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Article in *Personal and Ubiquitous Computing* · March 2013

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# Contextual usage patterns in smartphone communication services

Juuso Karikoski · Tapio Soikkeli

Received: 20 August 2011 / Accepted: 5 December 2011 / Published online: 30 December 2011  
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**Abstract** The mobile end user context has received a lot of attention from the mobile services industry lately. The location-based and context-sensitive information that are characteristic for smartphones can be utilized to study the use context of mobile end users. Accordingly, this article utilizes handset-based data in analyzing how the context of use affects the usage of smartphone communication services. The context is identified with an algorithm utilizing mobile network cell ID and WLAN data and resulting in five place-related contexts, namely *Home*, *Office*, *Other meaningful*, *Elsewhere* and *Abroad*. According to our analysis, voice calls are used least intensively in the *Home* context where the length of the voice calls is the longest, however. Email and SMS are used most intensively in the *Office* context, where the voice calls are the shortest in duration. Finally, mobile IM/VoIP and social media services are more free-time oriented as they are used most intensively in *Elsewhere* and *Other meaningful* contexts. The findings imply that people use smartphone communication services differently depending on the use context. However, context can be defined and identified in a number of ways, and this article presents only one solution that is highly dependent on the type of data collected.

**Keywords** Smartphones · Communication services · Context detection · Handset-based measurements

## Abbreviations

AP	Access point
CDR	Call data record
GPS	Global positioning system
IM	Instant messaging
ISO	International organization for standardization
MAC	Media access control
MCC	Mobile country code
MI	Mobile internet
MMS	Multimedia messaging service
SMS	Short message service
URL	Uniform resource locator
VoIP	Voice over internet protocol
WLAN	Wireless local area network

## 1 Introduction

The purpose of this article is to study how the use context affects the usage patterns of smartphone communication services. The article is a continuation to previous work on contextual patterns in mobile service usage [41]. The context detection algorithm in [41] has been developed further first in [16] and then in [36], and this article presents the most recent observations from a smartphone communication service usage perspective. Although smartphones have evolved to something more than just mere communication devices, communication services are still the most used mobile services and thus constitute an interesting research topic. They are also an interesting topic from a sociological perspective, because fundamentally they are used to form and maintain social networks between people.

With smartphones, we refer to mobile phones that are capable of installing third party application software. The

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empirical data for the research are collected from 140 early adopter smartphone users with handset-based measurements conducted in Finland during 2009 and 2010. The data are longitudinal as an average user has produced data for 134 days. Previously, the algorithm and the data used in this article have been utilized in studying smartphone usage sessions [37].

The context algorithm developed in [41] identified three different place-related contexts (*Home*, *Office* and *On the move*) by means of hourly logged cell IDs. The context detection is improved in the latest algorithm developed in [36] by identifying more contexts, namely *Home*, *Office*, *Other meaningful*, *Elsewhere* and *Abroad*. The context detection accuracy is also improved by clustering cells when needed and logging cell IDs seamlessly every time the cell ID changes as suggested in the future research in [41]. Furthermore, WLAN (wireless local area network) access point (AP) fingerprinting is used to identify the contexts in greater detail.

The scope of this article differs from [41] as it analyzes a more specific service category, namely the smartphone communication services. These services include all smartphone communication services, through which interpersonal communication is possible. The services are further divided into traditional operator-provided communication services, such as cellular voice calls, SMSs (short message service) and MMSs (multimedia messaging service), and mobile internet (MI) communication services, such as email, instant messaging (IM), voice over internet protocol (VoIP) and social media. A similar categorization has earlier been used in [19], for example.

The research on communication service usage and communication media choices has traditionally relied on subjective data gathered with surveys. With handset-based measurements, however, we can collect objective data on smartphone usage and do not have to rely on self-report data. However, these data collection methods should be treated as complementary and not substitutive, as there are benefits inherent to both methods. A great deal of research regarding mobile communication media choices is mainly focusing on traditional services such as voice calls and text messages. Services like IM and email have been studied in the fixed domain, but in the mobile domain, the research is limited. Thus, studying the contextual usage patterns in smartphone communication services is expected to be beneficial for many stakeholders. First of all, mobile operators can benefit from the analysis when planning their marketing strategies in terms of service offerings and consumer segmentation, for example. Social scientists studying the micro-level behavior of smartphone users and the related social networks and communication media choices are expected to benefit from the observations also. Lastly, smartphone application developers, especially in the area

of location-based and context-aware communication services, will find these observations beneficial. Accordingly, the research question of this article is as follows: *How does the use context affect the usage patterns of smartphone communication services?*

The article is structured as follows: first, the related literature is reviewed from use context and communication service perspectives. Second, the handset-based data collection method, the collected data and the context algorithm are presented. Then, the empirical observations of the data analysis are illustrated both from an overall perspective and from a communication service perspective. After the discussion, future research and limitations, the article is concluded.

## 2 Background and literature review

As said there has been some amount of work conducted in the area of communication service usage and context, but the research in the mobile domain has concentrated mainly on the traditional communication services such as voice calls, SMSs and MMSs. Elsewhere in the mobile domain, the effect of context on mobile services in general [41] and the effect of contextual factors on mobile games usage [23] have been studied, for example. The scope of this article is to study specifically communication services, and thus, the literature related to them and the use context are studied in more detail in the next subchapters.

