

End user context in analyzing mobile device and service usage

Tapio Soikkeli

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Abstract

Mobile devices and services are becoming an inseparable part of the human life. These devices and services are used for communication, information retrieval, entertainment and much more. The additional value, as well as the challenges in the mobile services domain relate to its ubiquitous, or the "anywhere, anytime" properties. The convenience and constant accessibility of services available within arm's reach of the consumer is a compelling value proposition. On the other hand, the usage situations vary and the users have varying needs and possibilities in different situations. This variation calls for understanding the user behavior and the services to dynamically adapt to the users' situations. Context refers to any information that can be used to characterize the situation of the user, and thus the utilization of context is considered relevant to building better and more personalized mobile services.

The purpose of this thesis is to study how to acquire and utilize information on the use context of a mobile end user from handset-based measurements and find out what general and contextual mobile device and service usage patterns the measurements reveal. The aim is to fill in a research gap in the intersection of small-scale empirical context-awareness research and market level mobile service usage research by leveraging the user-level, yet scalable nature of handset-based measurements. Handset-based measurements enable the collection of objective real life data on the usage of mobile devices, such as smartphones and tablets, of opted-in study participants. In addition to handset-based measurements, surveys and network measurements were used as complementary methods.

Mechanisms behind the observed mobile devices and services related user behavior are complex. In this thesis the general level mobile device and service usage is identified as communication and Web browsing oriented, occurring in bursts of activity and dominated by relatively short sessions. In addition, the usage varies between certain contexts. For example, the general home usage shows long but more infrequent usage sessions in comparison to other studied semantic places. The contextual results are, however, rather service specific. Finally, the largest variation is observed between users, with, for example, two magnitude differences in device usage intensity between light and heavy users. The results emphasize the need for personalized mobile services. The data collection capabilities of contemporary mobile devices enable diverse contextual information utilization for increasing the level of service personalization, for instance. Additionally, mobile devices provide more accurate tools for the more general human behavior research in the spirit of computational social science.

Keywords handset-based measurements, context, mobile devices, mobile services, user behavior, multi-method

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Mobiililaitteista ja -palveluista on tullut erottamaton osa ihmisten arkea. Näitä laitteita ja palveluita käytetään kommunikointiin, tiedonhakuun, viihteeseen ja moniin yhä uudensuunnaisiin käyttötarkoituksiin. Sekä mobiilipalveluilla tavoiteltava lisäarvo, että niihin liittyvät haasteet kumpuavat mahdollisuudesta tarjota näitä palveluita "aina ja kaikkialla". Jatkuvasti tarjolla olevat palvelut ovat monesti houkutteleva vaihtoehto sekä kuluttajalle, että palveluntarjoajalle. Toisaalta, ympäristöt ja tilanteet joissa kyseisiä palveluita käytetään saattavat vaihdella, ja käyttäjien palveluille kohdistamat tarpeet ja käyttömahdollisuudet voivat vaihdella näistä tilanteista ja ympäristöistä riippuen. Tästä syystä käyttäjien käyttäytymisen ymmärtäminen on tarpeellista, jotta palveluita kyetään mukauttamaan käyttäjän kulloiseenkin tarpeeseen ja käyttötilanteeseen. Termi konteksti viittaa informaatioon, jota voidaan käyttää käyttäjän tilanteen luonnehdintaan. Näin ollen konteksti on olennainen osa parempien ja yhä personoidumpien mobiilipalveluiden kehittämistä.

Tämän väitöskirjan tarkoitus on tutkia, kuinka päätelaitepohjaisten mittausten avulla voidaan kerätä ja hyödyntää tietoa mobiilikäyttäjän kontekstista. Lisäksi, tarkoituksena on tutkia, kuinka erilaisia mobiilipalveluita käytetään käyttökäytännöstä riippuen. Päätelaitepohjaiset mittaukset mahdollistavat objektiivisen tiedon keräämisen mobiililaitteiden, kuten älypuhelinien ja tabletti-tietokoneiden käytöstä käyttäjätasolla. Väitöskirjassa hyödynnetään kolmea eri päätelaitepohjaisilla mittauksilla kerättyä aineistoa. Päätelaitepohjaisten mittausten lisäksi työssä käytetään kyselytutkimuksia ja verkkomittauksia täydentävinä tutkimusmenetelminä.

Tässä väitöskirjassa mobiililaitteiden ja -palveluiden käytön havaittiin painottuvan kommunikaatioon ja Web-käyttöön, olevan purskeista ja koostuvan pääasiassa suhteellisen lyhyistä käyttösessioista. Lisäksi, käytön havaittiin vaihtelevan eri käyttökonteksteittain. Esimerkiksi kotona käyttösessioita on harvemmin, mutta ne ovat pidempiä verrattuna muihin tutkittuihin semanttisiin paikkoihin. Huomattavaa kuitenkin on, että kontekstuaaliset tulokset vaihtelevat selvästi palveluittain. Suurin vaihtelu käytössä havaittiin kuitenkin eri käyttäjien välillä. Esimerkiksi ero älypuhelinien käyttöintensiteetissä on satakertaisessa suuruusluokassa pien- ja suurikäyttäjien välillä. Tulokset tähdentävät mobiilipalveluiden personoinnin tärkeyttä. Nykyaikaiset mobiililaitteet mahdollistavat monipuolisen kontekstiedon keräämisen ja hyödyntämisen esimerkiksi personoinnin tarpeisiin. Lisäksi päätelaitepohjaiset mittaukset tarjoavat aikaisempaa paremman mahdollisuuden entistä tarkempaan ihmisten yleisen käyttäytymisen tutkimukseen.

Avainsanat päätelaitepohjaiset mittaukset, konteksti, mobiililaitteet, mobiilipalvelut, käyttäytymisen, monimenetelmä

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Preface

This thesis project would not have been possible without the contributions of a number of people. Here I want to express my gratitude to them. First and foremost, I want to thank Professor Heikki Hämmäinen for supervising the thesis and providing guidance throughout the whole process. Furthermore, Heikki has always provided the necessary resources and freedom for me to conduct my research. For this, I am very grateful. I thank my preliminary examiners Professors Robin Dunbar and Lauri Frank for devoting time to review and comment on the thesis. I am also very honored to have Professor Harry Bouwman as my opponent in the thesis defense. A big thank you goes to my co-authors Benjamin Finley, Juuso Karikoski and Antti Riikonen for their time and effort put into our joint research work.

During the thesis process, I worked in the Network Economics research group of the Aalto University Department of Communications and Networking. The years spent in the group were enjoyable time, and the thanks for this go obviously to my great colleagues: Arturo Basaure, Jaume Benseny, Thomas Casey, Mikko Heikkinen, Michail Katsigiannis, Pekka Kekolahti, Tapio Levä, Timo Smura, Henna Suomi, Juuso Töyli, Alexandr Vesselkov and Nan Zhang. The discussions during coffee brakes and lunches, twice a year sports events and the occasional after-work beers contributed to the nice memories.

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Helsinki, March 4th 2016
Tapio Soikkeli

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List of Abbreviations

3G	Third Generation
4G	Fourth Generation
AAA	Authentication, Authorization, and Accounting
AP	Access Point
CDR	Call Detail Record
CID	Cell ID
ESM	Experience Sampling Method
GDP	Gross Domestic Product
GGSN	Gateway GPRS Support Node
GPRS	General Packet Radio Service
GPS	Global Positioning System
HCI	Human Computer Interaction
HTTP	Hypertext Transfer Protocol
ID	(unique) Identifier
IoT	Internet of Things
IP	Internet Protocol
LAC	Location Area Code
MAC	Media Access Control
MCC	Mobile Country Code
MMS	Multimedia Messaging Service
MNC	Mobile Network Code
MSISDN	Mobile Station International Subscriber Directory Number
NNS	Nearest Neighbor Search
NT	Network Traffic

OS	Operating System
PC	Personal Computer
PDF	Probability Density Function
QoC	Quality of Context
RADIUS	Remote Authentication Dial-In User Service
RP	Research Problem
RQ	Research Question
SEL	Socioeconomic Level
SMS	Short Message Service
SSID	Service Set Identifier
TCP	Transmission Control Protocol
TPR	True Positive Rate
URL	Uniform Resource Locator
WLAN	Wireless Local Area Network

List of Publications

This doctoral dissertation consists of a summary and of the following publications which are referred to in the text by their numerals

- 1.** Soikkeli, Tapio; Karikoski, Juuso; Hämmäinen, Heikki. 2014. Context classification framework for handset-based end user studies. *J.UCS. Journal of Universal Computer Science*, volume 20, issue 14, pages 1964-1986. ISSN 0948-695x. DOI 10.3217/jucs-020-14-1964.
- 2.** Soikkeli, Tapio; Karikoski, Juuso; Hämmäinen, Heikki. 2013. Characterizing smartphone usage: Diversity and end user context. IGI Global. *International Journal of Handheld Computing Research*, volume 4, issue 1, pages 15-36. ISSN 1947-9158. DOI 10.4018/jhcr.2013010102.
- 3.** Karikoski, Juuso; Soikkeli, Tapio. 2013. Contextual usage patterns in smartphone communication services. Springer-Verlag London Limited. *Personal and Ubiquitous Computing*, volume 17, issue 3, pages 491-502. ISSN 1617-4909. DOI 10.1007/s00779-011-0503-0.
- 4.** Soikkeli, Tapio; Riikonen, Antti. 2015. Session level network usage patterns of mobile handsets. In: *Proceedings of the 13th International Conference on Telecommunications (ConTEL 2015)*, July 13-15, Graz, Austria. IEEE. Pages 1-8. ISBN 978-1-4799-8971-3. DOI 10.1109/ConTEL.2015.7231229.
- 5.** Finley, Benjamin; Soikkeli, Tapio. SUBMITTED. Multidevice Mobile Sessions: A First Look. Elsevier. *Pervasive and Mobile Computing*. ISSN 1574-1192.
- 6.** Soikkeli, Tapio. 2015. Comparison of context-aware predictive modeling approaches: Semantic place in inferring mobile user behavior. Emerald Group Publishing Limited. *International Journal of Pervasive Computing and Communications*, volume 11, issue 3, pages 323-346. ISSN 1742-7371. DOI 10.1108/IJPCC-01-2015-0003.

Author's Contribution

Publication 1: Context classification framework for handset-based end user studies

The idea for this publication was formed by Soikkeli. Soikkeli was the head author of the publication and wrote the manuscript. Soikkeli, Karikoski and Hämmäinen reviewed and edited the publication together.

Publication 2: Characterizing smartphone usage: Diversity and end user context

The idea for this publication was formed jointly with Karikoski and Hämmäinen. Soikkeli was the head author of the publication and wrote the manuscript. Soikkeli participated in collecting the data, and the data analysis was conducted by Soikkeli. Soikkeli, Karikoski and Hämmäinen reviewed and edited the publication together.

Publication 3: Contextual usage patterns in smartphone communication services

The idea for this publication was formed jointly with Karikoski. Karikoski was the head author of the publication and wrote the majority of the manuscript. Soikkeli developed the context detection algorithm, derived the contextual information and linked it with communication service usage data. Soikkeli and Karikoski reviewed and edited the publication together.

Publication 4: Session level network usage patterns of mobile handsets

The idea for this publication was formed jointly with Riikonen and Hämmäinen. Soikkeli was the head author of the publication and wrote the majority of the manuscript. Soikkeli and Riikonen reviewed and edited the publication together.

Publication 5: Multidevice Mobile Sessions: A First Look

The idea for this publication was formed jointly with Finley. Soikkeli and Finley analyzed the data and wrote, reviewed and edited the publication together.

Publication 6: Comparison of context-aware predictive modeling approaches: Semantic place in inferring mobile user behavior

Soikkeli was the sole author of this publication.

