# Smartphone Interactions Change for Different Intimacy Contexts

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**Abstract.** Emerging mobile applications on a growing scale adapt their functionalities and the way these are provided, leveraging the user's contextual information, without the need of explicit settings setup from the users side. However, this contextual information, *e.g.*, location and other environmental information, may not fully represent the users' context. There are other contextual features related to the user's social context that may be considered. In this paper we introduce an example of such contextual information - the *intimacy* context information, and we investigate if smartphone users change the way they interact with their smartphones depending on their intimacy state. We performed a 4 weeks 20-users study, with participants using their own smartphones in daily life environments, and being sampled for their intimacy perception. Our results show how intimacy context changes and relate to the smartphone usage. Therefore our research contributes by introducing new context information - intimacy, which can be leveraged by developers to create mobile applications automatically adapting to provide different services, functionalities and content depending on the intimacy level of the situation the user is in.

**Keywords:** context-awareness, self-application adaptation, mobile application, interaction design, social context.

## 1 Introduction

Developers are designing mobile applications that can be customized by users to provide them with the best experience. The customization is usually made through a set of settings that offer the possibility to define some static cause-effect actions. A simple example can be a messaging application that provides the possibility for the users to customize how they are notified of new messages - via a full screen pop-up, with message preview and phone screen ON, simple notification icon, with or without message preview, any possible sound, vibration and LED light colors combination, or different combinations of all the above, depending on the contact or group of people, and so on. All these settings may overwhelm the users that may just do not explore all the functionalities of the application [1]. Users may not be able to fully exploit the potential of these applications, either because they are not aware on how to set up the application to enable different behaviors, or they just agree upon the default settings,

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because the set up seems to be cumbersome. In addition, usually these settings are static, so recalling the example, if the user decides that she/he wants a given new message notification type, the application will always notify the user in that way, in any situation. That can irritate the user, if this setting is not appropriate for some situations. The developers become aware of that and to address it, on a growing scale they develop new kinds of application-adaptations techniques to meet the users' needs and expectations [2–4]. Namely, developers are starting to use contextual information of the users to not only provide new functionality of their mobile applications, but also to adapt, based on the user's context, the applications functionalities and the way they are provided. There are mobile applications that after a very basic setup are automatically adapting to the user context, to the extreme example by *Google Now*, that is not even requiring a minimal set up, but acts autonomously from the beginning and "settings and preferences" of the application are mostly derived from the user's actions. However, the number of these mobile applications is still very little compared to the total available ones, and new techniques and a diverse types of user's contextual information is still to be explored [5]. To enable it, we need to research new contextual clues, in particular the ones that are considering the user as a human being with a set of motivational and attitude traits, and exploit these [6]. Towards this end, in our research we focus on one of such traits and hereby we investigate if the *intimacy context* of the users is relevant to mobile applications' adaptation. Supported by the literature [7, 8], we define the intimacy context of a user as *her/his level of comfort in her/his current contextual situation* [9]. For the purpose of this explorative research we let the users to interpret this definition themselves, and we have interviewed them for their understanding and operational definition of their intimacy context.

Supported by the literature [8], we assume that the intimacy context is composed by several contextual information such as the number and kind (*e.g.*, strangers, friends, family members) of people around the person, the familiarity of the current place, and so on. For example imagine being in a very busy public bus commuting from home to work, you will be with a lot of people, some that you see everyday (*i.e.,* commuting acquaintances) and a lot of them that are complete strangers for you. Now imagine being at home either alone, or with your significant others, having dinner around a table in a comfortable chair. In our research (at large) we aim to understand in which of the two situations, the users likely feel more intimate, thus more comfortable. We hypothesize that the intimacy context can be a very rich representation of the users' feelings about their current contextual situation, and can be then leveraged for an adaption of mobile applications provisioning.

In the research presented in this paper we particularly aim to answer the following questions: How the interaction of the user with a smartphone may change depending on her/his current intimacy context? What are the implications of understanding the user's intimacy on the mobile applications design?

Answering the questions above can bring new possibilities for developers that are striving to make their applications more usable and useful for their users, in different circumstances. If we consider our simple example about the messaging application, we may think how the notification of a new message may automatically be adapted to the user intimacy context. For example if the user is in an intimate situation (*i.e.*, at home, possibly with her/his family) the notification for a new message may be presented as a full screen pop up, with the content of the message displayed in it (given the assumption that there are less privacy issues when at home with people the user trust) accompanied by the smartphone screen ON, a longer notification sound and a LED blinking (to attract the user attention probably focused elsewhere). Instead, when the user is in a less intimate context (*i.e.*, in a bus full of strangers) the notification may need to be more discreet without showing the message content in a pop-up (so people around cannot read it), but just using the normal notification system of the smartphone, and without emitting a very long and loud sound or just vibrating. Of course these settings may be reversed or refined following the user needs and/or behavior patterns.

In this paper we focus on understanding the human perception of intimacy in daily life environments, and particularly we present an user study that we employed to understand if the interaction with the smartphone (*e.g.*, applications usage type and ways of interaction) changes depending on the users' intimacy context and if this intimacy context can be modeled from the users' behavior. In the rest of this paper we provide a description of the methods employed in our user study and the summary of data collected. We then present and discuss the results of the study, which show that intimacy is involved in how smartphones are used. Furthermore, we present related work on application adaptability using contextual information. Finally, we conclude this paper with a discussion on the future work opportunities.

## 2 User Study

In this section we present the methods employed to collect the intimacy ground truth and the parameters describing how the users were interacting with their smartphones.