### 2.1 Use context

Several definitions of context have been suggested in earlier research and a good classification of them is provided in [7]. These definitions, although inadequate in the author's opinion in [7], are categorized into two classes—definitions by examples and by synonyms. The first category includes definitions such as the following: “context is location, the identities of nearby people and objects, and changes to those objects” [31], and the second category includes synonyms for context such as *environment* (e.g., [44]). Moreover, it has been suggested that the notion of context has a dual origin in ubiquitous computing—on the one hand, it is a technical notion, and on the other hand, it is a notion drawn from social science [8]. The following definition for context is provided in [7]: “Context is any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves”. Thus by strictly following the definition of context in [7], time would be a context and place would be a context. However, as has been suggested in [2], researchers should not strive for an overall

definition of context, but rather define it for the area in which the researcher is present. Thus, our definition of context follows the definition in [7], but it is also affected by the type of data we are able to collect. In the scope of this work, the entities are the user and his or her mobile device. It is assumed that a user has only one mobile device and that it is carried by the user all the time. Thus, the mobile phone is used to gather information that can characterize the situation of the user. The weight in this work is mainly on place-related contexts, but it has to be remembered that context definitely is much more than a place or a location as is reminded in [17]. The other elements are still difficult to identify and measure, however.

The context algorithm developed in this work combines the place and time information of a user in an attempt to put a meaning to a particular place. The algorithm results in an output of the following place-related use contexts: *Abroad*, *Home*, *Office*, *Other meaningful* and *Elsewhere*. *Other meaningful* refers to a context where a considerable amount of time is spent, but which does not have the characteristics of a *Home* or *Office*. For instance, parents' or girlfriend's apartment could be an *Other meaningful* context for a user. *Elsewhere* on the other hand refers to something else than a meaningful place, such as on the move and other not so frequently visited places. *Home*, *Office* and *Abroad* contexts are self-explanatory.

There have been efforts of standardizing the definition of context by the International organization for standardization (ISO) [15], for example. However, context depends on the user's internal and social interpretations which are continuously changing [13], and thus some argue that the entire concept might be of no use [38]. We believe it is of use, especially in the mobile domain, and as pointed out in [40], an empirical user-centered approach is needed to understand mobile contexts. Our approach is a clear step toward this as real empirical behavioral data are collected from users directly from their smartphones. The smartphone is also carried always with the users and is a personal device enabling a user-centric view on the usage patterns and related contextual factors.

## 2.2 Communication services

Communication services differ in their value created to the end user. Value depends, for example, on the strength of the tie [12] between the persons communicating or if the service is used for maintaining or extending social networks as discussed in [21], for example. It has also been shown that as ties become stronger between people, there is a greater tendency for them to draw on multiple media to communicate with their personal networks [14]. Communication media choices depend on a variety of factors [4, 5]—the characteristics of the information need, that is,

the task, the characteristics of the user and the context of the user all affect the choice of communication media. Furthermore, the research shows that the task characteristics and the context of the user play a more prominent role in media choices than the characteristics of the user. It has also been argued in [28] that the choice depends on contextual characteristics of the existing relationship between the persons communicating such as location, relationship origin, communication content and relationship intensity. Thus, when considering using communication media, context seems to be an important factor in the selection process. Empirical research on mobile communication media and use context is very limited. In addition to traditional survey-based studies (e.g., [21, 28, 33]), handset-based measurements have been used in [24, 25, 34, 41], for example. These studies differ in their definition of context as well as in the services studied, but nonetheless, the main results are worth reviewing.

Results from previous handset-based studies imply that voice calls and SMSs receive relatively more usage at home and voice calls also tend to be significantly longer at home. On the other hand, email and IM are used mostly on the move [41]. Moreover, similar results have been acquired in an analysis utilizing the algorithm developed in [16] and a different data set [34]. Use context has also been studied in terms of time of day, home versus roaming, handset battery life and weekday versus weekend where time of day and international roaming affected the usage of almost all the mobile services [25]. Among other things, it is concluded that lower battery life significantly increases the likelihood of using basic voice service over other services. Furthermore, when roaming internationally, the likelihood of voice call usage decreases significantly, while the likelihood of SMS usage increases. For MMS, there were no significant effects. Furthermore, the propensity of users making a phone call in different locations or contexts using a data collection apparatus similar to the one used in this article is studied in [24]. It is observed that the propensity to call from home on the mobile phone is low compared to other types of places. Moreover, propensities to call are highest during the mobility periods. It is argued that these results are due to the availability of communication resources—at home, the fixed phone is mostly used, while on the move, the mobile phone is the only resource available.

A questionnaire study in Japan was conducted to explore the effect of context on mobile Internet user behavior [33]. Context was measured in terms of time and location and four *meta-locations* were defined—home, work/school, commute and leisure time. It is found that home and work/school have higher than average primary usage of email/chat. It is also argued in [21] that the working context supports the usage of email. It has to be noted, though, that

email/chat is usually provided as a service by the mobile operator in Japan in a similar manner as SMS is provided by the operators in the European markets. Furthermore, the authors conclude that exploitable patterns of mobile Internet usage based on context are difficult to find and suspect that psychological or psychographic factors may be more important in influencing the usage.

The communication channel choices of adolescents were studied in Israel using a survey in [28]. The channels were divided into face to face, phone and online. It is argued that the choice depends on contextual characteristics of the existing relationship between the persons communicating. The contextual characteristics were defined in terms of location, relationship origin, communication content and relationship intensity. However, location was measured as the distance between the communicators, and thus, it is not directly comparable to our location-based context.

