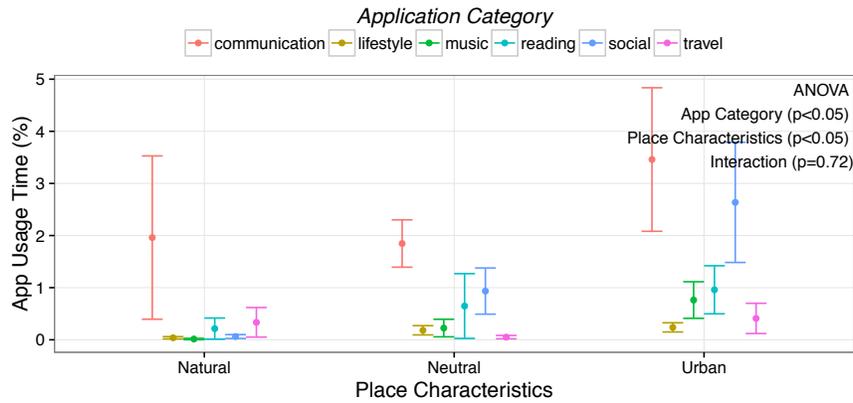


Fig. 15. Results for role of urban and natural nature of places in influencing users’ application usage behavior. In this plot the dots represent the means and the bars represent the standard deviations.

6.3.2 *Effects on App Usage Time.* As shown in Figure 13, our results demonstrate that there is a statistically significant main effect of place characteristics (for distressing-relaxing dimension) and app category on app usage time, $F = 3.82$ ($p < 0.05$). However, there is no statistically significant interaction between the effects of place characteristics (for distressing-relaxing dimension) and app category on app usage time. This indicates that only the overall app usage time varies depending on the place is distressing or relaxing, rather than users’ behavior for using specific apps. Finally, a Tukey post-hoc test (by setting α equal to 0.05) reveals that users’ overall app usage time is lower at distressing places compared to other places.

6.4 Urban vs Natural Places

In this sub-section we compare users’ interaction with notifications and apps at urban and natural places. Places that were coded as urban include shopping malls, train stations, residential and industrial areas. Places such as

pubs, restaurants, college and university areas are considered as neutral, whereas places such as green spaces and lake side areas are rated as natural.

6.4.1 Effects on Attentiveness and Receptivity. The analysis for measuring the effects of place characteristics (for urban-natural dimension) on users' interaction with notifications reveals that there is a statistically significant difference only in their receptivity ($F = 16.09$, $p < 0.05$), but not in their attentiveness to notifications. As shown in Figure 14, a Tukey post-hoc test (by setting α equal to 0.05) reveals that users are least receptive to notifications when they are spending time at nature related places, and they are most receptive at urban places. This can be due to the fact that people do not want to engage with mobile notifications while spending time at natural spaces.

6.4.2 Effects on App Usage Time. As shown in Figure 15, our results demonstrate that the main effect of place characteristics (for urban-natural dimension) is statistically significant, $F = 4.19$ ($p < 0.05$). However, there is no statistically significant interaction between the effects of place characteristics (for urban-natural dimension) and app category on app usage time. This indicates that there is a significant difference only in users' overall app usage time (all categories considered together), rather than their behavior for using specific apps at urban, neutral and natural places. Finally, a Tukey post-hoc test (by setting α equal to 0.05) reveals that users' overall app usage time is lower at natural places compared to other places, indicating that they do not engage with phones at such places.

7 DISCUSSION AND LIMITATIONS

In this paper we have presented an in-situ study for investigating users' interaction with mobile notifications and apps while performing different activities and at locations with different characteristics. To the best of our knowledge, this is the first study that analyzes the interactions with real-world notifications and app usage at such a fine-grained level. We believe that the findings of this work can be used to build effective notification mechanisms. Moreover, the findings of this paper can be used as a basis for the development of predictive applications for personalization that rely on the analysis of users' current locations and not only on their past behavioral patterns.