1. Introduction

1.1 Background and motivation

During the past few decades mobile devices and mobile services have evolved tremendously and at an ever-increasing pace. The traditional cellular mobile phone from the 1990s with calling and Short Message Service (SMS) functionalities introduced the masses to the conveniences of mobile communication. Later developments in the forms of mobile broadband data, mobile Internet and increasingly more capable mobile devices and networks have led into a proliferation of mobile services. Modern mobile devices, such as smartphones and tablets, and particularly the services offered via them are becoming an inseparable part of the human life. Even in the short term visions the mobile device will act as an identity, wallet, car and house keys, communication and social media hub, news service and entertainment center, to name a few.

At the end of 2014 50 % of the world's population had a mobile subscription, 40 % of the subscriptions included a mobile broadband connection and 36 % of the subscriptions were used with a smartphone. Projections for the respective numbers for 2020 are 60 %, 70 % and 60 %. Furthermore, the mobile data traffic in the world is anticipated to grow tenfold between 2014 and 2020 and the mobile ecosystem's direct contribution to the world's GDP (Gross Domestic Product) at the end of the period is projected to be 4.2 %.¹ This all means that the majority of the world's population can be soon reached by mobile services provided over the mobile Internet. New opportunities will unfold not only for the more traditional electronic service providers, but also increasingly for the so-called brick and mortar businesses when they expand to the mobile domain.

The additional value, as well as the challenges in the mobile services domain relate to its ubiquitous, or the "anywhere, anytime" properties. The convenience and constant accessibility of high-quality services available within arm's reach of the consumer is a compelling value proposition. On the other hand, the usage situations vary and the users have varying needs and possibilities in different situations. The varying needs and possibilities call for understanding mobile user behavior and the services to dynamically adapt to the users' situa-

¹ Information on the mobile subscription, mobile broadband connection, smartphone penetration, mobile data traffic and the projected GDP numbers was obtained from The Mobile Economy 2015 report by GSMA (Groupe Speciale Mobile Association) (http://www.gsmamobileeconomy.com/GSMA_Global_Mobile_Economy_Report_2015.pdf).

tions. Thus, new approaches from service providers are needed to address these challenges.

In computer science context-awareness is a term referring to the idea that computers and applications running on these computers can sense and react based on what is happening in their environment. In mobile computing research context-awareness is extended to include also the user of the mobile device by utilizing the mobile device itself, and possibly additional sensors and information, to approximate the user's context or situation (see, e.g., Schilit et al., 1994). In the early phases, context-awareness in mobile computing was typically empirically studied with a few prototype devices in a prototype environment. The goals of the studies were relatively narrow, for example, limiting to developing and examining a system where a binary change in the user's environment triggers a pre-planned action in the system. On the more theoretical level context definitions, classifications and utilization models have been developed to serve context-aware computing both on a specific task level and on the more general level. However, the more general level theory has been somewhat disjoint from the empirical studies.

Additionally, context-aware computing studies have been disjoint from the traditional mobile service usage studies. This is understandable, because mobile service usage research comes from a more economics oriented domain and has traditionally relied on self-report methods, such as surveys and interviews. Also, market level data have been used in studying mobile service usage on the high level. In addition to the challenges linking self-report service usage studies to the computational context-awareness work to explore the effects of the users' real world situations on the service usage, the self-report method is inherently susceptible to different response biases. Market level analysis, on the other hand, misses user-level particulars almost entirely, thus ignoring the effects of user diversity behind the overall results. Moreover, traces of contextual service usage patterns are not visible in market level data.

The increased capabilities of mobile technologies have, however, induced the emergence of new data collection methods for objectively studying mobile user behavior on user-level. These methods have on their part boosted a research field called computational social science (Lazer et al., 2009), which relies on massive amounts of digital trace data collected from individuals. Handset-based measurements (called also device monitoring) are a method for collecting objective user-level data for analyzing mobile service usage. Handset-based measurements provide a possibility to collect data on the actual service usage, but in addition they enable collecting other behavioral and contextual data from the user's device and correlating this additional data with the service usage data. Handset-based measurements were pioneered by Raento et al. (2005) with their measurement platform ContextLogger and Eagle & Pentland (2006) with their Reality Mining project. Verkasalo (2009a) conducted one of the first handset-based measurement studies on the effect of context on mobile service usage. The technology for the measurements is relatively new and thus the literature in the field is still limited. With that said, however, these types of measurements are currently gaining popularity not only in the technical and

computational fields, but also in fields such as psychology (Miller, 2012). New measurement platforms such as the Funf framework (Aharony, 2012) and data collection efforts (Laurila et al. 2013; Stopezynski et al., 2014; Wagner et al., 2014) have been introduced. Furthermore, the growing numbers of new mobile devices like tablets and smartwatches, and sensor networks, provide possibilities for even more pervasive analysis.

Studying how mobile devices and services are used in the real world and investigating contextual patterns related to the usage is important for mobile service providers, and also from the perspective of the more general human behavior research. For example, mobile service providers and application developers can utilize this knowledge for developing services and applications that adapt better to the users' needs and capabilities. On the other hand, the pervasiveness of mobile devices and their usage in people's everyday life, combined with the new measurement possibilities, can reveal new insights regarding basic human behavior (see, e.g., Barabasi, 2005 and Miller, 2012).

This thesis utilizes handset-based measurements to empirically study the contextual usage of mobile devices and services. The aim is to fill in a research gap in the intersection of small-scale empirical context-awareness research and market level mobile service usage research by leveraging the user-level, yet scalable nature of handset-based measurements. The thesis contributes also to the emerging field of computational social science. This thesis and its results may be valuable for academics and practitioners in the fields of context-awareness, mobile services, mobile marketing and social sciences.

1.2 Objectives and scope

The thesis as a whole aims to address a wider research problem (RP), to which the individual publications provide partial answers. The research problem is stated below:

RP: How to characterize, analyze and model contextual usage of mobile devices and services utilizing handset-based measurements?

Handset-based measurements are the core method used in this thesis, as the research problem indicates. In addition to the core method, the thesis utilizes complementary methods such as surveys and mobile network measurements. The complementary methods are used to supplement the core method and provide additional viewpoints for the core results. The research questions (RQ) of the thesis are:

RQ1: How to define and categorize mobile end user context as a synthesis of theoretical and practical viewpoints and acquire contextual information utilizing handset-based measurements?

RQ2: How to measure mobile device and service usage from handset-based data, and what types of mobile usage patterns do the measurements reveal?

RQ3: How are mobile devices and services used depending on certain use contexts of the mobile end user?

RQ4: How to incorporate contextual information into modeling the usage of mobile devices and services?

The results addressing the research questions are discussed from mobile service providers' point of view, as well as, from an academic point of view, concerning mainly context-awareness, mobile service usage and human behavior research. The empirical results of the thesis are acquired by measuring and analyzing the real world usage of mobile devices and services in combination with contextual data linked to the users of the devices and services.

Table 1 shows how the publications of the thesis are related to each other in terms of the four research questions formulated above. The table briefly describes also the method or data source utilized in the individual publications. Each method and data source is presented in detail in Chapter 4. Regarding the research process, the conceptual basis for the notion of context in this thesis, and principles of contextual information acquisition from handset-based measurements are laid out in Publication 1. Publication 6 provides empirical analysis related to the contextual information acquisition in practice.

Table 1 Relations of the publications in the research process

Pub.	Topic	Q1	Q2	Q3	Q4	Method/data source
1.	Context classification framework for handset-based end user studies	X				Literature review, Own previous studies
2.	Characterizing smartphone usage: Diversity and end user context		X	X		Handset-based measurements, Survey
3.	Contextual usage patterns in smartphone communication services			X		Handset-based measurements, Survey
4.	Session level network usage patterns of mobile handsets		X	X		Handset-based measurements, Network measurements
5.	Multidevice mobile sessions: A first look		X	X		Handset-based measurements
6.	Comparison of context-aware predictive modeling approaches: Semantic place in inferring mobile user behavior	X			X	Handset-based measurements, Survey, Experience sampling

Publications 2-5 provide empirical analysis of mobile device and service usage and contextual patterns in mobile device and service usage utilizing differ-

ent types of mobile services and different contextual elements describing the users' context. Finally, Publication 6 investigates approaches to utilizing certain contextual information in modeling mobile service usage.

To further position the thesis, the definitions of some of the key terms used are in order:

Mobile device: a small computing device, typically small enough to be handheld. Smartphones, tablets and smartwatches are examples of mobile devices.

Mobile service: refers to services that can be used by a mobile device. In the context of this thesis it refers also to mobile applications (see the definition below).

Mobile application: a computer program designed to run on mobile devices. Usually it acts as a gateway to using mobile services.

User: a person who uses a mobile device and a mobile service.

Usage: refers mainly to post-adoption usage. For example, we analyze usage only with those users who have already adopted all the services under analysis.

Context: any information that can be used to characterize the situation of an entity (Dey, 2001). In this thesis the entity is the user. For more elaborate discussion on context as a concept refer to section 2.2 and Publication 1.

Smartphone: a mobile phone with an advanced mobile operating system which combines features of a personal computer operating system with other features useful for mobile or handheld use.

Tablet: a mobile computer with a touchscreen display, circuitry and battery in a single device.

Session: a period of time that is used to do a particular activity. In this thesis the activity is mostly mobile services usage and session acts as one measure of this usage.

Handset-based measurements: imply that data are collected from handsets, that is, handheld mobile devices. In this thesis especially smartphones and tablets are considered as handsets.

Empirical analysis: refers to research approaches seeking 'to gain knowledge of the world, that is, of the reality in which we live', as de Groot (1969, p.1) has defined.

1.3 Research approach

The research in this thesis is multidisciplinary as it combines theories, models and methods from engineering, computer science and social sciences. The research is user behavior-oriented and the main focus is on analyzing user-level patterns related to the usage of information technology products and services. Furthermore, the results are discussed from an economic viewpoint. Hevner et al. (2004) identify two main research paradigms in the context of information technology and related systems: behavioral science and design science. According to Hevner et al. (2004), behavioral science paradigm has its roots in natural sciences, is reactive, and seeks to develop and justify theories that explain and predict organizational and human phenomena. The design science

paradigm, on the other hand, has its roots in engineering and the science of artifacts, is proactive, and seeks to create innovations in the spirit of problem solving. Additionally, behavioral science methods rely on data collection and empirical analysis, whereas design science methods aim for assessing the quality and effectiveness of artifacts.

Based on the ideas of Hevner et al. (2004) and March & Smith (1995), Järvinen (2004) has developed taxonomy of research approaches (**Figure 1**). On the first level of the taxonomy research approaches are divided into *Approaches studying reality* and *Mathematical approaches*. Mathematical approaches form their own class, because they do not concern any specific domain in reality, but rather focus on proving a certain theorem, lemma or assertion. According to the taxonomy, Approaches studying reality include five distinct sets of approaches. In *Conceptual-analytical approaches*, the researcher starts from assumptions, premises and axioms and based on these derives a theory, model or framework. Alternatively, the researcher starts from the theories, models and frameworks of previous studies and integrates these using logical reasoning. *Theory-testing* and *Theory-creating approaches* are approaches for empirical studies. For example, laboratory studies, surveys, field studies or case studies are conducted to collect data from reality. Based on the empirical studies, existing theories, models and frameworks are tested and possibly refined, or in the lack of existing ones new theories, models and frameworks are created. Finally, the research stressing utility of innovations (the domain of design science) is divided into *Innovation-building* and *Innovation-evaluating approaches*. Innovation-building is concerned on whether an innovation can be used for a particular task. Innovation-evaluating, on the other hand, is concerned on how well an innovation performs a particular task.