Recently, huge mobile phone data sets have become available for researchers. There have been many studies utilizing mobile operators' call data records (CDR) that have analyzed the location of consumers in terms of cell IDs and the communication in terms of phone calls and SMSs. For example, in [6], the authors claim that voice calls are used for coordination calls just before face-to-face meetings. Furthermore, a large data set of mobile phone service usage was analyzed in [39], and the authors concluded among other things that email is used uniformly across communities, while IM/chat displays a strong community-based segregation in the mobile domain. In a related survey study [21], a similar result was found indicating that IM is used to maintain a small network of other IM users rather than to connect to new ones. However, as the MI communication services are usually not controlled by the operators, the usage is not visible in the CDRs. Thus, research is needed where a broader picture of the mobile services used by the consumers can be acquired. Handset-based measurements are one such research method, but the number of participating users is naturally lower than in studies utilizing CDRs of millions of users.

### 3 Methodology and data

This chapter first shortly presents the handset-based data collection method and introduces the data collected. Second, the context detection algorithm is presented. For more information about the method and the algorithm, see [18] and [36], respectively.

#### 3.1 Handset-based data

The handset-based measurements were conducted in the OtaSizzle project of Aalto University, and the data

collection process is documented in detail in [18]. In this chapter, the measurements and the collected data are presented shortly. In addition to the OtaSizzle project, context or location-related handset-based data have been collected at least in Helsinki University of Technology's COIN and MoMI projects [42], HIIT's Context project [30], MIT's Reality Mining project [9], Rice University's LiveLab project [32] and in the PlaceLab at Intel Research [22]. A good review of using mobile phones as sensors for social research is provided in [10].

The OtaSizzle handset-based measurements are implemented with data collection software installed in the users' smartphones. These users have opted-in to participate in the measurements, and thus, we are able to collect context-sensitive data about real user behavior directly from the users. After the software is installed on the device, data collection starts and the data are preprocessed and stored locally in the device. After compression and encryption, the data are sent daily to the data collection servers. The data are aggregated from all participants and exported to the OtaSizzle researchers. The users in the OtaSizzle measurements are all students or staff of the Aalto University, and they have been identified as early adopters regarding mobile devices and services [18], and the sample is biased toward Finnish male students in their early twenties. The data collection software used in the OtaSizzle measurements is called MobiTrack. This mobile audience measurement platform measures real-life user behavior, usage of devices and mobile services and various technical parameters. The data types collected include application usage, application installations, processes, battery levels and charging, Bluetooth and WLAN entries, phone calls, SMSs, MMSs, URL (uniform resource locator) entries, network sessions and uploads. The software supports Symbian, Google Android, Windows Mobile and BlackBerry platforms. However, in this work, only the Symbian version of the software was used. For more information about MobiTrack, see [43] and [18].

The handset-based data used in this study were collected during 2009 and 2010. In total, there are data collected and contexts identified from 140 Symbian smartphone users. All the users have at least 3 weeks of active data production, and an average user has produced data for 134 days. Regarding the data types, the cell ID-based location data and the WLAN scan data are used in the context detection part of this work. When studying the usage of smartphone communication services, the application foreground data, and phone call, SMS, MMS and email data depicting the actual calls made and messages sent are used. Application foreground data are collected when an application is visible to the user in the foreground of the device's screen. Thus, for example, background applications and processes are not considered in the analysis.



### 3.2 Context detection algorithm

The algorithm is documented in detail in [36], and the basics of the algorithm are presented in this chapter. The algorithm has two parts that work also separately—cell ID-based context detection and WLAN scan-based context detection. First, the cell ID-based context detection is performed as all the users have created cell ID data. Then, the WLAN scan-based context detection is performed to verify and give more accuracy to the results extracted from the cell ID data. However, it is possible that an individual user lacks WLAN data. An attempt was also made to detect the social context of the users by means of Bluetooth data, but as data collection required the users to have their Bluetooth radio on (as opposed to the case with WLAN radio), we were not able to collect enough data to draw any conclusions about the social context.

Mobile devices in a cellular network can recognize the base station they are connected to according to its cell ID. This information is collected with our data collection software every time a cell ID changes to construct a time-stamped data log of the cell IDs. Thus, by looking at the data, we know under which base station the user resides. The algorithm recognizes how many times a given cell is visited, when it is visited and how much time is spent there. Using some time-based heuristics and this information, the importance of the location in that cell can be determined. The heuristics applied are based on people's daily routines and backed by statistical data on how Europeans spend their time [11]. For example, on weekdays, people tend to be at work during daytime and at home during nighttime. First, the algorithm detects whether a user is abroad by using the mobile country codes (MCC) associated to the cell IDs. The country of residence is the MCC with the most cell IDs, and other MCCs are treated as abroad. If a user is detected as being abroad, no further context detection is performed, and the context is simply *Abroad*. The second part of cell ID-based context detection clusters adjacent cells into a cell cluster, if necessary. Sometimes, even a stationary mobile device can jump back and forth between adjacent or overlapping cells, and thus the corresponding cells need to be clustered. In the last part, a context is detected and assigned to a cell or a cell cluster. As introduced above, the contexts are *Abroad*, *Home*, *Office*, *Other meaningful* and *Elsewhere*.

A mobile device with a WLAN radio can sense a number of WLAN APs within a range of typically around 100 m. The unique MAC (media access control) addresses of all the sensed APs are logged with our data collection software every 30 min or every time a user uses his or her WLAN. In addition to the MAC addresses, the software also collects the signal strengths of the APs. The basic idea behind the WLAN scan-based context detection is to

recognize a WLAN fingerprint of a particular location, which is the MAC address list with the corresponding signal strengths. These fingerprints are then compared to each other with the number of APs they have in common and the Spearman rank-order correlation coefficient of the ordered relative signal strengths. If the fingerprints are similar enough, they are assigned to the same place. Similar heuristics as in the cell ID-based context detection are then used to assign contexts to the places. Because the WLAN scans are performed only every 30 min (and when the user connects to an AP), the WLAN scan-based context detection is mainly used to increase the accuracy of the cell ID-based context detection of the static or significant contexts such as *Home*, *Office* or *Other meaningful*. No *Elsewhere* context is detected with WLAN scan data.