### 2.1 Participants' Recruitment

We recruited 20 smartphone users, out of a total of 30 users that are participating in our Mobile Quality of Life Living Lab (mQoL)[1] at University of Geneva. 10 users were excluded, either because they are part of the faculty or because they did not accept to participate in the study. All the participants in this study were already using one of the Android OS smartphones provided by the Living Lab to them (Samsung Galaxy Nexus with Android OS 4.0+) for at least 6 months, so we assume they are expert smartphone users. The participants were involved in the study for 24 to 36 days (average of 29 days). There were 6 female and 14 male participants, aged 20 to 58.

[1] `http://www.qol.unige.ch/mQoL.html`

## 2.2 Study Methods

The study participants first were asked to visit our laboratory to install our study application on their smartphones. They were instructed on how to use it. The application is fully automated: starts when the phone boots, runs continuously in the background, stops when the battery level on the phone is low (less than 20%), and is able to auto-update. Participants were asked to run the application on their phones for at least 4 weeks.

To simplify the participants' task, the only requirement for them was to answer to an Experience Sampling Method (ESM) survey whenever notified by the application on their smartphone. The ESM approach assumes an automated annotation diary where the person does not need to remember to take note of her/his context (therefore minimizing the recall error), but is asked by the system to answer specific questions, *i.e.*, estimate her/his current context randomly during the day [10]. In addition to the users' answers to the ESMs, we automatically collected smartphone usage information that we explain in details in the following sections. All the answers to the ESMs and the usage information were recorded in the smartphone's internal memory and opportunistically sent over the network (when the user was connected to WiFi) to our dedicated server.

### 2.2.1 ESM: Collecting the Intimacy Ground Truth

Our ESM survey was issued every day with 8 random uniformly distributed survey notifications, between 8am-10pm, on the participant's smartphone. Additional ESMs appeared each time the participant plugged his/her phone for charging. We monitored how many surveys were issued and then actually answered and completed. The survey was composed by a single question asking about the participant's subjective feeling of intimacy, ranging from '*completely*' [intimate], '*yes*', '*more yes than no*', '*more no than yes*', '*no*', '*not at all*' [intimate]. These answers were designed based on the relevant literature in the domain [7, 8].

### 2.2.2 Smartphone Usage Information Collection

We automatically collected several information to derive how the smartphone was used such as when the screen was switched ON/OFF, when the user was interacting with the phone after the unlock phase (*i.e.*, after inserting the screen lock code), current applications running, and any touch that the user was performing on the screen [11].

*2.2.2.1 Screen Events.* We logged all the ON/OFF screen events provided by the Android OS. The ON event is triggered each time the screen is switched ON, i.e., when the user presses the smartphone button to wake it up from standby. The OFF event is triggered whenever the screen goes OFF, so the phone enters standby, and may be the consequence of the user pressing once again the ON/OFF button of the smartphone or when the phone reaches maximum time of screen ON before standby defined by the user in the settings of the OS. We were logging the event type, either ON/OFF together with its the timestamp.

*2.2.2.2 Presence Events.* We were collecting a user PRESENT event every time the user unlocked the phone (e.g., by inserting the unlock code, or simply by sliding the unlock button) and so started to interact with the smartphone. As before, we log this event together with its timestamp.

*2.2.2.3 Applications Running.* When a user was starting to interact with the phone (i.e., a PRESENT event was triggered) a log of all the applications used is created. There is not an explicit Android OS event signaling that an application is opened or closed. Therefore, we were launching a service that was monitoring which was the application on top of the stack of the running applications accessible with the Android OS API. We were performing this check every 10 seconds and whenever there was a switch in the stack top we were logging the current application as the current in use. In our log file we were registering, as reported by the Android OS: (1) the current timestamp (in ms), (2) the full package name of the application, (3) the unique ID (UID) assigned by the OS whenever an application is installed, (4) the current process ID (PID) on which the application is running, (5) a flag stating if the application has requested the permission to access the network, thus able to access the Internet.

*2.2.2.4 Screen Touches.* We were registering each time the user was touching the screen surface. The events were captured thanks an invisible overlay on the system UI.

## 2.3 Data Analysis

We conducted our analysis in a hierarchical way. We started by the analysis of *screen* and *presence* events, then we analyzed *applications* at their category level (we categorized application used using the same categories of Google Play store: Lifestyle, Social, Productivity, etc.), finally we picked the category, *Communication*, with the highest number of different and most used applications. *Screen Touches* were included transversally in all the steps.

The first step of the analysis was to define which were the valid transitions in which the smartphone can be following the paths given from the *screen* and *presence* events. This was necessary to remove some invalid records resulted from the data loss. Therefore, we defined the state machine depicted in Fig. 1 where we present the transitions that we are going to consider for our analysis (ON-OFF, ON-PRESENT, PRESENT-OFF, OFF-ON).

In a second step, for each single valid *transition* identified in the entire dataset (*i.e.*, all participants together) we derived (Fig. 2): (1) its day of the week and hour of the day (2) the transition duration (state-to-state time interval), (3) how many applications were switched in between PRESENT and OFF states (*app_switched*), (4) the number of touches, (5) the median of the intervals between touches (*m_touches*).

As a third step we analyzed each single *applications used* and for each of them we noted: (1) day of the week and hour of the day, (2) the application category (derived from Google Play store), (3) the usage time, (4) the number of touches, (5) the median of the intervals between touches (*m_touches*).