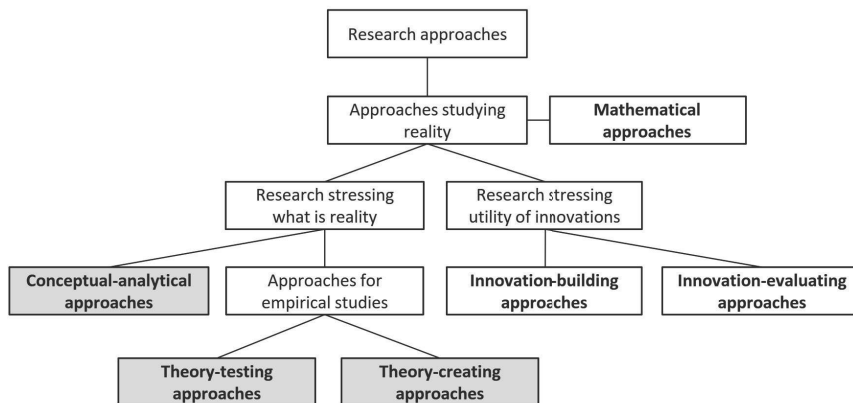


Figure 1 Taxonomy of research approaches (adapted and modified from Järvinen, 2004)

Traditionally, *hypothesis-driven* methods have been considered as the backbone of scientific advance. In the hypothesis-driven approach of conducting research the idea (or hypothesis) comes first and then data are gathered to test the idea (Kell & Oliver, 2004). This is also called the hypothetico-deductive approach and is in principle a reverse of the more inductive *data-* and *tech-*

nology-driven approaches which start with data (technology) and then derive the ideas. Kell & Oliver (2004) argue that a place for both types of approaches exists in science, not as competitive, but as complementary. Together the approaches form an iterative cycle. Schweitzer & Vespignani (2012) believe that the current era of increasing availability to unprecedented amounts of data is (r)evolutionizing science and raising the importance of the data-driven approaches. Schweitzer & Vespignani (2012) identify as one of the targets to identify new empirical laws emerging from the massive datasets.

Based on the above considerations the research approach of this thesis can be framed. Most of the research in the thesis has started with data exploration and the hypotheses and ideas are at least partly results of this exploration. This pushes the research more towards the data-driven than the hypothesis-driven paradigm. However, the hypotheses and ideas resulted from the earlier research have definitely guided later research, demonstrating the iterative cycle mentioned by Kell & Oliver (2004). The thesis also belongs to the behavioral science paradigm rather than the design science paradigm. The thesis utilizes mainly approaches for empirical studies. However, Publication 1 falls to the category of conceptual-analytical approaches. As Church et al. (2015) argue, handset-based measurement studies have their unique particulars concerning the generalizability of results and theory creation. Panels of mobile device users shed light on the usage of these particular user subsets during a particular time-window and thus the most solid theory-creation calls for meta-analysis over the research conducted by the whole community. With this said, this thesis is a part of that *theory-creation* process. While this thesis as a whole is not testing any particular theory or a coherent set of theories, the different parts of the work are grounded to the relevant theoretical backgrounds. These include theories in user and human behavior research, context research and mobile service usage research. As the results in the different parts of the thesis are compared with the theoretical backgrounds, the thesis also utilizes *theory-testing* approaches. In **Figure 1**, the approaches utilized in the thesis are highlighted.

1.4 Thesis structure

The structure of the thesis overview part is as follows. After the Introduction, Chapter 2 introduces the theoretical background relevant to the thesis. This includes the theoretical backgrounds on user and human behavior research, context and context-awareness research, and mobile service usage research. In Chapter 3 related empirical research on user behavior in the mobile domain and contextual mobile service usage is reviewed and discussed. The methods and data utilized in the research of this thesis are introduced in Chapter 4. The main results of the thesis are presented in Chapter 5. The results are divided into four parts: developing contextual information acquisition, mobile usage patterns and user behavior, contextual usage patterns and contextual user modeling. The results answer the research problem together and are also summarized at the end of the results chapter. Finally, Chapter 6 discusses the

implications of the results from academic, as well as, from mobile service providers' perspectives. Also, the limitations of the work and future research items are discussed.

2. Theoretical background

The theoretical background of the thesis is divided into three subsections: user behavior research, context research and mobile service usage research. The thesis draws from all the three research domains for answering the research problem. Previous human and user behavior research sets the theoretical background to examining and interpreting human behavioral patterns in general and to measuring this behavior with suitable metrics. Previous context research sets the background to understanding the term context in the mobile computing domain and discusses the approaches to utilizing contextual information in the domain. Finally, previous mobile service usage research sets the background to measuring and classifying mobile service usage and for relating such research to the business aspects of mobile service provisioning.

2.1 Human and user behavior

In the case of human beings, behavior is defined as *'the way a person acts or behaves'* (Merriam-Webster, 2015) or *'the actions or reactions of a person in response to external stimuli'* (Kilkki, 2012). Even based on just these two definitions, it is easy to understand that human behavior research is a very wide domain with numerous research topics spanning over many disciplines. Some of the disciplines are psychology, social neuroscience, cognitive science, sociology, economics and anthropology, to name a few. Interdisciplinary research fields related to human behavior and close to the topic area of this thesis are, for example, Human Computer Interaction (HCI) research and the already mentioned computational social science. HCI observes how humans interact with computers and designs technologies that allow humans to interact with computers in novel ways (Card et al., 1983). Computational social science is concerned with computational approaches to social sciences, that is, using computers to model, simulate and analyze human and social dynamics (Cioffi-Revilla, 2010).

User behavior research becomes a sub-domain of human behavior research, if we see user as *'a person who makes use of a thing'* (Kilkki, 2012). User behavior corresponds to the actions and reactions related to the thing (e.g., a mobile device or service) in response to external stimuli (induced by the thing or other external factors). Studying user behavior is often tied to business considerations related to the service or product the user is (or will be) using. Un-

Understanding user behavior helps, hypothetically, in developing and enhancing the service or product and to maximize revenue while minimizing the costs of the service provider or the product manufacturer (Reichl et al., 2015). Behavioral analytics is an application area of human and user behavior research in the data-rich domains of e-commerce, online-gaming, mobile and web-application development and fraud detection.

This thesis draws from the more general human and user behavior research to measure and understand mobile devices and mobile services related user behavior.

2.1.1 Behavioral patterns

It is a widely accepted hypothesis that patterns exist in human behavior. The existence of these patterns means that the behavior of humans exhibits some regularities rather than being completely irregular. The regularities can arise from the basic needs of human beings, such as sleeping and eating or they can be a result of some of the more complex cultural constructs such as the five-day working week. These patterns can be found on the population level, as well as on the individual level. Behavioral patterns related to *i)* human actions, *ii)* time usage, *iii)* social interactions and *iv)* mobility are particularly interesting from the mobile services usage perspective. Additionally, the population level patterns hide considerable *v)* diversity on the individual level patterns across different individuals.

Human actions are the driving force behind the dynamics of many social, technological and economic phenomena (Barabasi, 2005), and for this reason the identification and the modeling of patterns of human actions is highly important (Malmgren et al., 2009). In the literature, individual actions are often called (action) *events* and the dynamics in the event occurrence is measured in *inter-event times* (e.g., Barabasi, 2005; Malmgren, 2008). Inter-event time τ denotes the time between consecutive events. Traditionally, models of human dynamics have approximated the timing of human actions with a Poisson process, which assumes that τ is exponentially distributed (e.g., Haight, 1967). The assumption behind the Poissonian approach is that human actions are randomly distributed in time. More recent research based on more elaborate data collection capabilities such as Barabasi (2005) and Vazquez et al. (2006) argue that the occurrence of human actions is better approximated by heavy-tailed or Pareto distributions of the inter-event time. In particular, they propose a power-law distribution (a type of heavy-tail distribution) for modeling human actions. The probability density function of a power-law distribution for τ takes the form of $P(\tau) \sim \tau^{-\alpha}$, where the exponent α is empirically observed to take values close to 1 (Barabasi, 2005; Vazquez, 2006) in human activity. In heavy-tail distributions the tails of the distributions are not exponentially bound. In the case of the power-law this means in practice that short bursts of events are followed by long inactivity times. While small values of τ dominate the distribution, very high values are significantly more common than in the case of the Poisson process.

Power-law in describing human activity has gained increasing attention and empirical research claims that many activities follow this distribution. The activities include letter correspondence (Oliveira & Barabasi, 2005), e-mail correspondence (Barabasi, 2005), file downloads (Johansen & Sornette, 2000), broker trades (Vazquez et al., 2006), web browsing (Dezö et al. 2006), library usage (Vazquez et al., 2006) and telephone communications (Candia et al., 2007), just to name a few. The interest around power-law is partly due to its alleged prevalence also in many other types on natural and human phenomena, possibly demonstrating some universality of the distribution. For example, the intensities of earth quakes (Newman, 2005), the sizes of wildfires (Newman, 2005), the gamma ray intensities of solar flares (Newman, 2005), the degrees of metabolites in the metabolic network of the bacterium *Escherichia coli* (Huss & Holme, 2007), the occurrences of words in a book (Newman, 2005) and the intensities of wars (Small & Singer, 1982), again to name a few, are claimed to follow the power-law.

However, also more skeptical views on the prevalence of the power-law in human activity, and in other natural phenomena exist. Clauset et al. (2009) argue that many of the presumed power-law observations lack a proper statistical backing. Stumpf & Porter (2012) question the universality claims about power-law as well. They emphasize the quest for finding the mechanisms behind the observed distributions, whether power-law or not. In his widely recognized work Barabasi (2005) proposes (by utilizing e-mail data) a decision-based queuing process as the generative mechanism behind the bursty or power-law nature of human dynamics. The hypothesis behind this is that individuals execute tasks based on some perceived priority – high priority tasks are executed rapidly, while low priority tasks can wait for a long time before execution. However, Stouffer et al. (2005) argue that the results of Barabasi (2005) are an artefact of the experimental setup and thus not generalizable.

Malmgren et al. (2008) propose that the distribution of τ is a consequence of the circadian and weekly cycles of human activity and model this as a cascading non-homogenous Poisson process (utilizing e-mail data). In short, the process combines a primary non-homogenous Poisson process that accounts for the periodic (circadian and weekly) activity and a secondary process as a homogenous Poisson process that accounts for “the cascades of activity”. The cascades of activity refer to situations where humans presumably try to optimize their time usage or efforts by cascades (cf. bursts) of task execution. An example of this might be sending multiple e-mails while in front of the computer or doing all the shopping at once rather than returning shortly back for incremental purchases. Jo et al. (2012a) were able to separate the weekly and circadian patterns from human activity logs (telephone communication data) and thus demonstrated that part of the associated inter-event time distributions arise from these patterns. The remaining part of the distributions showed bursty heavy-tailed behavior, but the authors left the finding of the mechanisms behind this for future work. One possible mechanism behind a part of smartphone and other mobile device usage is the habitual checking of the dy-

namic content provided by the device (Oulasvirta et al., 2012). This checking habit might then spur users also to do other things on the device.

As already discussed, *time usage* is an integral part of human activity and human actions are often measured against time. The questions of how people allocate their time between different activities and when these activities take place are relevant in many domains. Nation-wide time-use studies, such as OSF (2011) are interested on the amount of time people spend doing various activities, such as paid work, childcare, volunteering and socializing. Patterns emerge and show that, for example, in the context of paid work the five-day, from Monday to Friday, 35-40 hour working week dominates in Finland (OSF, 2011). In studying mobile service usage, time usage patterns associated to the service usage are among the common results. The patterns are usually demonstrated to follow the circadian activity of humans, that is, the usage occurs mainly during daytime and peaks during lunch time and in the afternoon commuting time. Examples include mobile app use (e.g., Falaki et al., 2010; Böhmer et al., 2011) and mobile phone calls (Candia et al., 2008). Also other human related behavior from social media usage patterns (Golder et al., 2007) to blood pressure patterns (Neutel & Smith, 1997) follow, quite predictably, the human circadian rhythm (Czeisler et al., 1999).