In the last step of the algorithm, the two parts are combined together with WLAN context information overriding the cell context information. Thus, for example, two significant places under one cell or cell cluster can be distinguished from each other by means of WLAN data. For more detailed information about the heuristics, clustering and fingerprinting methods used for context detection in general, see [36].

In contrary to what was suggested in future research in [41], GPS-based (global positioning system) context detection was not implemented to the algorithm. This was mainly because the data collection software did not support the collection of GPS data. Moreover, the challenges regarding battery consumption and the needed line of sight with regard to GPS data collection would have limited the possibilities of using GPS data in context detection. However, GPS has been previously used, for example, in [1, 26, 29] in finding significant, important or meaningful places.

## 4 Empirical observations

This chapter presents the empirical observations of the data analysis. First, the overall smartphone usage in different contexts is presented, and then, the contextual usage of communication services is studied in detail.

### 4.1 Overall smartphone contextual usage

The overall smartphone contextual usage observations are summarized in Fig. 1. As expected, *Home* context accounts for roughly two-thirds (66%) of the total time spent per day. That means that 16 h per day on average are spent in *Home* context. This result agrees with other time usage studies conducted in Europe [11]. *Office* context accounts for 8% of the time spent in different contexts. However, it has to be noted that not all the users have *Office* context

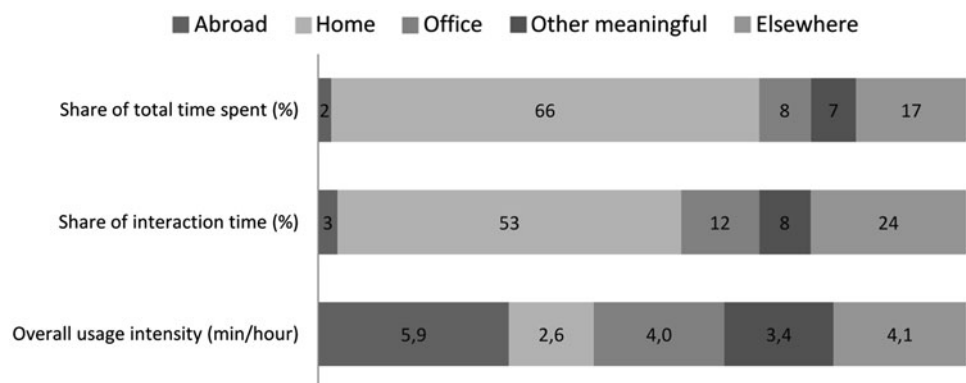
detected. This is mainly because of the sample used that is biased toward students who do not necessarily have regular working/studying times. If a user does not have an *Office* context detected, then the possible studying/working hours belong mainly to the *Other meaningful* context. In total, the *Other meaningful* context accounts for 7% of the total time spent. From the other contexts, *Elsewhere* accounts for 17% of the time spent and *Abroad* for 2%. In the remainder of this article, the *Abroad* context is excluded, because of the limited amount of data generated abroad.

If we look at the share of contexts per hour of day (Fig. 2), we can see how the users' presence at different contexts varies during the day. The figure resembles the observations in [16, 41]. There is a peak in the *Home* context during early morning hours and a dip in the early afternoon. *Office* context follows the common working hours, and the transfer from *Home* to *Office* and vice versa shows quite clearly. The *Elsewhere* context peaks during early evening but does not show any clear peak during the morning commuting time. This is probably because afternoon and evening commuting is most likely accompanied with other activities (such as going to the groceries store),

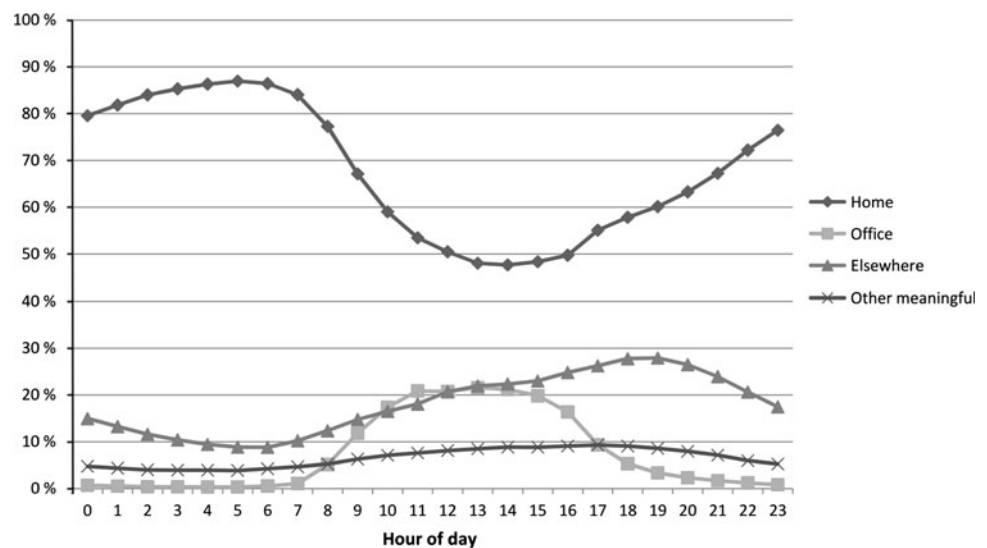
and morning commuting happens more directly. The *Other meaningful* context accounts for less than 10% throughout the whole day and peaks during late afternoon.