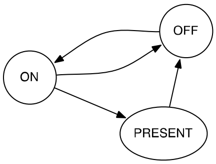


**Fig. 1.** State machine representing valid transitions between *screen* and *presence* events

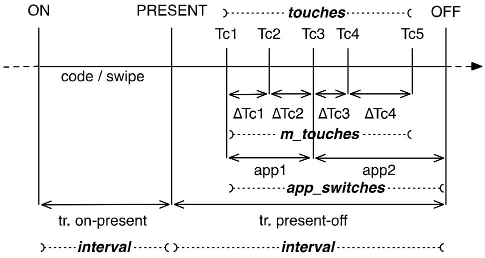


**Fig. 2.** The transition model presenting variables considered in our research, especially in the present-OFF transition

The fourth step consisted of the assignment of the *intimacy state* (as declared by the participants answering the ESM survey) to each *transition* and *applications use*d. We considered an *intimacy state* valid for a window of 15 minutes (7.5 minutes before and 7.5 minutes after the ESM answer is specified, a reasonable time in which the intimacy state would remain constant). All the measurements of *transitions* and *applications used* falling inside these 15 minutes window were assigned to the current *intimacy state* of the user that generated the data. When there was no *intimacy state* specified, we marked the data with a "NA" *intimacy state*.

In the fifth step we performed a quantitative analysis of the *applications used*. We removed all the records without an *intimacy state* and we identified which were the most used categories of applications. We selected the category with the highest number of different *applications used*. As we are going to present in the results section, the *Communication* category was the most used.

Finally with all this information we created several models to observe the evolution of the *intimacy state* under different combinations of the data depicted in the previous steps. We are going to present the most significant model results together with basic statistics about the full data set in the Results section.

### 2.3.1 Modeling Methods

As first step we performed a cleaning of the data from extreme values for each subset: *screen* and *presence* events transitions, *applications used*, and *Communication category*. Then, we created our intimacy models using the variables we depicted above.

*2.3.1.1 Data Cleaning.* In order to avoid the influence of outliers in temporal variables (*i.e.*, resulting in long transition times), most probably generated by data loss when logging and transmitting the data to the server, we cleaned the dataset from extreme values for the subsets' variables, enabling us also to further define bounds of variables in which we want our data to be modeled. Data was removed either by considering the variable's distribution (*i.e.*, cutting the "long tails" by fixing a maximum value at the third quartile of the data) or by common sense (*i.e.*, removing the unreasonably long time intervals for some variables).

For the full set of data we considered only the records that were recorded from 5h in the morning to midnight (removed 5.2% of data) as most indicative, as Fig. 5 shows intimacy state ground truth are infrequent over night.

For *screen* and *presence* events transitions we removed all the data with any of the followings characteristics: (1) *interval*s longer than 180 seconds (8.8% of data meeting this condition), (2) more than 10 *app_switches* in the same session (0.1% of data meeting this condition), (3) the *m_touches* out of the third quartile, values less or equal 1.72 seconds (6.5% of data meeting this condition), and (4) the *m_touches* with NA value due to 0 or 1 touch in the interval considered (26.2% of data meeting this condition). As a result, in total we have removed 28.4% of the data (meeting one or several of the above conditions). In addition, given that apart the *interval* time of the session in the transitions *on-off*, *on-present*, and *off-on* there was no data (no interaction of the user with the smartphone) we also subset the data to deal manly with the transition *present-off*.

Then, for *applications used* we removed all the records with any of the following characteristics: (1) usage *interval*s longer than 180 seconds (16.8% of data meeting this condition), (2) we removed all the applications not belonging to the categories of: *Communication*, *Social*, and *System* as minor contributors in the data (25.4% of data meeting this condition, with the extra fact that we also removed our logger application records), (3) the *m_touches* out of the third quartile, values higher or equal 1.87 seconds (16.3% of data meeting this condition), and (4) the *m_touches* with NA value due to 0 or 1 touch for the app entry considered (65.2% of data meeting this condition), for a total of 75.4% removed data (meeting one or several of the above conditions). Finally, for the last data subset, given that the *Communication* category is a subset of the cleaned *applications used*, we did not need any further manipulation.

*2.3.1.2 Modeling Procedure.* For each subset of data, *using all its data records*, we generated all the possible models defined by all the possible combinations without repetitions of the subset of variables. The model variables were combined using the additive method only (*e.g.*, with three variables: intimacy=var1+var2+var3). We processed these models' definition with the Ordinal Regression Model (ORM) approach [12], because of our ordinal intimacy scale, from 1="most intimate" to 6="least intimate". Then, for each subset we selected the most significant model (smallest $\chi^2$ *test* p-value) using the *ANOVA's* $\chi^2$ *test* [12] between each generated model and the baseline model. The baseline model is represented only by the intimacy threshold coefficients (*i.e.*, 1|2, 2|3, 3|4, 4|5, 5|6) without any model variables coefficient, *i.e.*, a model without description parameters, just based on the "raw" distribution of intimacy states. In addition we analyzed how all the models composed by a single variable were related to intimacy (*i.e.*, evaluating their $\chi^2$ *test* p-value and confidence intervals).

The most significant models, presented in details, were recreated with 60% of randomly sampled data from the full data set and we tested against the remaining 40%. We generated the model and test data set 10 times (denoted in machine learning as 10x Cross Validation). When possible, we plotted the predictions probabilities for each intimacy state for the different model variables, and we obtained similar results between all the 10 different trials.

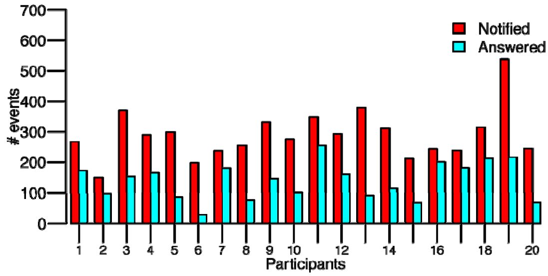


**Fig. 3.** Notified/answered ESM surveys per a participant

# 3 Results

We present the results divided in two main parts. In the first part, we present the basic statistics about the data set we collected (Section 3.1-2). In the second part, we present a more detailed view of the models used to analyze how smartphone's usage variables, as derived from the collected data, are related to intimacy (Section 3.3).