Another set of human behavioral patterns interesting in the light of mobile service usage, as well as in many other domains, are the *human mobility* patterns. Traditionally, human mobility (a spatiotemporal phenomenon) has been modeled with the random walk (Pearson, 1905) and Lévy flight (Mandelbrot, 1982) models (Brockmann et al. 2007). However, the more sophisticated measurement methods, usually including CID (Cell ID) or GPS (Global Positioning System) traces of mobile phone users, have provided new insights on human mobility. Studying movements of 100,000 mobile phone users Gonzalez et al. (2008) state that individual humans follow relatively simple and reproducible mobility patterns. Behind this is the fact that people usually return to a few highly frequented locations, such as home or the workplace. Also, for example, Bayir et al. (2010) show that individual mobile phone users visit frequently and spend most of the time only in a few top places. The underlying regularity of individual human mobility introduces, in general, high predictability on the mobility and, furthermore, lack of variability in the predictability across the population (Song et al., 2010). However, as McInerney et al. (2013) point out, humans once in a while “break the habit” and deviate from their regular mobility patterns (e.g., a weekend trip or sick leave). These deviations are a lot harder to predict.

Patterns of *social interactions* are an inherent part of user behavior related to mobile device and service usage. Traditionally, and still in a dominant manner, mobile devices are used to communicate and keep in touch with one’s social circles. Furthermore, the rise of (mobile) social media services has put mobile devices into a central position for managing one’s social network. According to the work of Dunbar (1998) and Hill & Dunbar (2003), personal social networks consist of a series of layers with around 5, 15, 50 and 150 members. The inner layers are associated to stronger ties and higher emotional

closeness. Social dynamics in one's social network affects the activities of the individual, including mobile device usage. For example, the usage of mobile communication services depends on the interplay of the individual's need to communicate to others and the others' need to communicate to the individual. Salehan & Negahban (2013) show that a larger social network is related to increased communication and more intensive usage of mobile social networking applications. Eagle & Pentland (2006) highlight the fact that the social environment of a person varies according to time and place, but shows, however, regularities in a manner similar to human mobility.

Finally, a note on *diversity* in human behavior across individuals is in order. Even though population level patterns on human behavior can be successfully extracted and some of the individual level behaviors show considerable regularities, human behavior is subject to considerable population variability when compared with any other species (Norenzayan, 2011). Falaki et al. (2010b) observed magnitudes of differences in smartphone usage intensities between users. While the majority of people follow roughly similar diurnal patterns to each other, considerable individual-level variation has been observed, for example, in digital daily cycles (Aledavood et al., 2015). Gonzalez et al. (2008) highlighted the regularities in human mobility patterns on the individual level, but pointed out also that, for example, the travel distances between individuals varied considerably. And although in the work of Hill & Dunbar (2003) the average (outer layer) size of a social network is close to 150 members, the range in the study is from less than 20 to nearly 400 members.

2.1.2 Units of measurement

While the previous section focused on patterns in human and user behavior, this section concentrates on the basis and units of measurement related to measuring human and user behavior and patterns in it. As mentioned in the previous section, human actions are typically measured as *events*. In studies such as Barabasi (2005) an event occurs at a point in time and thus does not have any length. The type of an event can be specified as an email event or a telephone call event, for example. In the literature the analysis on the actions depicted by events is mainly focused on *inter-event times*, that is, the time between consecutive events (e.g., Malmgren et al., 2008). This is a simplified view on human actions, because in real life an action contains also more than a point in time of occurrence and the action type.

Allen (1983) describes a system for reasoning about *temporal intervals*. Temporal intervals are present in a wide range of circumstances and the problems in handling them arise in a multitude of disciplines. Allen's system is therefore intended to be general. Some types of human actions can be considered as temporal intervals. For example, a telephone call can have a starting time and an ending time that differ from each other. While the analysis of events is mainly restricted to inter-event time and sequential relations between events, temporal intervals provide possibilities for a richer analysis of the relations between intervals. Specifically, the system of Allen (1983) introduces thirteen basic relations between two finite time intervals. The relations

are *distinct* (a pair of intervals are described by one and only one relation), *exhaustive* (any pair of intervals can be described by one of the relations) and *qualitative* (no numeric time spans are required). As the last condition indicates, the basic approach does not explicitly consider how long the inter-interval times or the intervals themselves are. However, the basic approach can be extended to include these (Publication 5).

A *session* is a unit of user behavior measurement arising from Web usage research (e.g., Arlitt, 2000; Meiss et al., 2009). According to the general definition, session is '*a period of time that is used to do a particular activity*' (Merriam-Webster, 2015). Thus it is closely related to the temporal interval. However, in the Web usage research, as well as, in mobile device and service usage research (e.g., Falaki et al., 2010a; Hintze et al., 2014a) the definition of the particular activity dictates how the session is constructed. For example, a Web session in Arlitt (2000) is a sequence of page requests close enough together. The closeness is determined in inter-request time. If the inter-request time between two requests exceeds some threshold, the requests belong to different Web sessions. A page request is an event-like action, but by combining them an approximation of a period of time describing some activity, e.g., Web browsing, can be constructed. In a similar fashion, a session can be constructed of time intervals or smaller sessions close to each other. For example, Hintze et al., (2014a) construct smartphone usage sessions from a set of individual application usage sessions. The logic behind this being that an activity of interacting with a smartphone is a set of consecutive application usages. Session, as described here, is a richer unit of measurement compared with events or temporal intervals in a sense that it has duration, content and an inner structure to be analyzed in addition to type, inter-session times and relations between sessions.

Human mobility is measured as spatiotemporal correlations, that is, a location in time. Approaches utilized for measuring human mobility range from the activity-travel diaries (Kwan, 2000) to tracking the movements of dollar bills (Brockmann et al. 2007). Recently, however, tracking the whereabouts of mobile phones has become the most viable option from measuring human mobility. People carry the phones with them and the phones are trackable by different means. Mobile phone is in principle connected to a mobile base-station at any given time and the location of the base-station is known at least by the mobile operator. Gonzalez et al. (2008) utilized a mobile operator's CDR (Call Detail Record) to track the mobility of mobile phone users. Technically, the id (CID) of a base-station is recorded into CDR whenever the user has an incoming or outgoing call or a text message. A base station can cover a rather large area and the temporal granularity of the calls and messages varies. Thus, the accuracy of this approach is limited. With dedicated data logging software (e.g., Arahony, 2012) installed into a capable enough phone (e.g., a smartphone) it is possible to monitor the whereabouts of the phone practically continuously. Depending on the capabilities of the device this approach permits the monitoring of the device's GPS location (latitude, longitude) and surrounding WiFi and Bluetooth beacons in addition to CID. For example, Liu et

al. (2012) and Eagle & Pentland (2006) discuss and implement WiFi-based and Bluetooth-based location tracking of smartphones, respectively. The problem with these approaches is the varying spatial distribution of the beacons. The GPS-based approach (e.g., Rhee et al., 2007) is accurate outdoors, but has limitations indoors. Furthermore, continuous GPS usage can drain the battery of the device.

Social interaction is any relationship between two or more individuals and social interactions are formalized and measured usually by utilizing the construct of a social network. A social network is a set of social actors (e.g., humans) and a set of dyadic ties between the actors (Wasserman, 1994). Social network analysis studies these structures to identify, for example, local and global patterns. The measurement and analysis of the real world social networks has seen approaches from the tracking of exchanged Christmas cards (Hill & Dunbar, 2003) to mobile phone data, including call and messaging logs and the tracking of device co-location (Eagle et al. 2009). Also, data from social network services, such as Facebook and Twitter provide unprecedented possibilities for social network analysis. However, different sources of social network data might lead into different social network constructs even for the same actors.

2.2 Context

Context is a diversely used term and concept. I will briefly consider it and its background on the general level, but then move towards the more focused definitions and research related to this thesis. The word context has its roots in the Latin word *contextus*: *‘joining together’* or *‘to weave together’* (con- *‘together’* + *texere ‘to weave’*) (Online Etymology Dictionary, 2015). In the modern day language context is defined as *‘the circumstances that form the setting for an event, statement, or idea, and in terms of which it can be fully understood’* (Oxford Dictionaries, 2015). Furthermore, context has a more specified meaning in linguistics, being *‘the parts of something written or spoken that immediately precede and follow a word or passage and clarify its meaning’* (Oxford Dictionaries, 2015), and context is a studied concept in traditional (e.g., Karttunen, 1974) and computational (e.g., Miller, 1995) linguistic research.

Another field relatively rich in context research is computer science. Ubiquitous (or pervasive) computing is a domain of computer science concerned in computing that is made to appear anytime and everywhere (Weiser, 1991). Context-awareness (Schilit, 1994) originates from ubiquitous computing and is a concept related to the computer being aware of its environment or surroundings. In the case of mobile computing, the mobile computer such as a smartphone can be utilized as proxy to also approximate the user’s context (e.g., Eagle & Pentland, 2006). This thesis is mainly concerned with the context of a mobile device end user. Thus, the remaining three subsections focus on context definitions, context categorizations and context utilization ap-

proaches appearing in the domains of ubiquitous computing and human computer interaction.

2.2.1 Defining context

Dourish (2004) portrays context as a rather difficult concept to define: *‘Context is a slippery notion. Perhaps appropriately, it is a concept that keeps to the periphery, and slips away when one attempts to define it.’* However, many attempts to define context exist in the literature. Dey (2001) describes the early context definitions in the ubiquitous computing domain either as enumerations of examples or choosing synonyms for context. Enumeration of examples includes referring to context as location, the identities of nearby people and objects and changes to these objects (Schilit & Theimer, 1994). Synonyms of context include, among others, the environment (Brown, 1997; Ward et al., 1997) and the situation (Rodden et al., 1998). Dey (2001) argues that these types of definitions are not operational enough. Examples enumerate only so far, and thus the definitions can be overly restrictive. Synonyms, on the other hand, do not provide any additional information besides describing the same concept with a different word. Schilit et al. (1994) and Pascoe (1998) provide somewhat more applicable definitions of context. Schilit et al. (1994) state that context essentially describes *‘where you are, who you are with, and what resources are nearby’* and Pascoe (1998) defines context as *‘the subset of physical and conceptual states of interest to a particular entity’*. Dey (2001) himself provides one of the most widely cited context definitions in the ubiquitous computing and HCI domains: *‘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.’*

The above described context definitions take a positivist view on context and handle it as a representational problem (Dourish, 2004). In other words, context is seen as something that is i) *a form of information* that can be known, ii) *delineable*, iii) *stable* and iv) *separated from activity*, meaning that an activity happens in context. Dourish (2004) proposes an alternative, phenomenological, view on context and frames context as an interactional problem. In this view i) rather than being information, *context is a relational property*, ii) rather than being delineated and defined in advance, the *scope of contextual features is defined dynamically*, iii) rather than being stable, *context is an occasioned property* and iv) rather than being separated, *context arises from activity*. The view on context proposed by Dourish (2004) originates from the qualitative social sciences research tradition as opposed to the quantitative physical science tradition behind the representational view. Current ubiquitous computing and HCI related context-awareness research relies still on the representational view of context because the interactional view is harder to realize in practical applications. Also the remaining two subsections handle context mainly as a representational problem.

Finally, a note on the terms *context* and *information*: the definition of *context* in Dey (2001) includes *information*, that is, *context is information*. How-

ever, other literature also uses the term *context(ual) information*. In this thesis *context* and *contextual information* are used interchangeably.