To study how long the user interacts with the smartphone in different contexts, we conducted an analysis of non-voice applications. The shares of interaction times per contexts are the following: *Home* 53%, *Office* 12%, *Other meaningful* 8% and *Elsewhere* 24% (Fig. 1). Thus, our observations indicate that most of the interaction time with the smartphone happens in *Home* context as was also argued in [41]. The average interaction time per day per user is 74 min, which is very close to the 69 min that was reported in [41]. According to our observations, the *Home* context appears as the context where the overall usage intensity (measured on user level as interaction time in minutes per hour spent in context) is the lowest (2 min 37 s per hour). This is natural as the sleeping hours are included in the overall usage intensity analysis. However, even if we exclude the regular sleeping hours (from 1 a.m. to 7 a.m.) from analysis, *Home* context still has the lowest intensity of usage from all of the contexts. The other contexts are very close to each other in terms of intensity, with *Elsewhere*

**Fig. 1** Overall smartphone usage in different contexts



**Fig. 2** Share of contexts per hour of day



having the largest overall usage intensity of 4 min 7 s per hour. For more detailed information about the overall smartphone contextual usage, see [36].

The mobile service classification framework in [35] is used in the service usage intensity analysis with an exception of combining the messaging and calling classes to a single class called communication. This framework is developed as a result of an extensive literature review on mobile service classification. Figure 3 depicts selected application class launch intensities in different contexts. The service usage intensity is measured on user level as actions (i.e., application launches, voice calls made or messages sent) per interaction time in the context. It has to be noted that in the overall usage intensity analysis in Fig. 1, the total time spent in a context was used as the denominator instead of the interaction time. The reason for this is that in the service usage intensity analysis, the idea is to study how intensively the users have used a given service when interacting with the smartphone in a given context. On the other hand, the overall usage intensity analysis studies how intensively the users interact with the smartphone while being in a given context. If a given user does not have actions in a certain context, then the user's usage intensity is zero and will be taken into account in the analysis.

The communication application class dominates the overall usage in all contexts suggesting that the smartphone is used everywhere mainly for communication purposes. Furthermore, voice calls are not included in this classification, because they do not have an application specific Symbian UID (unique identifier) and are thus not considered as applications in the analysis. Notable is also that communication applications have the highest intensity in the *Office* context. This implies that the personal smartphone is used for communication also while working or studying. Business/productivity applications such as

calendar, personal information management and office documents are used most intensively in the *Office* context as one could expect.

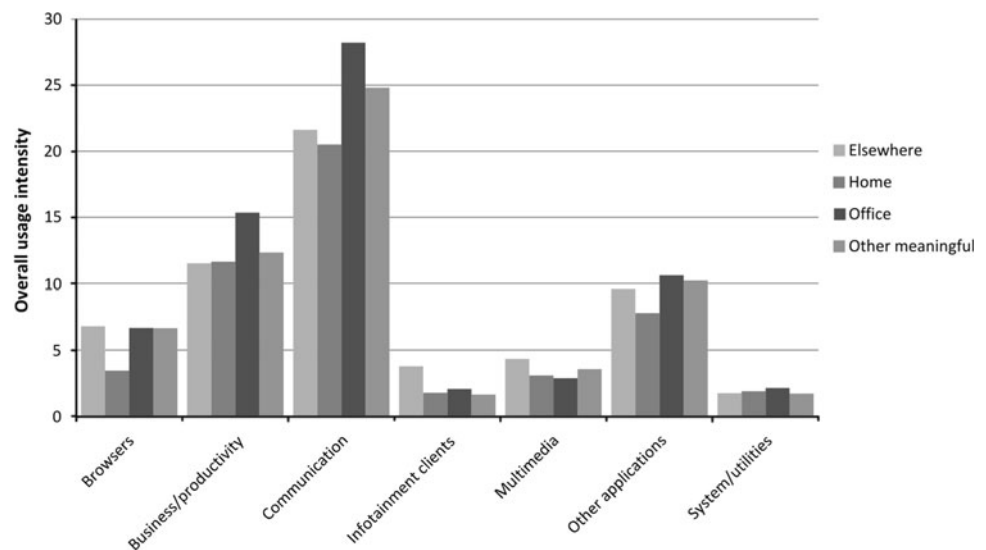
#### 4.2 Contextual usage of communication services

Now that we will analyze communication services in detail, we must first clarify how the usage is measured. In Fig. 3, only the application launch intensities were used in the analysis. However, more detailed analysis will be conducted in this chapter. In addition to the application launches, we can measure the actual communication from the traditional services, that is, voice calls, SMSs and MMSs. Actual communication refers to calls made, messages sent and duration of voice calls in seconds. Moreover, if the users use the native email application of the device instead of a third party email application (e.g., Gmail), then we can measure the actual emails sent as well. From the rest of the communication services, we can only measure if and for how long the service was used. It is thus not possible to measure whether messages were actually sent during an application usage session or whether the service was just used for reading old messages, for example. The analysis is limited to studying the context of outbound communication when applicable, and the context is not considered when, for example, receiving a call.

Figure 4a and b depict the communication application launch intensities in different contexts. As voice calls do not have an application specific Symbian UID, their usage will be analyzed from the actual outbound communication data and not from the application data.