## 3.1 ESM Survey and Automatic Data Results

Overall a total of 5801 ESM notification surveys were randomly issued to the participants of the study. On average the answer rate was 48.62% (total answers: 2776) and in Fig. 3 we show how each participant contributed to these numbers. The participation is not uniform and some participants were slightly more active than others, however that did not influence our research at this stage, hence we do not discard any user as an "outlier".

In Fig. 4 we show how the participants answered their ESMs. Most of the time participants declared to be in an intimate state and less often in a non-intimate one. The overall probability distribution for each intimacy state is: 42.5% *completely* [intimate], 27.8% *yes*, 7.2% *more yes than no*, 7.4% *more no than yes*, 11.2% *no*, 3.9% *not at all* [intimate].

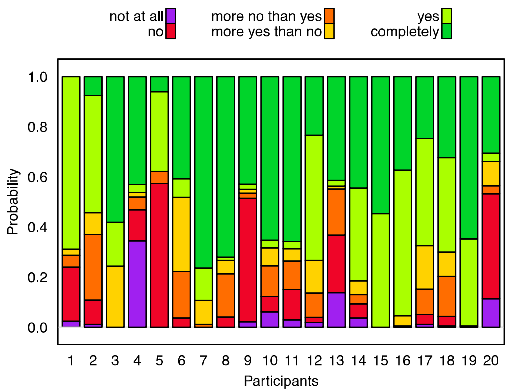


**Fig. 4.** Distribution of intimacy states per participant

**Table 1.** Basic statistics for transitions subset, 1=on-off, 2=on-present, 3=present-off, 4=off-on

| | Max | | | | Mean | | | | Std | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Var. / Tran.** | **1** | **2** | **3** | **4** | **1** | **2** | **3** | **4** | **1** | **2** | **3** | **4** |
| interval [s] | 334 | 459 | 28870 | 39360 | 13.4 | 3.77 | 118.2 | 197.8 | 16.5 | 10.4 | 618.5 | 1084.8 |
| app_switched | 0 | 0 | 19 | 0 | 0 | 0 | 1.96 | 0 | 0 | 0 | 1.9 | 0 |
| touches | 9 | 7 | 1335 | 0 | 0.1 | 0.04 | 33.5 | 0 | 0.7 | 0.3 | 70.3 | 0 |
| m_touches [s] | 33.1 | 55.1 | 54.3 | 0 | 4.24 | 4.44 | 1.45 | 0 | 6.5 | 11.6 | 1.7 | 0 |

In general for *screen* and *presence* events transitions, before cleaning the data, we have a total of: 18048 ON-OFF, 19625 ON-present, 19357 present-OFF and, and 36923 OFF-ON for a total of 93953 transitions. We have removed the invalid transitions (*i.e.*, not following the transition model Fig. 1) resulting from some data loss, as follows: 271 OFF-OFF, 491 OFF-present, 153 ON-ON, 758 present-ON, and 1290 present-present, accounting for a total of 2963 (3.15%) discarded records. As expected ON-present and present-OFF transitions are almost symmetric and OFF-ON cover almost all other transitions starting with the *ON* event.

The number of transitions that were assigned with an intimacy state is 12181 (14.6% of the total) and the probability distribution is: 36.9% *completely* [intimate], 28.8% *yes*, 7.3% *more yes than no*, 6.6% *more no than yes*, 14.3% *no*, 6.1% *not at all* [intimate]. In Table 1 we present the statistics for the variables we extracted for each transition, before data cleaning, (as explained in the data analysis section above) taking in account all the participants and transitions being tagged with.

The general statistics for the *applications used* are as follows: in total we have identified 326 different applications being used by participants (over a total of 35 categories), but for the further analysis, we retained only the applications that were used at least 50 times (along the study) and only when intimacy state ground truth was available, leaving us with a total of 24 (7%) applications, with an intimacy states probability distribution for these, as follows: 41.2% *completely* [intimate], 27.9% *yes*, 7.2% *more yes than no*, 6.9% *more no than yes*, 12.4% *no*, 4.4% *not at all* [intimate]. The applications selection process leads to 7 (20%) different categories over a total of 35 categories. In Table 2 we present a summary of the variables selected for *application used*.

**Table 2.** Basic statistics for application used

| Variable | Min | Max | Mean | Std |
|---|---|---|---|---|
| interval [s] | 0 | 180400 | 455.5 | 3770.8 |
| touches | 0 | 1251 | 14.9 | 55.1 |
| m_touches [s] | 0.01 | 13580 | 4.756 | 162.4 |

Furthermore, the *Communication* category has the highest number of *applications used*. In this category we have a total of 11 applications that can be further separated in 4 sub-categories: *Browser* (3 apps), *Email* (3 apps), *Phone* (1 app), and *Messaging* (4 apps).

### 3.2 Intimacy in Time

Two variables in common for *screen* and *presence* events transitions and *applications used* that relate to the time of interaction with the smartphone are: the day of the week and the hour of the day. In Fig. 5 we plot the probabilities for each intimacy state (from 'completely' to 'not at all', in different colors) for each *day of a week* (separate graphs, Sun-Sat) and *hour* (X axis). From the graph we can note how the period from midnight to 5h is not well covered by the intimacy state ground truth, *i.e.*, there were not many ESM responses from the participants. This is partially due to the fact that our random ESM events where issued only in waking hours, *i.e.*, from 8h to 22h, and usually people sleep at this time of the night. The intervals from 5h to 8h and from 22h to midnight are covered by the fact that the survey is issued whenever the phone was un/plugged from the charger and potentially by the fact that some of these are also late answers to earlier-triggered notifications in the interval 8-22h. From Fig. 5 we conclude that the general trend for study participants is to be more intimate in the early morning and in the evening and, additionally Sunday seems to be the most intimate day in a week. The least intimate hour seems to be the ones around noon in a weekdays and Saturday.