2.2.2 Categorizing context

Rather than categorizing context itself, Van Bunningen et al. (2005) classify context categorization schemes into two classes: *conceptual* and *operational*. Conceptual categorizations are based on the meaning and conceptual relationships between context. Operational categorizations, on the other hand, are based on how context is acquired, modeled and dealt with.

In the existing literature, conceptual categorizations schemes are somewhat more common. Dey et al. (2001) introduce four categories of context: *identity*, *location*, *status* (or *activity*) and *time*. Identity refers to a unique identifier assigned to an entity. Location refers not only to the coordinates of an entity, but it may also indicate the semantic meaning of the particular place, elevation or orientation of the entity, for example. Status refers to the characteristics of an entity. Time is used in conjunction with other contextual information to provide a timestamp or indicate a time period. Schmidt et al. (1999) divide context into two high level categories: *Human factors* and *Physical environment*. The high level categories are then divided further. Human factors are composed of *User*, *Social environment* and *Task*, whereas Physical environment is composed of *Conditions*, *Infrastructure* and *Location*. The lower level categories can be further divided. *Conditions*, for instance, can include light and one element of light can be the wavelength. In the context categorization of Schmidt et al. (1999), time adds a historical dimension as context history is regarded as an important factor in approximating the current context. Other more recent conceptual categorizations are provided, for example, by Xu et al. (2009) categorizing context into *Personal context* (profile, emotion, mobility, social state, and intention or task) and *Environmental context* (where, with whom, what resource, temporal and physical condition). Hong et al. (2007) categorize context into *Computing context* meaning the hardware configurations used, *User context* referring to all the human factors and *Physical context* indicating other information provided by the real-world environment.

An example of an operational context categorization scheme is provided by Henricksen & Indulska (2004). They categorize context based on the principal sources of contextual information for describing the context of an end user of a context-aware application as *Sensed*, *Static*, *Profiled* and *Derived*. Sensed context refers to information acquired by physical and logical sensors and is usually frequently changing. Static context refers to information which is user-provided and persistent. Profiled context is also user-provided information, but less persistent than static context. Derived context is information that is derived from the information of the other context categories. Perera et al. (2014) categorize the operational perspective of context into *Primary* and *Secondary* context. Primary context means information retrieved without any sensor data fusion operations or derivation (e.g., pure GPS coordinates), whereas Secondary context is any information that can be computed by using the Primary context. Razzaque et al. (2007) call their operational categoriza-

tion scheme as *Measurement categorization*. It includes *Continuous* (value changing continuously), *Enumerative* (a set of discrete values), *State* (a binary value) and *Descriptive* (e.g., as entity 1 *near* entity 2) context.

2.2.3 Utilizing context

Perera et al. (2014), present a context lifecycle model for contextual data in context-aware systems. The context lifecycle model separates four distinct phases that need to be considered when utilizing context in context-aware systems. The phases are: 1) *context acquisition*, 2) *context modeling*, 3) *context reasoning* and 4) *context dissemination*.

The context acquisition phase covers the techniques for acquiring raw contextual data. These include considerations on different acquisition processes (for example, the operational approach by Henricksen & Indulska (2004)), data sources (for example, directly from the device or through some mediator service), different types of sensors to be used (physical, virtual or logical), and data collection frequencies, meaning how often the data should be collected.

Context modeling considers the techniques for representing context. In a context modeling process contextual information is defined as attributes, characteristics, relationships with other contextual information, quality-of-context attributes and queries for context requests. Incoming contextual information is then accumulated in the defined format and made available for further use when required. Some of the most used context modeling techniques are key-value modeling, markup scheme modeling (e.g., with ContextML by Knappmeyer et al., 2010), graphical modeling (e.g., with Unified Modeling Language (UML)), object based modeling, logic based modeling and ontology based modeling (e.g., with semantic technologies (Allemang & Hendler, 2011)).

Context reasoning refers to techniques for inferring new, higher level, knowledge from the available contextual information. Perera et al. (2014) classify the reasoning techniques into six categories: supervised learning, unsupervised learning, rules, fuzzy logic, ontological reasoning, and probabilistic reasoning. Finally, context dissemination refers to techniques for delivering the contextual information. Some of the techniques include query, that is, sending the information upon a formulated request, and subscription, that is, sending the information upon agreed rules (for example, periodically or after a certain event).

2.3 Mobile service usage

Covering the general characteristics of (consumer) services at length is out of the scope of this thesis. However, a very brief background glance is in order to understand mobile services better. Grönroos (1992) identifies four basic characteristics of traditional consumer services: *intangibility* (non-material), *inseparability* (of production and consumption), *heterogeneity* (difficult to standardize) and *perishability* (no transferring or reselling). Electronic services (e.g., van de Kar, 2004) show, however, some distinguishing characteris-

tics compared with the more traditional services. Based on Hofacker et al. (2007), e-services themselves are intangible, but need tangible media; service and consumption of e-services can be separated; e-services are homogenous (but allow personalization) and e-services can be copied, shared and their use does not equal consumption. Mobile services are a specific subset of electronic services (Bouwman et al., 2008). In the case of mobile services, mobility on the part of the user, the devices and applications is assumed, or at least prepared for.

From the mobile services perspective, this thesis focuses on measuring, examining and analyzing user behavior related to mobile service usage (see, e.g., Van Der Heijden & Junglas (2006)). This section aims at providing the theoretical background on what to measure and how to measure it in terms of mobile service usage. Additionally, a brief review of the business models behind mobile services is presented.

2.3.1 Measuring and classifying mobile services

Kivi (2009) provides a classification of the methods and measurement points for measuring mobile service usage. The measurement points in this classification are: *end-users*, *usage monitoring systems*, *network nodes* and *servers*. Collecting data on mobile user behavior and service usage directly from end-users includes methods such as surveys and usage diaries. Surveys are conducted on samples of real end-users once or periodically for time-series data. Online or paper diaries provide more continuous data which is possibly more accurate and granular. Usage monitoring includes both user monitoring and device monitoring. Device monitoring is a commonly used method in PC, Web and TV usage research. Contemporary mobile devices provide possibilities for mobile device monitoring (see, e.g., Karikoski (2012)). Methods for collecting data from network nodes include the utilization of accounting systems and network traffic measurements. Examples of accounting systems are the CDRs of mobile operators and the AAA (Authentication, Authorization, and Accounting) systems of IP (Internet Protocol) access providers. Network traffic (e.g., TCP/IP traffic) measurements can be conducted at various intermediate network nodes between the user devices and servers (see, e.g., Kivi (2006)). Finally, service usage and related user behavior can be studied by collecting server log files. Servers behind Web services, search engines and proxies are a convergence point of the usage of the particular services. Paraphrasing Arahony et al. (2011), the methods related to end-users and usage monitoring systems as measurement points constitute a *bottom-up* data collection approach, whereas, the network node and server related methods constitute a *top-down* approach. The bottom-up approaches provide granular data on user level, whereas, the top-down approaches provide access to big volumes of users and data, compromising, however, on the granularity of the user-level data.

Smura et al. (2009) built a framework for analyzing the usage of mobile services on top of the methods and measurement point classification of Kivi (2009). Via the measurement points described by Kivi (2009), one can reach four distinct technical components of a mobile service system: *device*, *applica-*

tion, network and *content*. The measurement points show varying strengths in covering the technical components. For example, end-user methods and server side measurements show the biggest limitations regarding the network(s) used, whereas, network node measurements have limited visibility to the applications used. Device monitoring, on the other hand, is limited to the devices monitored. In addition, the framework presents further classifications under each technical component. For example, the classification of devices includes mobile phone, smartphone, tablet, laptop, etc. Application classification includes calling, messaging, browsing, multimedia, games, etc. Network classification includes mobile networks, WLAN, offline, etc. Finally, content classification includes mobile calls, mobile messaging, Internet calls, Internet messaging, Web sites, etc. For the complete classifications refer to the actual article of Smura et al. (2009).

Also other authors have provided classifications of mobile services, but without an explicit link to the underlying technical components or usage measurement methods. For example, Bouwman et al. (2008) classify mobile services into *information services* (e.g., news and weather), *communication and messaging services*, *entertainment services* (e.g., games, music, TV), *transaction services* (e.g., mobile payments and banking) and *business services* (e.g., mobile supply-chain management). Other mobile service classifications for different purposes using different criteria include Pura & Heinonen (2007), Holma et al. (2007) and Velez & Correia (2002).

2.3.2 Business models for mobile services

As the research problem of this thesis is discussed also from the mobile service provider point of view, a brief theoretical background on the fundamentals of providing (context-aware) mobile services is covered. Reflecting the thesis results through theoretical business models is one approach to position the results based on relevant issues in mobile service provisioning.

Chesbrough and Rosenbloom (2002) define a business model as the description of an organization or network of organizations involved in creating and capturing value from technological innovation. Bouwman et al. (2008) propose a mobile services specific business model framework. It is based on solving central design issues in *Service* (design issues: targeting; value-creating elements; branding; customer retention), *Technology* (design issues: security; quality of service; system integration; accessibility for customers; management of user profiles), *Organizational* (design issues: partner selection; network openness; governance) and *Financial* (design issues: pricing; division of investments, costs and revenues; valuing contributions and benefits) domains.

de Reuver & Haaker (2009) use the model of Bouwman et al. (2008) as a basis and identify design issues the most relevant for context-aware mobile services, the definition of context-aware service being: *'it operates while using context-related information other than explicit input related to the logic of the application'* (Abowd et al., 1998). The identified context-aware service specific design issues divided by the domain are: *Service* (targeting; value-creating elements [personalization, context-awareness]; generation of trust),

Technology (security; system integration [intelligence for personalization]; management of user profiles), *Organizational* (role division; network openness; governance) and *Financial* (pricing; division of costs and revenues; multiple revenue models).

3. Related empirical research

Empirical research related to mobile service usage and mobile end-user context utilizing data collected from mobile devices have adopted roughly two approaches. As discussed in section 2.3.1, an approach based on device monitoring can be classified as a bottom-up approach. In practice this means that dedicated monitoring software is installed into the mobile devices of the users. The software monitors actions on the device and collects, stores and sends to (researchers') servers the related data. In a top-down approach, the data is collected from aggregation points (network nodes) in the mobile network, rather than directly from individual devices. As mentioned in section 2.3.1, the mobile operator CDRs are cumulating points for this data. Also network traffic at a particular network node can be monitored. These are called Network Traffic (NT) measurements (Kivi, 2009).

The bottom-up approach provides a more granular view on the usage of an individual device. However, the user sample size is usually rather small. The top-down approach, on the other hand, provides a network-wide coverage in the best case. This can mean user sample sizes that are counted in millions. The top-down approaches usually require collaboration with mobile operators, for example, by requesting a CDR dataset or a measurement possibility at a network node. Observation periods are normally counted in months for CDR datasets and in a couple of weeks for network traffic measurements. In the device monitoring the observation period ranges from weeks to more than a year.

The related empirical research reviewed in this section focuses on data-driven mobile service and mobile end-user context related research. The core approach of this thesis is bottom-up (the handset-based measurements²). Thus slightly more weight is put into reviewing this type of research.

3.1 Bottom-up research

The bottom-up type of research for studying mobile service usage and the contextual aspects of mobile user behavior has a relatively short history. The devices such as smartphones and tablets, which enable the installation of the monitoring software, have been on the market for a rather short time. Howev-

² More information on handset-based measurements and related data can be found from the methods and data chapter of this thesis (Chapter 4).

er, activity in this area has increased notably in the recent years. One reason for this is the increased capabilities of the devices themselves, tools for developing suitable software and possibilities for distributing the software (e.g., Google Play³ and Apple's App Store⁴). Another reason is the increased interest from the social sciences in using device monitoring, for example, in psychology research (Miller, 2012). The literature review in this section focuses, however, on the most related research to this thesis. This includes mobile service and application usage studies, studies considering the contextual aspects of the users, and the combinations of the two. Furthermore, the research reviewed is purposefully distributed rather evenly along whole the timeline of the research history. **Table 2** summarizes the literature reviewed in this section.