There are some applications that are specific for the Symbian platform such as *Messaging* and *Message editor* in Fig. 4b. From these two services, it is not possible to separate whether SMS or email was used, and thus they are

**Fig. 3** Application class launch intensities



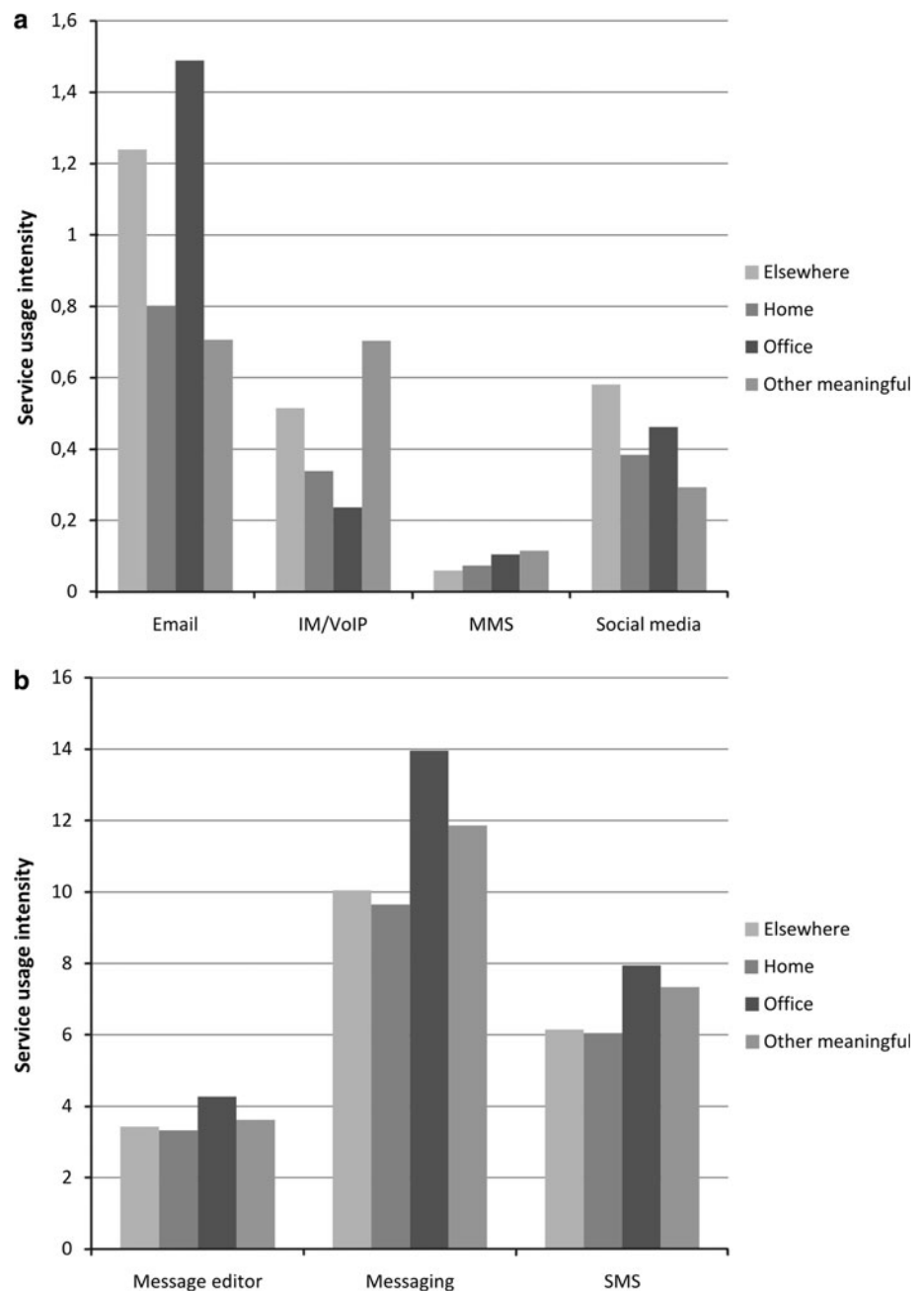


not analyzed further. However, the other communication services can be analyzed. Figure 4b indicates that SMS is used most intensively in all contexts with *Office* context having the largest usage intensity. This result was already reflected in the application class analysis in Fig. 3. Email is also most intensively used in the *Office* context indicating that it is used mainly for working or studying related activities (Fig. 4a). It was also concluded in [41] that messaging applications are used most (in terms of time allocation) in *Office* context that agrees with our observations. On the other hand, IM/VoIP applications (Fig. 4a) are used most intensively in *Elsewhere* and *Other mean-*

*ingful* contexts. As these two contexts correspond to the *On the move* context that was used in [41], the findings that IM is used most (measured with share of all actions) while on the move, agree with our observations as well. From the rest of the services, MMS received quite low usage with most intensive usage in *Other meaningful* context, while social media applications were used most intensively in *Elsewhere* context (Fig. 4a).

Voice calls are included in Figs. 5a, b and 6, which depict the outbound communication service usage intensity and the outbound voice call duration in different contexts, respectively.

**Fig. 4** **a** Email, IM/VoIP, MMS and social media application launch intensities. **b** Message editor, messaging and SMS application launch intensities