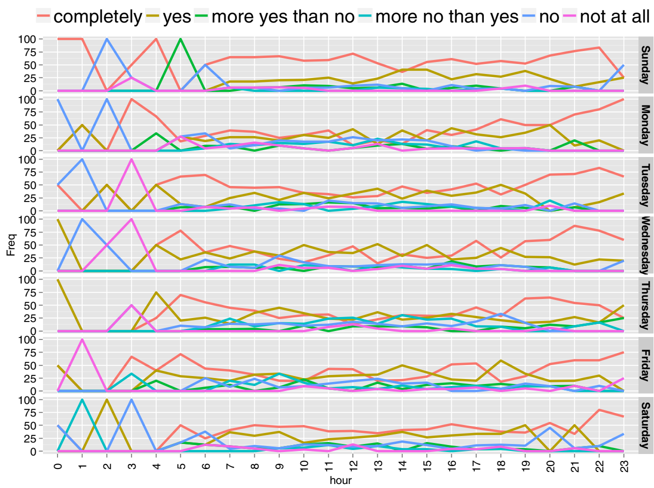


**Fig. 5.** Frequency for each intimacy state for each hour and day

### 3.3 Intimacy Models Results

We present the intimacy models divided in three main categories: (1) Present-Off transaction models, (2) Applications used models, and (3) Communication category models.

#### 3.3.1 Present-Off Transition Models

For the data concerning the *transitions event present-OFF* we generated models with the combination of the variables: *hour*, *day*, *interval*, *app_switched*, *touches*, and *m_touches*. We obtained a total of 63 models (combinations without repetition of the

**Table 3.** Most_Sign_Tr model variables significance (0 '***', 0.001 '**', 0.01 '*', 0.05 '.', 0.1 ' '), confidence intervals (CI)

| Variable | P-value (*chisq*) | CI 2.5% | CI 97.5% |
|---|---|---|---|
| hour | $8.9*10^{-6}$ *** | -0.058 | -0.023 |
| day | 0.001 ** | 0.025 | 0.107 |
| app_switched | 0.001 ** | -0.180 | -0.044 |

6 variables from this subset, taking 1, 2, 3, 4, 5, 6 variables at time). Out of 63 models, 4 were not significant (p-value > 0.05), 59 were significant (among them 41 had p-values < 0.001). The models composed by a single variable contributed in the following way (p-value ordered from most to least contributing): $p=2.4*10^{-5}$ variable *hour* (rank 28), $p=2.3*10^{-3}$ for *day* (rank 44), $p=2.4*10^{-3}$ for *app_switched* (rank 45), $p=2.3*10^{-2}$ for *interval* (rank 57), $p=1*10^{-1}$ for *touches* (rank 61, not significant), and $p=3.7*10^{-1}$ *m_touches* (rank 63, not significant).

For space reasons we present details of only the most significant model: denoted as *Most_Sign_Tr* build based on the variables *hour+day+app_switched*. The model has a p-value < $2.3*10^{-8}$, and a condition number of the Hessian (cond.H) = $1.7*10^{4}$ (measures if the model is ill defined; cond.H > $10^{6}$ [12], indicates that the model can be simplified), and maximum model gradient (max.grad) = $6.38*10^{-13}$ (a value indicates if the model converges: usually for value max.grad < $10^{-6}$ [12])).

*3.3.1.1 Present-Off Transition Most Significant Model Details.* In Table 3 we present how the single variables contribute to the Most_Sign_Tr model and their confidence intervals. From the table is possible to observe how the variables contribute to the models and particularly from the confidence intervals we conclude that the most likely values of the variables are in between a small range.

*3.3.1.2 Present-Off Transition Most Significant Model Prediction Results.* In Table 4 we present summary statistics of the variables for the whole data set based on which we defined the model and tested it to obtain the predictions (data is divided per intimacy state).

Fig. 6 presents one of the plot of the probabilities for each intimacy state as resulted from the *hour+day+app_switched* model prediction (total subset size 1957 records, data to define the model 1174 and testing size 783). Across the Fig. 6, we can note how the probability to be *completely* intimate increases with the hour of the day, changes depending on the day of the week (in particular *Sunday* is more intimate than the rest of the week, as already observed from Fig. 5), and has different behaviors depending on how many applications are switched in the *present-off* transition. The more applications are switched, the higher is the probability to be in a *completely* intimacy state.

### 3.3.2 Applications Used Models

For the *applications used* we generated models with the combination of the variables: *hour*, *day*, *interval*, *application*, *category*, *touches*, and *m_touches*, we obtained a total of 127 models. Out of them one was not significant (p-value > 0.05), 126 were

**Table 4.** Basic statistics of Most_Sign_Tr model data after cleaning

| Var | Stat | Intimacy State 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|---|
| hour [5h-23h] | min | 5 | 5 | 6 | 6 | 5 | 5 |
| | max | 23 | 23 | 23 | 21 | 22 | 23 |
| | mean | 13.7 | 13.9 | 14.2 | 12.4 | 12.2 | 12.9 |
| | std | 4.8 | 4.2 | 4.2 | 3.5 | 4.3 | 4.2 |
| day | min | 0 | 0 | 0 | 0 | 0 | 0 |
| | max | 6 | 6 | 6 | 6 | 6 | 6 |
| | mean | 2.8 | 3 | 3.7 | 3 | 3.1 | 2.8 |
| | std | 2 | 1.9 | 1.9 | 1.7 | 1.8 | 1.9 |
| app_switched | min | 0 | 0 | 0 | 0 | 0 | 0 |
| | max | 9 | 9 | 6 | 6 | 7 | 7 |
| | mean | 1.7 | 1.8 | 1. 5 | 1.8 | 1.6 | 1.5 |
| | std | 1.2 | 1.2 | 1 | 1.2 | 1.3 | 1.5 |