However, we do not have sufficient evidence to claim that our findings are generalizable as they are based on a specific demographics, i.e., university students. In the future, we plan to conduct the same analysis on a larger scale with different demographics in order to understand if there are statistically significant differences in the general population. It is worth noting that the methodology proposed in this paper can be applied to heterogeneous populations. This will require a sufficiently large number of participants for each demographic group. It is also interesting to point out that in the study presented in this paper the coders are from the same demographic group. If we aim to introduce diversity in our dataset, we also have to recruit coders of similar demographics, which is not trivial in general.

On the other hand, it is also worth noting that a similar analysis of non-homogeneous population based on the aggregation of the results would not be correct either. This is because users of different demographics would have variability in terms of app usage and notification interaction behaviors, which could not be aggregated. One may consider recruiting a larger and more diverse group of participants to study how certain user behaviors may remain (statistically) stable or differ along specific demographic dimensions.

Similar to other studies in this area, our investigation also has some limitations that stem from our decision to collect data *in-the-wild* with minimum interaction with users. When it comes to the computation of users' attentiveness (i.e., seen time) to a notification, we can only detect it if a user unlocked the phone. We assume that all notifications are seen when a user unlocks the phone, which is a realistic assumption. However, it might happen that a notification arrives when the user is already engaged with the phone. In such a case, we assume that the user will see the notification immediately and consider its seen time as zero. This is a common limitation in most of the interruptibility studies relying on passive sensing [23, 30]. In our dataset 6.85% of the

overall notifications were delivered when users were already engaged with their phones. However, 62% of these notifications arrived with high priority and, for this reason, they were forced to appear as popups on the top of the phone's screen; this indicates that these notifications were definitely seen immediately. As a consequence, there are only 2.6% of the overall notifications that were assumed as seen immediately as they arrived with low priority when users were engaged with their phone. At the same time, it is very unlikely that users take a long time to view notifications while using their phones. Therefore, the impact on our results related to notification seen time could be considered negligible.

Similarly, for computing users' receptivity to notifications, it is possible that some notifications were misclassified as dismissed. In fact, they might have been actually attended by the users on another device or they might have been just read on the lock screen and ignored because they did not require further actions. It is worth noting that we have removed notifications from reminder apps as they always trigger alerts that do not require any further actions. We computed the percentage of notifications clicked for each app and those that have this value as zero are considered as reminder apps. Our dataset contained 1.45% of such notifications, and given such a small amount of uncertain labels (i.e., whether these notification were actually clicked or not), we believe that our results for receptivity of notifications would have a negligible impact of this limitation. Moreover, identifying notifications of other apps that were dismissed because they do not require any further action is not possible in the current mobile platforms.

Finally, another limitation is that we relied on users' daily self-reported activities through questionnaire responses. Since this is not a controlled lab experiment, there might be some cases where users' recollection might not be completely precise. This is a common problem of *in-the-wild* diary-based studies [9].

8 CONCLUSIONS

In this paper we have presented an in-situ study with the aim of investigating a series of fine-grained contextual factors, including daily activities and characteristics of places visited, which influence users' interaction with mobile phones. The contributions of this study are twofold. First, we focused on identifying the factors that impact the user's attentiveness and receptivity to notifications. Second, we investigated how users' app usage behavior changes when they are at places reflecting different characteristics such as boring, happy and natural places, to name a few.

Through a mixed method of automated mobile phone logging and ESM sampling we have obtained a dataset of *in-the-wild* notifications, app usage events and ESM reports about daily activities from 26 students at a UK university. We have analyzed the data to show that users' attentiveness and receptivity are associated to their different daily activities as well as the characteristics of locations visited. Moreover, we have shown that user interaction and usage patterns are associated to different place characteristics and activities.

Our research agenda includes a larger study involving different cohorts of participants and the analysis of causal relationships in our dataset using the methodology described in [36].

9 ACKNOWLEDGEMENTS

This work was supported by The Alan Turing Institute under the EPSRC grant EP/N510129/1, at UCL through the EPSRC grants EP/L018829/2, at Cambridge and UCL through the EPSRC grant EP/I032673/1, and at Austin through NFS grant BCS-1520288.

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