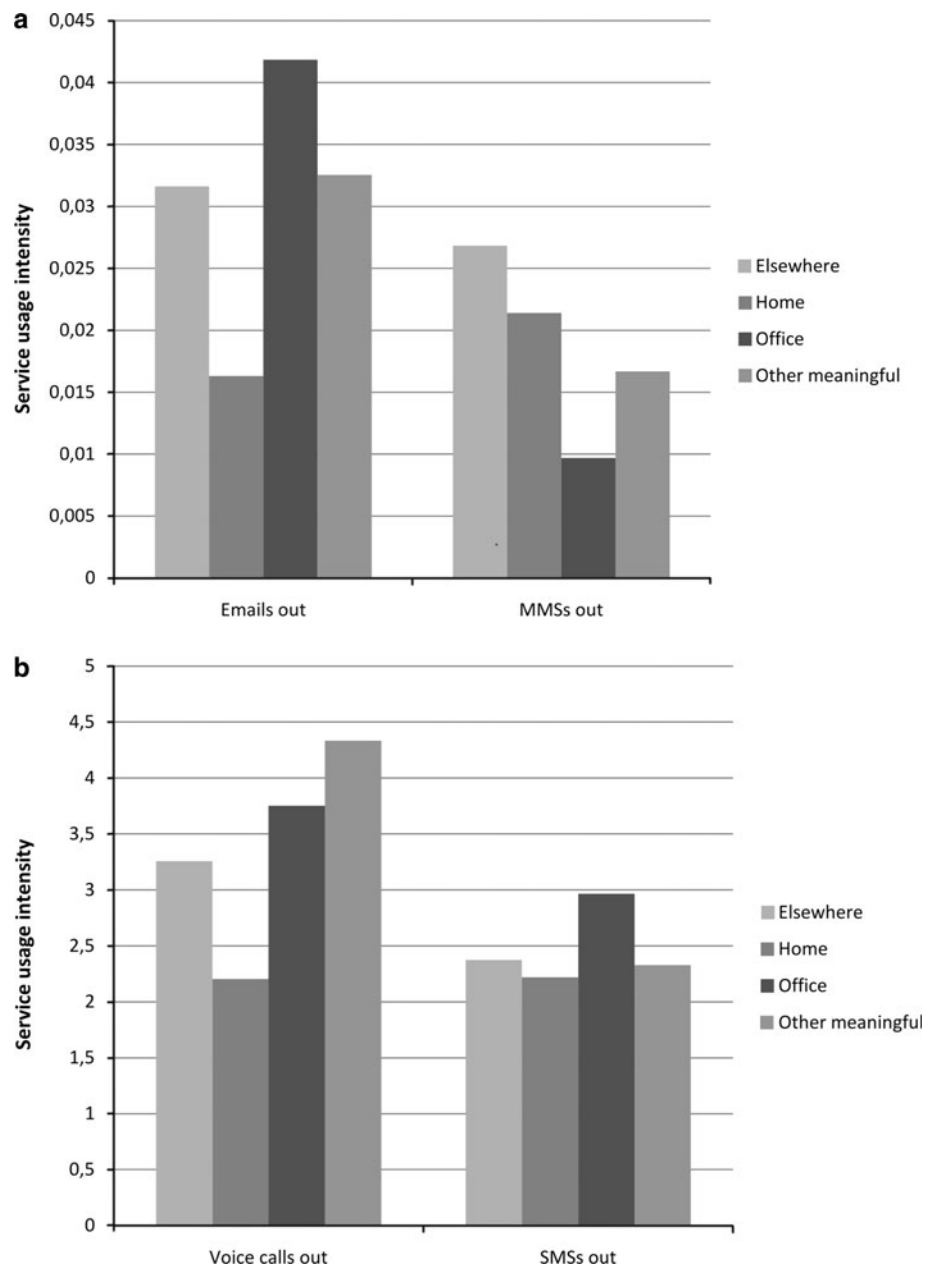


The main conclusions from these figures are that voice calls are used least intensively in the *Home* context where the length of the voice calls is the longest, however. On the other hand, SMSs are most intensively sent in the *Office* context where the voice call length is the shortest. It is agreed in [41] that the outbound voice calls are the longest at home and that the propensity to call from home on the mobile phone is low compared to other types of places [24]. Following the observations from our application analysis, emails are sent most intensively in the *Office* context. It is also agreed in [33] that work/school have higher than average primary usage of mobile email.

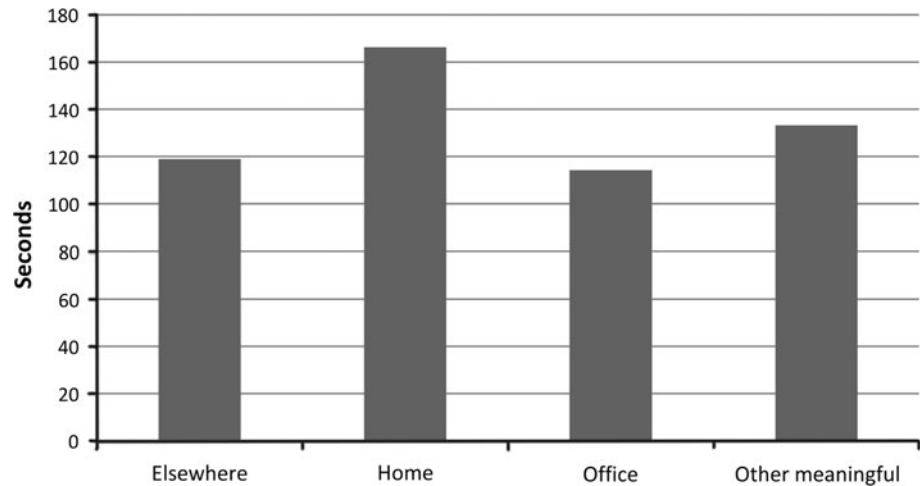
## 5 Discussion

The observations presented above indicate that when measured with application launches and actual messages sent, messaging (i.e., email and SMS) services are used most intensively in the *Office* context. Email is perceived widely as a business communication medium, and our observations indicate that in addition to the basic fixed office usage of email, mobile email is also used most intensively in office environments. There might also be a need for discrete personal communication in office environments, which explains the intensive usage of SMSs there. Furthermore, limited time resources may be present

**Fig. 5** **a** Outbound Email and MMS service usage intensity.  
**b** Outbound voice call and SMS service usage intensity



**Fig. 6** Outbound voice call duration



in office environments when compared to home environments which explain the short and long durations of voice calls in *Office* and *Home* contexts, respectively. From the other services, mobile IM/VoIP and social media applications seem to be more free-time oriented being used most intensively in *Elsewhere* and *Other meaningful* contexts.