Table 2 Related empirical research from the bottom-up perspective

Project / Software	Research topic	Services	Context	Sample	Observation period	Citation
Reality mining	Sensing complex social systems from mobile phones	All available applications	Semantic place, Social	100 users	Nine months	Eagle & Pentland (2006)
Nokia360	Contextual patterns in mobile service usage	All available applications	Semantic place	324 users	~ 12 months	Verkasalo (2009a)
Custom software	Non-voice mobile phone usage	All available applications (no voice calls)	Location (area)	14 users	Four months	Rahmati & Zhong (2009)
SystemSens	Smartphone usage	All available applications	Battery level	255 users	Six months	Falaki et al. (2010b)
LiveLab	Measuring smartphone users in the field	All available applications	Location (area)	25 users	One year	Sephard et al. (2010)
Appazaar	Mobile application usage	All available applications	Time of day, Location	4100 users	~ Five months	Böhmer et al. (2011)
Lausanne data collection campaign	Analysis of mobile applications and context	All available applications	Location, semantic place, time of day, Social	77 users	Nine months	Do et al. (2011)
OtaSizzle	Spatiotemporal correlations of handset-based service usages	Web, Calling, SMS, email, other apps	Time of day, Semantic place	124 users	16 months	Jo et al. (2012b)
Nokia360	Energy efficiency of mobile handsets: Measuring user attitudes and behavior	Messaging, Voice calls, Business & Productivity, Browsing, Multimedia	Battery level	358 users	Four months + three months	Heikkinen et al. (2012)
Lausanne data collection campaign	Semantic place prediction	-	Semantic place + multiple sensed context elements	112 users	18 months	Zhu et al. (2013)
Device Analyzer	Mobile device usage characteristics	All available applications (names hashed - separable, not identifiable)	Semantic place, form factor	1585 users	Four months	Hintze et al. (2014)
Custom software	Physical activity recognition	-	Location, activity	19 users	20 hours	Blachon et al. (2015)
MobiDAC	Mobility and utilization analysis in ubiquitous systems	All available applications	Location, battery level	22 users	Four months	Piatkowski et al. (2015)

The work of Eagle & Pentland (2006) is one of the earliest and most cited research articles from the bottom-up perspective. It was part of the Reality Mining project of the Media Lab of Massachusetts Institute of Technology (MIT)

³ Google Play: <https://play.google.com/store?hl=en>

⁴ App Store: www.apple.com/appstore

and among the pioneering work in the area. Eagle & Pentland (2006) utilized device monitoring software developed by Raento et al. (2005) to collect device (Nokia 6600 smartphone) usage and sensor data from 100 users (the students and staff of MIT) over a nine-month period. The results of the work include the recognition of the users' semantic places such as home, work and other place based on cell tower information and Bluetooth. The work also shows that among the users voice calls were the preferred mode of communication and that camera application was the most used other-than-communication application - with the highest usage at work. Eagle & Pentland (2006) infer also social networks or "social circles" among their user population, based on communication and movement patterns. Overall, the work has been highly influential to the subsequent research in the area.

Location as a type of contextual information is present, one way or another, in almost all of the considered work. Rahmati & Zhong (2009) and Shepard et al. (2011) refer to location as different distinct areas (not specified further) the users are located and use their devices. Rahmati & Zhong (2009) examine, for example, how the overall usage of the devices differs in the top ten (the most time spent) location areas (based on WiFi access points) of the users. Shepard et al. (2011) present a LiveLab data collection platform and examine, for example, how Web access differs in the top ten location areas (based on WiFi) of the users. Both studies identify relationships between location and mobile device and service usage. Böhmer et al. (2011) limit their location analysis to the USA vs. Europe and on-airport vs. off-airport. For example, Europeans used the browser more and Americans used sports and health applications more. On-airport was associated more to browser usage than off-airport. Additionally, all three studies observed that communication services dominate the usage.

A step towards the more derived type of contextual information is the semantic place. A semantic place refers to a location or place that has some particular meaning for the user. Zhu et al. (2013) is based on the winner solution of the semantic place prediction task introduced in the Mobile Data Challenge (Laurila et al., 2013). Zhu et al. (2013) utilize advanced feature engineering and machine learning techniques to derive semantic place information from all the available device monitored data. The underlying sensed contextual data includes cell tower, WiFi, Bluetooth and acceleration data and data on the application usage history, to name a few. Semantic places detected include home, the home of a friend, workplace/school, the workplace/school of a friend, restaurant or bar, shopping center and vacation spot. Workplace/school and home were clearly the easiest to detect. Other, less elaborate semantic place detection approaches have been combined with an examination of mobile service usage in the different semantic places. Verkasalo (2009a) is one of the first and concludes that multimedia and Internet services are used more actively "on-the-move", while the more traditional voice call and SMS services are more evenly distributed among home, workplace and "on-the-move". Do et al. (2011) observe that voice calls are associated with moving (bus stops, parks, shopping centers), while SMS is associated with stationary indoor places such as home and work. These two services also dominate the overall usage, fol-

lowed by Web and multimedia usage. Jo et al. (2012b) and Hintze et al. (2014b) use similar approaches to study smartphone usage in different semantic places. Jo et al. (2012b) report, for example, that Web usage is the most intensive (usage per time unit) in “on-the-move” type of places. Hintze et al. (2014b) report that the duration of usage sessions is the longest at home and the shortest at the workplace. Hintze et al. (2014b) examine also the effect of the form factor (smartphone vs. tablet) to device usage. They report that while the number of tablet usage sessions (per time unit) is lower than in the case of smartphones, the tablet sessions are generally longer. This leads to relatively similar overall usage times between the devices. However, tablet usage is mostly associated to the home context.

A few of the bottom-up studies also consider the social context of the users. Do et al. (2011) examine it as proximity to other users based on surrounding Bluetooth devices. They observe that the usage of communication services, such as voice calls, SMS and email increases when the number of surrounding Bluetooth devices increases. Studies such as Falaki et al. (2010b), Heikkinen et al. (2012) and Piatkowski et al. (2015) consider the battery level as one aspect affecting mobile device usage, and vice versa. However, for example Heikkinen et al. (2012) conclude that no significant differences are observed on usage patterns at different battery levels. Blachon et al. (2015) utilize device monitoring data for activity recognition. In particular they utilize location, acceleration and audio (from the microphone) data. The activities under examination are sitting, walking, standing, lying, in stairs, stationary, running, unstable and jump. While the study did not correlate mobile service usage to the activities, this is certainly one avenue for future research.

Additionally, all of the reviewed bottom-up research utilizes time as one important contextual factor. First of all, all data points are usually time-stamped. Some of the work utilizes temporal patterns in detecting semantic places (Eagle & Pentland, 2006; Verkasalo, 2009a; Do et al., 2011, Jo et al., 2012b; Zhu et al., 2013; Hintze et al., 2014b). Finally, some of the work explicitly examines the effect of time (time of day, day of week, etc.) to the usage of mobile services (Böhmer et al., 2011; Do et al., 2011; Jo et al., 2012b). For example, Böhmer et al. (2011) observe that gaming reaches its peak usage during late evening and overall usage peaks during early evening.

Putting context related issues aside for a moment, some of the bottom-up research also considers the more general aspects of measuring mobile service usage. Falaki et al. (2010b) introduce application sessions and interaction sessions. Application sessions refer to distinct time periods of using a certain mobile application. Interaction sessions refer to distinct time periods of device interaction. This means that an interaction session can include multiple application sessions. Falaki et al. (2010b) define an interaction session as the time the device’s screen is on. Rahmati & Zhong (2009) use this same definition, while Böhmer et al. (2011) and Hintze et al. (2014a, b) define interaction or usage session as an “application chain” where consecutive application sessions are time-wise close enough together. The usage results are then consequently reported, for example, in session lengths and sessions per time unit. Also, di-

versity across users in device and service usage is a commonly reported result in most of the studies.

3.2 Top-down research

In principle the technological enablers for the top-down type of research in the area of mobile service usage have been in place longer than for the bottom-up type of research. For example, mobile operators have collected CDRs for the purposes of charging and billing their customers as long as the related services have been offered. However, the operators have been reluctant to offer the data for research (or any other external) purposes mainly because of customer privacy issues. Compared with the bottom-up approaches, the top-down approaches offer fewer possibilities for studying mobile services and especially the related contextual aspects. The released CDRs for research purposes are basically logs of service usage, usually limited to traditional voice calls and SMS messages. In addition, every time a call or a message is sent or received, the CID of the mobile network cell tower the phone is connected to is recorded. This means that the available location data is approximate and discrete (available only for the times of calling or messaging activity) as opposed to the practically continuous location data available through the bottom-up approaches. The records include also (usually anonymized) phone numbers of the users. Linking the communication activities between users has provided new possibilities for social network analysis.

Network traffic measurements are a way to study the usage of network services on the whole network level. Utilizing device identification (see, e.g., Scientiamobile, 2015) it is possible to pinpoint traffic generated only by mobile devices. Network traffic measurements, however, do not capture any offline usage (which is available through the bottom-up approaches) and is very limited regarding contextual information. The literature review in this section focuses on the relatively limited set of top-down type of research which considers mobile services and (with a few exceptions) relates them to some contextual aspects. The work reviewed does not necessarily focus explicitly on these contextual aspects, but they are reviewed here as examples of the possibilities provided by the top-down approach. **Table 3** summarizes the literature reviewed in this section.

Kivi (2007) and Smura et al. (2011) utilize network traffic measurements to examine the usage of a limited set of mobile data services in Finland. Kivi (2007) concludes that Web browser is the dominant source of data traffic and local content (e.g., news) dominate the Web browsing. Additionally, the diurnal distribution of mobile browsing traffic is relatively uniform during weekday daytimes. Smura et al. (2011) complement the results of Kivi (2007) with a comparison of handset-generated traffic to laptop-generated traffic. They report that on handsets both Web browsing and email dominate over other traffic when compared with laptops. On laptops, this other traffic is largely peer-to-peer traffic, which is practically non-existent on handsets. The two studies did not consider any additional contextual information. An example of a net-

work traffic measurement study also considering contextual information is Shafiq et al. (2014). The contextual information is mobile network performance (derived from multiple features extracted from the network) and Shafiq et al. (2014) examine how it impacts the mobile video user engagement. The results include modeling approaches for predicting whether a user completely downloads or abandons a video.

Gonzalez et al. (2008), de Montjoye et al. (2013) and Iqbal et al. (2014) study primarily human mobility patterns. They, however, utilize CDRs for the purpose and as a by-product produce results related, for example, to the bounds of location data resolution when utilizing CDRs. For example, de Montjoye et al. (2013) quantify voice call frequencies and durations and link the density of network cells to the population in the area. The former provides a view on the temporal resolution of CDR data and the latter on spatial resolution. Iqbal et al. (2014) show the frequencies of voice calls on per user level, providing a view on the user diversity. These are all important aspects in Quality-of-Context (QoC) (e.g., Buchholz et al., 2003) assessments if CDRs are to be used for such purpose. Furthermore, the mobility patterns themselves can produce insights on mobile service usage.