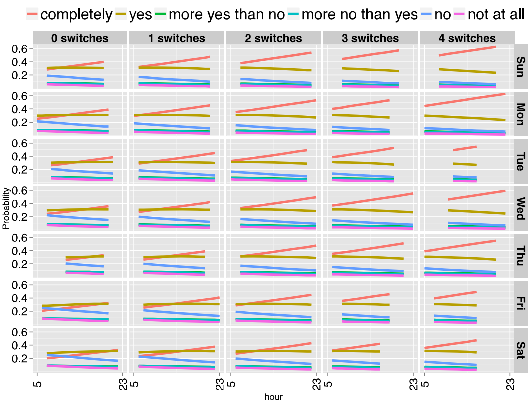


**Fig. 6.** Probability (left Y axis) for each intimacy state depending on *hour* (bottom X axis), *day* (right Y axis), and *app_switches* (top Y axis)

significant (among them 118 p-values < 0.001). The models composed by a single variable contributed in the following way (p-value ordered from the most to least contributing): $p=1.4*10^{-14}$ for *application* (rank 63), $p=8.5*10^{-5}$ *touches* (rank 107), $p=1.5*10^{-4}$ *hour* (rank 110), $p=2.1*10^{-4}$ *m_touches* (rank 111), $p=1.4*10^{-3}$ *day* (rank 122), $p=7.6*10^{-3}$ *interval* (rank 125), $p=2.2*10^{-1}$ *category* (rank 127, not significant). As before, we present details of the most significant model denoted as *Most_Sign_App* composed by the variables: *hour+day+app+touches*, with its p-value $< 2.9*10^{-19}$, cond.H = $5.4*10^{6}$, max.grad = $1.95*10^{-7}$.

*3.3.2.1 Applications Used Most Significant Model Details.* In Table 5 we present how the single variables contribute to the Most_Sign_App model and their confidence intervals. Also in this case we have variables that are significant for the models, in particular application and hour. Application CI are omitted, due to lack of space, i.e., we would need to list results for 20 applications. Differently from the other models we are not going to plot results of predictions for this case. Due to model size (4 variables) is difficult to plot these results, needing 4 + 1 (probability) dimensions.

**Table 5.** Most_Sign_App model variables significance (0 '***', 0.001 '**', 0.01 '*', 0.05 '.', 0.1 ' ') and confidence intervals (CI)

| Variable | P-value (*chisq*) | CI 2.5% | CI 97.5% |
|---|---|---|---|
| hour | 0.005 ** | -0.041 | -0.007 |
| day | 0.011 * | 0.012 | 0.090 |
| application | $1*10^{-9}$ *** | omitted | omitted |
| touches | 0.034 * | -0.004 | -0.000 |

**Table 6.** Most_Sign_Com model variables significance (0 '***', 0.001 '**', 0.01 '*', 0.05 '.', 0.1 ' ') and confidence intervals (CI)

| Variable | P-value (*chisq*) | CI 2.5% | CI 97.5% |
|---|---|---|---|
| day | 0.06 . | -0.003 | 0.103 |
| sub_cat [Email] | 0.002 ** | -0.959 | -0.050 |
| sub_cat [Messaging] | 0.002 ** | -0.851 | -0.226 |
| sub_cat [Phone] | 0.002 ** | -1.667 | -0.342 |
| touches | 0.003 ** | 0.430 | 1.174 |

### 3.3.3 Communication Category Models

For the *Communication category* we generated models with the combination of the variables: *hour*, *day*, *interval*, *sub-category*, *touches*, and *m_touches*. We obtained a total of 63 models. Out of them 2 were not significant (p-value > 0.05), 61 were significant (among them 51 p-values < 0.001). The models composed by a single variable contributed in this way (p-value ordered from the most to least contributing): $p=3.3*10^{-4}$ for *sub-category* variable (rank 42), $p=3.3*10^{-4}$ *m_touches* (rank 43), $p=4.5*10^{-4}$ *touches* (rank 45), $p=2.4*10^{-2}$ *interval* (rank 59), $p=2.4*10^{-2}$ *day* (rank 60), $p=3.2*10^{-1}$ *hour* (rank 63, not significant). As before, we present details of the most significant model, this time denoted as *Most_Sign_Com* based on the variables *day +sub_category+touches*, with its p-value $< 8.1*10^{-6}$, cond.H $= 4.8*10^{5}$, and max.grad $= 1.91*10^{-12}$.

*3.3.3.1 Communication Category Most Significant Model Details.* In Table 6 we present how the single variables contribute to the Most_Sign_Com model and their confidence intervals. In this case for the Most_Sign_Com model we have the day variable, presenting not significant contribution to the model. Instead, sub_category and touches are significantly contributing to the model. CI shows how, in general, variables are supported by their values enclosed in a small interval.

*3.3.3.2 Communication Category Most Significant Model Prediction Results.* The predictions for the Most_Sign_Com model are presented in Fig. 7 (total subset size is 1213 records, model definition size 728 and testing size 485). In Table 7 we provide a summary of statistics about the two variables of the model for the data from which we sampled the model definition and testing data.

The *Messaging sub_category* is the one related to the most of the touches per its usage session, and particularly on *Sunday*. *Email* and *Phone* have very little interaction, *i.e.*, very few touches per session. *Browser* has a regular short number of *touches* across the week. The intimacy states change with the number of *touches* (particularly in *Messaging*, but also in *Browser*). In *Messaging*, the *completely* intimacy state probability increases by increasing the number of touches. Instead in *Browser* with very few *touches* we have a higher probability for the *no* intimate state that decreases slightly when the *touches* increase (*Saturday* may indicate a general trend for the week).