These observations together with results from related research indicate that different mobile communication services and communication media are used for different purposes and that context is one of the key factors affecting the value that a medium creates to the users. People use multiple media to connect to each other [3], and thus, the resulting social networks also differ. Accordingly, social network analysts should not rely on a single data set portraying the social network, but instead use multiple data sets to really understand how the users are connected to each other. This finding has also previously been reported in [20, 27], for example. The observations are also interesting from a mobile operator perspective. Since different mobile communication services are used for different purposes, operators should not be afraid of the MI communication services directly substituting their traditional communication services as observed also in [19], for example. Operators should strive to segment their customers based on their communication service usage profiles or *personal communication systems* [3]. Then, the service offerings of the operators should be tailored for each segment to maximize the value created to the customers. Finally, application developers in the area of context-aware or location-based services can utilize the developed context algorithm in implementing or developing their own solutions.

Context is naturally not the only factor affecting communication media choices. Other possible variables include the strength of the tie between the persons communicating. For example, mobile IM/chat is used mainly in tight communities, while email is used uniformly across communities [39]. Furthermore, the stronger the tie between

people, the more media they tend to use to communicate to each other [14]. Thus, using multiple data sets in social network analysis becomes even more salient when the ties get stronger. The availability of communication media resources affects the selection process also. For example, in our study, it could be argued that more communication media choices might be available in *Home* and *Office* contexts than in *Elsewhere* or *Other meaningful* contexts. Moreover, the user characteristics affect the communication media choices. For example, it was observed in [21] that young students, such as the ones participating in this research, manage a more general configuration of relationships through multiple media. Workers on the other hand seem to manage different sets of relationships through each medium. Furthermore, the term *social affordance* has been suggested in [3] that posits that the choice of communication media depends on the congruency between opportunities that the medium provides and the characteristics of the ties with whom the medium is used to communicate.

### 5.1 Future research

The context algorithm will be developed further by acquiring so-called ground truth data to verify the detected contexts. This will happen by implementing on-device questionnaires with the data collection software that prompt the users to tag their most significant places. By doing this, we can verify whether the contexts detected by the algorithm conform to the contexts tagged by the users. The GPS-based context detection will also be an item for future research. This functionality can be implemented to the data collection software but was not used in this study because of the challenges regarding battery consumption and the needed line of sight. In addition to the place-related contexts that we have used in this study, also the social context should be identified. An attempt was made in [36]

to detect the social context using Bluetooth data, but it proved to be insufficient. Other sensors of the smartphone, such as the microphone, could also be used to detect the social context. The context detection can be further developed by using data collected from the accelerometer as done in [32], for instance. However, the more data you collect from the smartphone, the more energy the device consumes. Thus, it has to be planned carefully what data are to be collected and how these data complement each other in the best possible manner.

## 5.2 Limitations

As already mentioned in the background section, defining context is not an easy task. Some researchers have even doubted if the concept can be defined at all or if it is too ambiguous by nature [38]. Our definition of context relies heavily on location and time, and we have not intended it to be an overall definition. Rather we have defined it with our research area and available data in mind as suggested in [2]. Although the collected data are of objective nature and not self-reported by the participants, there is some amount of subjectivity in determining which applications belong to which class, for example. This subjectivity has been minimized by using an application classification framework, developed as a result of extensive review on mobile service classification literature [35]. The sample used in this study is biased toward early adopters of mobile services and devices and it limits the external validity of the results. However, studying MI communication services that are not yet adopted by an average smartphone user yields better results with this kind of a sample. The usage patterns of these early adopters might also reflect the usage patterns of the average user in the future.

## 6 Conclusions

The effect of use context on smartphone communication service usage patterns was studied in this article. The empirical data used in the analysis were collected with handset-based measurements from 140 early adopter smartphone users in Finland. Using the cell ID and WLAN data and a purpose-built algorithm, we were able to identify five different place-related contexts, namely *Home*, *Office*, *Other meaningful*, *Elsewhere* and *Abroad*. After context detection, the overall usage of the smartphone and the usage of communication services were studied in different contexts. As a result, we conclude that although voice calls are used least intensively in the *Home* context, the length of the voice calls is the longest there. Moreover, the length of the voice calls is the shortest in the *Office* context where messaging services, such as email and SMS,

are used most intensively. Finally, other MI communication services, such as IM/VoIP and social media, are more free-time oriented with most intensive usage in the *Elsewhere* and *Other meaningful* contexts. We believe that these findings imply that context is one of the key factors affecting the selection of mobile communication media. The empirical observations presented in this article must be treated with care; however, as our definition of context is case-specific and the external validity of the results can be questioned. We believe, however, that these observations are valuable to several stakeholders including academicians and practitioners in the fields of context-aware computing, mobile operators and social psychology. With that said, more research, both regarding context detection and communication media choices, is definitely needed.

**Acknowledgment** The work has been supported by the OtaSizzle research project that is funded by Aalto University's MIDE program and Helsinki University of Technology TKK's "Technology for Life" campaign donations from private companies and communities. The work was carried out in the Econ@Tel COST605 context with support from the MoMIE project and the Future Internet Graduate School (FIGS). The authors wish to thank MobiTrack Innovations Ltd. for providing the mobile audience measurement platform. The sponsoring from Nokia and Elisa to this work is also acknowledged.

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