CDR datasets are suitable for studying social interactions between users. As the datasets often include all users of the mobile operator, the underlying social networks can be relatively extensive. Szabo & Barabasi (2006) observed that the underlying social network of a user (identified by SMSs and voice calls) affects the usage of other communication services (email and instant messaging). For example, email is used rather uniformly across the whole network while instant messaging is more strongly community-based. Karsai et al. (2012) identified that SMS links in the social network are balanced (both parties active), whereas voice call links are strongly unbalanced. Calabrese et al. (2011) detected the users' home and workplace from the CDR logs, based on temporal voice call patterns under different mobile network cells. They observed that as the distance between two users' homes increase, the probability of face-to-face meetings decrease. However, the probability of voice calls between the users stayed relatively constant regardless of the distance. Furthermore, the users about to co-locate (meet face-to-face) increase the frequency of their voice call communication before the meeting and this increased frequency continues a while after the meeting. Calabrese et al. (2011), hypothesize that this is at least partly associated to coordinating the meeting and resolving possible follow-up matters. Finally, they conclude that people who more frequently call to each other also more frequently meet face-to-face.

As a somewhat different type of an example, Soto et al. (2011) utilize CDRs to infer Socioeconomic Levels (SEL) of the users. This is based on behavioral features extracted from the CDRs and includes calling, messaging, mobility and social interaction patterns of the users. It also involves finding the users' residential areas (homes) utilizing the CID logs and temporal calling patterns. The resulting predictive models achieved 80 % accuracy in predicting SEL.

Table 3 Related empirical research from the top-down perspective

Dataset source	Research topic	Services	Context	Sample	Observation period	Citation
Mobile operator (CDR)	Network effects in service usage	Voice calls, SMS, Email, IM	Social	Six million users	14 months	Szabo & Barabasi (2006)
Mobile operator (NT)	Diffusion and usage of mobile browsing	Mobile browsing	-	Four million	Two weeks	Kivi (2007)
Mobile operator (CDR)	Understanding human mobility patterns	Voice calls, SMS	Location	100000 users	Six months	Gonzalez et al. (2008)
Mobile operator (CDR)	Prediction of socioeconomic levels using cell phone Records	Voice calls, SMS	Location, Semantic place, Social, Socioeconomic level	500000 users	Six months	Soto et al. (2011)
Mobile operator (NT, CDR)	Usage of networks, devices, applications and content	Messaging, browsing, infotainment	-	4-6 million users	Two weeks	Smura et al. (2011)
Mobile operator (CDR)	Interplay between telecommunications and face-to-face interactions: a study using mobile phone data	Voice calls	Semantic place, Social (co-location)	One million users	12 months	Calabrese et al. (2011)
Mobile operator (CDR)	Dynamics in egocentric communication networks	Voice calls, SMS	Social	6 million users	Six months	Karsai et al. (2012)
Mobile operator (CDR)	Privacy bounds of human mobility	Voice calls	Location	1.5 million users	15 months	de Montjoye et al. (2013)
Mobile operator (CDR)	Development of origin–destination matrices using mobile phone call data	Voice calls	Location (origin, destination)	Seven million users	One month	Iqbal et al. (2014)
Mobile operator (NT)	Impact of network dynamics on mobile video user engagement	Mobile video	Network performance	500000 users	One month	Shafiq et al. (2014)

3.3 Context mapping

In this section, I map the related empirical research into an end-user context classification framework introduced in Publication 1. The framework views context from both conceptual and operational perspectives (see, e.g., section 2.2.2 of this thesis). The framework helps in positioning the related research in terms of contextual elements examined and the approaches used in acquiring the contextual data or information. The mapping considers all of the reviewed empirical research which utilizes information that can be used to characterize the situation of an end-user, that is, end-user context. The purpose of this mapping is to show, on one hand, the diversity of the related research and, on one hand, the linkages between them in terms of end-user context. Error! Reference source not found. shows the related research positioned on the framework.

Overall, the mapping shows that the related research concentrates mainly on location related context. This is not a surprise in the light that mobile devices are well equipped for location tracking. Furthermore, location has been traditionally considered the most important context in context-aware mobile computing. Social context related research is also relatively active, including social networks and physical proximity. Again, social situations are hypothesized to be one of the key drivers of human behavior.

Conceptual perspective

Operational perspective		Personal Context			Environmental Context			Time
		User	Social Environment	Activity/Task	Conditions	Infrastructure	Location	
Manually Provided Context	User identifier All of the references	Contact list Zhu et al. (2013)	Calendar entries Zhu et al. (2013)	Semantic place Do et al. (2011)				
	Sensed Context	Surrounding devices, Communication links Eagle & Pentland (2006) Do et al. (2011) Szabo & Barabasi (2006) Soto et al. (2011) Karsai et al. (2012)	Service/application usage Zhu et al. (2013) Soto et al. (2011)	Acceleration Zhu et al. (2013) Blachon et al. (2015)	Battery level, Form factor Falaki et al. (2010) Heikkinen et al. (2012) Hintze et al. (2014) Piatkowski et al. (2015)	GPS, Cell ID, WiFi, Bluetooth Eagle & Pentland (2006), Verkasalo (2008) Rahmat & Zhong (2009), Sephard et al. (2010) Böhmer et al. (2011), Do et al. (2011) Jo et al. (2012), Zhu et al. (2013) Hintze et al. (2014), Blachon et al. (2015) Piatkowski et al. (2015), Gonzalez et al. (2008) Soto et al. (2011), Calabrese et al. (2011) de Montjoye et al. (2013), Iqbal et al. (2014)		
Derived Context	Socioeconomic level Soto et al. (2011)	Social network, Surrounding people, Co-location Eagle & Pentland (2006) Do et al. (2011) Szabo & Barabasi (2006) Soto et al. (2011) Calabrese et al. (2011) Karsai et al. (2012)	Activity Blachon et al. (2015)	Network performance Shafiq et al. (2014)	Semantic place Eagle & Pentland (2006) Verkasalo (2008) Jo et al. (2012) Zhu et al. (2013) Hintze et al. (2014) Soto et al. (2011) Calabrese et al. (2011)			

Figure 2 Related empirical research placed on the context framework. Bottom-up research is in color blue and top-down research is in color red.

More recently, the increased data collection capabilities of the devices have also enabled more diverse end-user context related research. This is true especially for the bottom-up approaches, which can utilize the full range of the device capabilities.

The reviewed research is utilizing mostly sensed context. I refer here to sensed quite broadly, considering this category to include information which is available directly from the logged data, but not manually provided by the users. This includes, among others, logs of voice call-phone number tuples as direct indicators of communication links. Deriving higher level context from the underlying data is also rather popular especially for location and social dynamics related context. Derivation methods vary from heuristic models to sophisticated machine learning. Finally, it is evident that the overall picture painted by the research reviewed here is an artifact of the related research selection. I however, argue that it is still suggestive of the more general situation.

4. Methods and data

Bryman (2006) separates on high level three different types of approaches regarding research methods: *qualitative*, *quantitative* and *multi-methods* research. The latter is often called also as multi-strategy, mixed methods or mixed methodology research (Bryman, 2006). However, according to, for example, Creswell (2010) the definitions of the multi-method approach vary in terms of what is exactly being mixed or used together. Morse (2010) provides a distinguishing definition, stating that multi-method research is such that uses two or more methods rigorously, and complete in itself, and then triangulates to construct a complete whole. Mixed-method approach, on the other hand, is such that combines both qualitative and quantitative methods. Furthermore, this approach can be qualitatively or quantitatively driven. For example, quantitatively driven mixed-method research has a quantitative core method, which is supported by complementary qualitative (and possibly other quantitative) methods. A research method guide from JYU (2015) refers to multi-method research as a research utilizing multiple methods usually from the same generic type (i.e., qualitative or quantitative), however not commenting on the weights of the methods. Mixed-method research is again defined as a combination of qualitative and quantitative methods. Mingers (2001) advocates the desirability of multi-method approaches in information systems (IS) research. He calls this also *plurality* and does not explicitly define the types of the methods used. The arguments for multi-method research include the differentiated nature of the real world and that even single studies are not conducted usually in isolation, but rather as a part of a process that proceeds through a number of phases.

This thesis as a whole follows a multi-method approach. It utilizes more than one method and all of the methods fall into the category of quantitative research. However, this thesis does not follow the exact definition of Morse (2010), because the weights of the different methods are unequal. More specifically one method (handset-based measurements) is the core method and the other methods (surveys and network traffic measurements) have a complementary role. Furthermore, the thesis utilizes four distinct datasets, three of which are collected with handset based measurements and complemented with surveys and one which is collected with network traffic measurements. The handset-based measurements and the complementary surveys are implemented as (three separate) user panels. The term panel refers to collecting data with different methods from the same sample of users (or panelists) over

a long time period. Depending on the panel, the handset-based measurements spanned from one month to more than a year. The complementary surveys were administered to the panelists mainly at the beginning of the panel, at the end of the panel, or both. The network traffic measurements were a separate effort and the resulted data have relatively minor, but nonetheless a complementary role. The following three subsections describe each of the methods used, the corresponding datasets and linkages between the methods and the datasets.

4.1 Handset-based measurements

As discussed above, handset-based measurements are the core method of the thesis. The name of the method follows a convention originating from Verkasalo (2009b) and continued by Karikoski (2012). Furthermore, the publications of this thesis primarily use the name *handset-based measurements* when referring to the method. Another widely used name referring to the same method is *device monitoring* (e.g., Kivi, 2009). Handset-based measurements are a method for collecting quantitative behavioral data from smartphone and tablet users by installing a monitoring application to their devices. The data collected are granular and context-sensitive and thus, following the terminology of Arahony et al. (2011), the data have high “throughput”. This means that the data collected have high dimensionality, resolution, sampling-rate and amount of unique information. Mobile devices, and especially, smartphones are carried around by the users and are personal “always-on” type of devices. Thus, monitoring these devices provides unprecedented opportunities for studying user-level behaviors.

Large-scale handset-based measurements are a relatively novel method for collecting the mobile device related behavioral data. It was enabled by the introduction of the smartphone, the possibility to install third party software into these devices and 3G and 4G mobile networks. Despite the relatively short history of the method and the underlying technology, they have been identified as emerging and useful research tools, for example, in the social sciences (Raento et al, 2009). Also, researchers in the field of psychology have advocated smartphones as highly promising research tools as they have many qualities that surpass the existing tools (Miller, 2012). One of the earliest handset-based data collection efforts was the Helsinki Institute of Information Technology’s (HIIT) Context project. One of the outputs of the project was ContextLogger, a software tool for collecting reliably handset-based data. It was built on the ContextPhone platform introduced by Raento et al. (2005). The Reality Mining project of MIT utilized a version of ContextLogger (in addition to some other tools) in their data collection efforts (Eagle & Pentland, 2006). The Reality Mining Project has produced some of the most cited handset-based studies. The legacy of the Reality Mining Project is directly visible in the work of Arahony et al. (2011). They implemented and extended the ideas of Reality Mining and developed a framework for a social and behavioral sensing system (called Social fMRI). This work led into an open source handset-based data

collection tool called Funf. Later on, for example, the Copenhagen Networks Study utilized a modified version of Funf in their handset-based data collection campaign (Stopczynski et al., 2014). Other notable academic handset-based data collection efforts include the work of Falaki et al. (2011). They developed a smartphone monitoring tool called SystemSens and published results related, for example, to smartphone data traffic and diversity in smartphone use. Laurila et al. (2013) describe the Lausanne Data Collection Campaign set up by Nokia Research Centre. The handset-based data collected in the campaign was released for the Nokia Mobile Data Challenge and led into several academic publications. One of the most recent large-scale handset-based measurements campaigns is the Device Analyzer project of the University of Cambridge (Wagner et al., 2014). The Device Analyzer software is distributed via the Google Play store and with this approach the dataset has data from over 12500 users and is one of the most large-scale handset-based datasets. The next subsection provides descriptions of the handset-based data collection and datasets used in this thesis. More information on the handset-based measurements method in general can be found, for example, in Karikoski (2012) and Verkasalo (2009b).