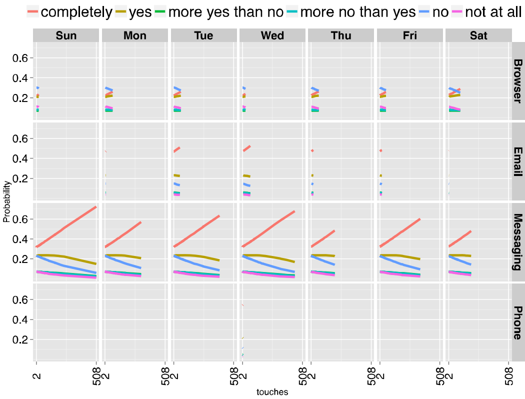


**Fig. 7.** Probability (left Y axis) for each intimacy state (colored lines) depending on *touches* (bottom X axis), *sub_category* (right Y axis), and a *day* (top Y axis)

**Table 7.** Basic statistics of *Most_Sign_Com* model data after cleaning (f=frequency)

| Var | Statistics | Intimacy State 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|---|
| day | min | 0 | 0 | 0 | 0 | 0 | 0 |
| | max | 6 | 6 | 6 | 6 | 6 | 6 |
| | mean | 2.9 | 3.2 | 3.9 | 2.8 | 3.2 | 2.9 |
| | std | 2 | 1.8 | 1.9 | 1.7 | 1.9 | 2.6 |
| sub_cat. | f(Browser) | 54 | 45 | 7 | 9 | 36 | 18 |
| | f(Email) | 43 | 25 | 10 | 5 | 17 | 4 |
| | f(Mess.) | 372 | 285 | 57 | 57 | 107 | 29 |
| | f(Phone) | 19 | 9 | 5 | 5 | 4 | 0 |
| touches | min | 2 | 2 | 2 | 2 | 2 | 2 |
| | max | 865 | 584 | 223 | 313 | 336 | 112 |
| | mean | 53.7 | 48.9 | 39.9 | 52.2 | 36 | 33.5 |
| | std | 76.1 | 68.3 | 46.9 | 60.2 | 44.4 | 25.6 |

## 4 Discussion

Based on the results, we conclude that there are some differences on how users interact with their smartphones depending on which intimacy context they are in. Effects of these interaction changes are mostly visible at the extreme intimacy states *completely* and *no*. Users are switching more applications when in a high intimacy context, writing shorter messages when in lower intimacy, and so on.

The *hour* and *day* variables are contributing to all the most significant models, from which we conclude that this time variable, together with the other variables we presented in this paper, is relevant to identify different user's intimacy patterns. *Hour* and *day* are very significant in the *present-OFF transition* as single variable in models of intimacy (high rank for single models variable), However, if we look at the *application used* set, time variables loose the significance, and they become even less relevant for the *Communication category* where *hour* alone is not even significant. We may conclude that probably time variables are also related to smartphone usage variables, as the usage of the smartphone is also influenced by the *hour* of the day and the *day* of the week. They become usage variables themselves. An extra note on these variables is that they are related and most probably they could be treated as an input to the models as interactive variables, instead of just addictive model terms, as we have done. These could be verified with further ANOVA tests on such model definition compared to the one we have already performed.

For the ***present-OFF transition*** model the only variables that alone are not significant to derive a single variable model for this set of data, are *touches* and *m_touches* that are related to each other. Namely, there are no particular changes on the number of touches or the interval between them for different intimacy states along the *present-OFF* interaction section with the smartphone. Also, as the *interval* variable alone is not so powerful, we conclude that the interaction time is also not a very good indicator for the user's intimacy state.

Furthermore, the *app_switched* variable changes depending on the intimacy context. In particular, as reported in Fig. 6 the higher the number of switches, the higher is the probability to be in the *completely* intimate state and less in the *no* intimate state. An interaction with the phone without switching applications (*i.e.*, when the user lands straight at screen application after the *present* event is generated) can indicate that the user may not be in an intimate situation. Instead, after four applications switches the probability to be intimate is higher.

Additionally, the *day* variable is mostly contributing for the differences between weekday and weekends, as on Sunday users tend to be more intimate (see Fig. 6 and Fig. 5). Finally, *hour* is the single variable most significant for intimacy state given our set of data. When one uses the phone in the morning he/she tends to be less intimate than when using it in the evening (Fig. 5).

For ***applications used*** model the application's *category* and *interval* variables are not significant for the intimacy state. Also *day* and *hour* variables, although they are present in the most significant models do not seem to contribute so much, as well as *m_touches*.

To indicate the most significant variables, *touches* and *application* we have plotted two sub-models of the most significant model: *hour+touches+app* and *hour+day+app* (not presented here for space reasons). From both plots we can observe how depending on which *application* is used we have a different probability on being on the *completely* intimate state. We can divide the 20 applications in two groups: one, composed by 14 of them (Email (2 apps), Messaging (4 apps), App Launcher (3 apps), Browser (1 app, small amount of data available), Contacts (1 app), Phone (1 app), Settings (1 app), and Social Contact (1 app)), where the *completely* intimate state is distinct from the other states. For an additional group of six apps (Browser (2 apps), Email (1 app), System (1 app), App Market (1 app), Social Network (1 app)), the probability of *completely* state is very close to the other most probable states, *i.e.*, such applications can be used in any state. For the moment we did not investigate further these differences.

Finally, for the other variables present in these models (as well as being the most significant ones), *hour*, *touches* and *day* are contributing as follows: *hour* as increasing high intimacy when reaching the end of the day, increasing number of *touches* increasing *completely* intimate probability, and *day* as the least contributing and significant only for Sunday.

For the last subset of data defining the ***communication category*** model, the temporal variables *hour*, *day* and *interval* are the least significant ones, probably because the temporal effect is reduced by the more equally distributed use of *Communication* applications across time. These variables are followed by *touches* and *m_touches* that relate to how the user interacts with the phone. In particular, in this data subset the number of *touches* depends on the *sub-category* variable. This *sub-category* variable combined with the *touches* and the *day* creates the most significant model of this subset. From Fig. 7 we can notice that for the *Messaging* (4 apps) sub-category, the longer are the messages or the conversation time (more *touches* to write longer messages or longer threads), the higher is the probability that the user is intimate. We can rationalize this finding as follows. We interact or text longer messages when we feel more confortable and secure in the environment we are at that moment (*i.e.* at home). From *Browser* (3 apps) we see that we tend to navigate with the mobile browsers when we are not intimate. If we do that with more *touches* (*e.g.*, we interact more by clicking on several links or we do not use bookmarks, but we type the website fully) it probably means, that we are more intimate. This assumption cannot be fully confirmed from our data, because the *Browser* interaction, in term of *touches*, is quite short.

### 4.1 Study Limitations

There are some limitations that are conditioning our approach. Particularly, self-selected applications and interactions, the participants were performing, may influence significantly the generalization of results. Additionally, by asking the current user intimacy randomly during the day is possible that the participant were mostly answering when they were mostly intimate, maybe more willing to interact with the smartphone (as the results of this study show). We assume that if a user is not intimate, *i.e.*, interacting with someone that she/he does not know or does not consider as a significant other, it is not really socially acceptable to interact with the smartphone. The solution to get less biased ground truth, could be to collect the ground truth much more often, but this will probably decrease the participant adherence to the study in the long term. Another important point about the ground truth is the subjectivity of the participants in stating their intimacy. We group all the data from all users in one single set of data from which we derived the three smaller data sets, as we have presented (namely, *transitions present-OFF*, *applications used*, and *Communication*). It would be interesting to see how our models perform using mixed models instead of just fixed effects models. In our future work, we will consider each user as a random variable and add it to our models and observe how our models behave.

With respect to the interaction variables collected, we can imagine that there are other ways to observe how a smartphone is used. For example we could include the battery [11, 13], device memory, and processing unit logs. It was for purpose to keep the set of variables small to perform this initial research exploration.

Furthermore, adding extra questions to the ESM survey, such as number of people around, who are these people, where is the participant, and so on. These questions would probably significantly contribute to understanding on how the phone is used with respect to these factors assumed to be determinant for intimacy.

Finally, the results suggest that we may need to redefine the scale of the intimacy states to a simpler one, like: *high*, *medium*, *low* intimacy levels. To better understand if this is the right direction a similar analysis performed for the results presented in this paper must be done by grouping *completely* and *yes* state in the *high* level, *more yes than no* and *more no than yes* in *medium* level, and *no* and *not at all* in *low* level.

## 5 Related Work Areas

There exist some related work in the area of the context, in which smartphone applications are used and, similarly to our approach, how it can help to adapt mobile apps. To best of our knowledge, no related work exists on the modeling of the intimacy context for mobile applications users. Only in our previous work [9], where we studied the possibility to use smartphones to determine the intimacy state of the user, we have a first attempt to define intimacy as contextual information. Differently from this work, in [9] we did not have any ground truth to confirm our assumptions. Shin *et al.* [14] widely analyses context factors in relation of the use of mobile apps. They performed a user study where they collected GPS and cellular network location (for location), app open/close events (for time), and battery charging patterns, and so on. They used the data to predict the next app used, thus be able to adapt the apps menu. Böhmer *et al.* [15] did an analysis on mobile apps' usage. The data was collected from over 4100 users. 22'626 different apps were used and 4.92 million events of app usages (*e.g.*, install, opened, closed) were collected. They analysed apps' usages with respect to the location, time, and chain of app usages context information. They presented how the analysis of this information can be used to improve the design of mobile apps, which it is also one of the goals of our future work. Ickin *et al.* [16] also investigated mobile apps' usages regarding the location (semantic place), time of the day, and connectivity (Quality of Service analysis). When participants were interviewed, they admitted that they learn how to maximize their own experience based on their previous apps usage experience, connectivity options and app needs at hand. There is definitely a need to provide to users automated mechanism to adapt the use of their smartphones and mobile apps. Floch *et al.* [17] presented the European research project MUSIC describing typical context (*e.g.*, noise, light, network, location, users interactions) and adaptation features (*e.g.*, alternative user interaction and provided functionalities) that are relevant for developing self-adaptive mobile apps. They propose a framework to help developers to make use of contextual information to reduce the development complexity of self-adaptive mobile apps. Intimacy could definitely be leveraged as the contextual information for application self-adaptation.

## 6 Conclusions

In conclusion, this paper presents a study on the intimacy context of smartphone users and applications usage patters in different intimacy states. Intimacy is new contextual information, directly related to the human being behavior and social context. We show that even considering a small set of variables we can model the interaction of the user with the smartphone and its change along her/his current intimacy. In particular, we present how the probabilities of being intimate or not are changing when considering variables as *day* of the week and *hour* of the day for *when* the smartphone is used, or *number of applications switched*, *application* used, or the number of *touches* performed for *how* the smartphone is used.

The future work areas relate to (1) investigating additional smartphone usage variables like social activities, battery information, memory usage logs, and so on and their relation to intimacy, (2) dividing the users in groups to identify different relations between their perception of intimacy in different contexts, (3) find methods and approaches to automatically estimate the intimacy perception from the data available from the smartphone, and (4) explore how knowledge of the intimacy context can imply the mobile applications' design decisions.

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