4.1.1 Datasets

Three distinct handset-based datasets were collected for this thesis. The first dataset (henceforth ‘Dataset 1’) was collected as a part of the OtaSizzle project (Lehväslaiho, 2009). The project was coordinated by Helsinki Institute of Information Technology (HIIT) and included collaboration partners such as the Department of Computer Science and the Department of Communications and Networking of Aalto University. The actual data collection of Dataset 1 took place between the beginning of September 2009 and the end of December 2010. The dataset includes data from 200 users. The users are mainly students and staff of Aalto University. Based on the users who stated their gender in the preliminary survey (66 % of all users) 86 % are male and 14 % female. Based on the users who stated their age on the preliminary survey (48 % of all users), the age of the users ranges from 19 to 56 with an average of 25.5. An average user produced 190 days of data. The data collection software was called MobiTrack and it was developed by MobiTrack Innovations Ltd. The software measured and collected data on real-life user behavior and the usage of devices, services and various technical data. The data include foreground application usage, application installations, voice calls, SMSs, MMSs, processes running on the device, battery levels and charging, Bluetooth and WLAN access point entries, mobile network CID entries, Uniform Resource Locator (URL) entries and network sessions. The software has supported Symbian, Google Android, Windows Mobile, BlackBerry and Apple iOS operating systems. However, most of the data in Dataset 1 are collected from Symbian devices. More information about the software can be found, for example, in Karikoski (2012) and Verkasalo (2010, 2012).

The second handset-based dataset (henceforth ‘Dataset 2’) was collected as a part of a course taught at the Department of Communications and Networking

of Aalto University. The actual data collection took place between the beginning of November 2011 and the middle of January 2012. The Dataset 2 includes data from 51 users. The users were mainly students attending the course and additionally a few staff members of Aalto University. All of the users stated their gender in the preliminary survey. 67 % of the users are male and 33 % female. 90 % of the users provided their age in the preliminary survey. The ages range from 23 to 46 with an average of 27. An average user produced 50 days of data. The data collection software was a newer version of the MobiTrack software and renamed as MyLife. Also the company providing the software went through changes and after being MobiTrack Innovations it was named as Zokem and the most recently as Arbitron Mobile Oy. The data collected are very similar to Dataset 1. However, in addition to the basic data collection, the software allowed sending pop-up questionnaires to the users. For example, a question coupled with a few answering options could be sent periodically or after some specific event. The questionnaire functionality will be discussed in more detail in the next subsection. The panel included Symbian (47 %), Google Android (31 %) and iOS (22 %) smartphones.

The third handset-based dataset (henceforth, Dataset 3) was collected as a part of the regular user panels of a company called Verto Analytics⁵. The data collection took place in February 2015 and lasted the whole month. This dataset includes data from 999 users. The panel in question was US based and the panelists were recruited online. The recruitment process included a preliminary survey and instructions to install the monitoring software into applicable devices (smartphone, tablet and/or PC). All panelists were paid for the participation. Again the data collected is similar to the other two datasets. However, the types of data available to the thesis research were somewhat more limited, including data on foreground application usage (including any kind of messaging applications such as SMS), application installations, voice calls, Uniform Resource Locator (URL) entries, network sessions and device information. The panel includes users who have used smartphones, tablets, PCs or any combination of these. However, for the purpose of this thesis only smartphone and tablet usage was considered. This limits the number of users to 561. 65 of these were smartphone and tablet users and 496 smartphone only users. Out of all smartphones in the limited dataset 80 % are Google Android devices and 20 % are iOS devices. Out of all tablets in the limited dataset 71 % are Google Android devices and 29 % are iOS devices. Demographic data related to Dataset 3 was not available for the purposes of this thesis.

Table 4 summarizes the datatypes collected for each of the three datasets. **Table 5** summarizes the datasets in terms of the data collection period and number of users and maps the dataset to the publications of the thesis. In addition to the overall number of users, the table also presents the number of users considered in the analyses of the different publications. For various reasons some of the users did not have coherent enough data for the particular analyses. More details can be found in the exact publications.

⁵ Verto Analytics: www.vertoanalytics.com

Table 4 Datatypes collected for the three different handset-based datasets

Type	Details	Dataset 1	Dataset 2	Dataset 3
Phone call	duration, type (in, out, missed)	X	X	X
SMS, MMS	number of messages sent/received, length	X	X	-
Application	foreground usage, installations	X	X	X
Browsing	HTTP traffic	X	X	X
Bluetooth scan	names, MAC addresses	X	X	-
WiFi scan	names, MAC addresses	X	X	-
Location	MCC, MNC, LAC, CID	X	X	-
Network session	bearer, IAP, uplink data, downlink data	X	X	X
Energy	battery and charging status	X	X	-
Pop-up questionnaire	semantic place, happiness	-	X	-

Table 5 Summary of the three handset-based datasets mapped to the publications

Dataset	Collection period	Users overall	Users analyzed	Publication(s)
Dataset 1	Sep 2009 - Dec 2010 (16 months)	200	140	2, 3, 4, 6
Dataset 2	Nov 2011 - Jan 2012 (2 months)	51	20	4, 6
Dataset 3	Feb 2015 (1 month)	999	561	5

4.1.2 Experience sampling

The version of the handset-based data collection software utilized for collecting Dataset 2 enables experience sampling from the users. The Experience Sampling Method (ESM) is a research method, which is used for asking the research participants to stop at certain times of day or during or after certain events to make notes of their experience in real time (Hektner et al., 2007). According to Hektner et al. (2007), experiences refer to any contents of consciousness of an individual. Usually some sort of signaling devices are used to prompt the participants to respond when needed. Traditionally, beepers have been used for the signaling and pen and paper for making the notes. More recently, however, more developed methods and devices have been used for the signaling and documentation in the form of computerized ESM (Feldmann Barrett & Barrett, 2001). A variant of computerized ESM was used during the data collection process of Dataset 2 to sample the experiences of the users related to the use of mobile devices and services.

In the version of ESM utilized for this thesis, smartphones were used as signaling and documentation devices. The ESM response data were collected in conjunction with the other handset-based data. The data collection software allowed triggering the questions based on time, based on some specific event or based on a combination of the former two. For example, a question could be triggered every other day at 3PM or after every tenth voice call. The questions triggered in conjunction with the handset-based data collection for Dataset 2 can be classified into two types. The first type was concerned with the strength of ties (e.g., friend, acquaintance, stranger) between users of communication services. A question inquiring the strength of the tie was triggered after the

usage of services, such as voice calls, SMSs, MMSs, Facebook and email. The triggering did not happen after every suitable usage event for not to become too intrusive. The second type of questions was concerned with the context of the user (semantic place, surrounding people, happiness). A set of questions inquiring the current place, current companion (alone, with a person, with a group) and the state of happiness (five steps from very unhappy to very happy) of the user was triggered at different times of day. For this thesis, the semantic place questionnaire is the most relevant (data utilized in Publications 4 and 6). The corresponding question asked from the users was: *Where are you?* The answer options were: *Home, Office or School, Other meaningful place and Elsewhere*. Instructions for the meaning of the options were provided. The definitions of these particular semantic places are discussed in more detail in the next subsection.

4.1.3 Contextual information acquisition

As mentioned at the beginning of section 4.1, data collected with handset-based measurements are rich in terms of contextual information. This thesis focuses on *mobile end-user context*⁶ available through handset-based measurements. Following the context definition of Dey (2001), this includes *any information, available through handset-based measurements, that can be used to characterize the situation of an end user*. In the spirit of the HCI and context-awareness related context definitions, the situation of an end user is closely linked with interaction between the user and the application the user is using. This means that information irrelevant to this interaction cannot be used to characterize the situation, and thus, is not context. For example, the weather outside might be irrelevant to sending an SMS to a friend. However, the weather outside might very well be relevant to using a mobile taxi dispatching service (see Xu & Yuan, 2009). In this thesis, I use a slightly more relaxed stance on the relevance of the information; information which is *hypothesized* to be relevant to the interaction between an end user and a mobile service or an application is considered context, until proven otherwise. On this basis, I talk about acquiring contextual information before explicit examination of its effect on the service usage. However, in some cases previous literature provides backing for well-educated hypothesizing on the existence of the effect.

With the handset-based measurement setup utilized in this thesis, we have access to mobile end user context provided manually and sensed (see, e.g., Publication 1 and Henriksen & Indulska, 2004). Additionally, a couple of methods were used for deriving mobile end user context. **Figure 3** shows the different types of contextual information acquired and utilized in this thesis on the end-user context framework introduced in Publication 1 and in section 3.3. Manually provided context were available through the use of ESM described in the previous subsection. I consider here as manually provided context also

⁶ From now on in the text the term *context* refers to *mobile end user context* for brevity, unless otherwise noted.

information acquired through the surveys administered in conjunction with the handset-based measurements. This includes, among others, age and gender information of the users. Sensed context were available through the actual data logs automatically collected and stored by the monitoring software. As discussed earlier, the software has access to various sensors and processes running on the device. Sensed context is any information describing the situation of the user and available directly through the sensor or process data logs (e.g., CID based location). Finally, derived context is any information describing the situation of the user and derived from the manually provided context sensed context, or both, using some derivation method(s). In this thesis semantic place derivation has a central role and thus the remainder of this section focuses mainly on this derivation process.

The goal of the semantic place derivation process is to detect up to five different semantic places for the users (*Abroad*, *Home*, *Office/School*, *Other meaningful place* and *Elsewhere*). Also, the derived semantic place information must be possible to map to any of the end user's handset usage data according to timestamps. In other words, the purpose is to know at which semantic place the user has been at any point in time during the data collection period. Of the semantic places considered, *Home* refers to a place, where the majority of nighttime is spent and *Office/School* refers to a place where the majority of regular office hours are spent. *Other meaningful place* does not have the characteristics of *Home* or *Office/School*, however, a considerable amount of time is still spent in this type of a place. For example, a parents' house or a place for a hobby can be an *Other meaningful place*. Places where small amounts of time are spent belong to *Elsewhere*. This includes places only passed by while on the move and not so frequently visited stores, restaurants, etc. All in all, places considered not that meaningful to a user. Finally, *Abroad* refers to places outside the country where the majority of the user's time is spent.

Datasets 1 and 2 provide CID and WLAN entry data for the purpose of semantic place derivation. The CID dataset is a time stamped sequence of the IDs of all the cell towers a user's handset has been connected to during the data collection period. Every 15 minutes or every time the user's handset connects to a new cell tower the data collection client generates an entry including a timestamp, CID number, MCC (Mobile Country Code), MNC (Mobile Network Code) and LAC (Location Area Code). In principle it is known all the time under which cell a user is. A mobile network cell covers a particular geographical area. The diameter of the area can range roughly from a few hundred meters to a couple of kilometers. In practice, for example, a user's home can be in an area where a couple of cells are overlapping. This results in oscillation in which even a stationary handset's connection jumps back and forth between the cells. Thus, the same place could be represented by several different CIDs. For the purpose of the semantic place derivation, such cells are clustered together to represent one place. More information on cell clustering can be found, for example, in Yang (2009) and Soikkeli (2011).

The WLAN entry dataset is a time-stamped sequence of WLAN Access Points (APs) the user’s device has detected within range during the data collection period. The data collection client forces the user’s device to make a WLAN scan every half an hour. Every AP sensed during a scan generates its own data entry including a timestamp (time of the scan), MAC (Media Access Control) address, SSID (Service Set Identifier) and signal strength. It can be thought that an AP set, with particular access points in it, represents a particular place. In other terminology, the AP set is a WLAN fingerprint of the place. By determining different places by using the unique MAC addresses and the signal strengths of APs it is possible to compress the WLAN data from a time-stamped sequence of AP sets into a time-stamped sequence of places (indicated, for example, by an assigned unique place ID). In short, similar enough fingerprints represent the same place. More information on WLAN fingerprinting and detecting places based on the fingerprinting can be found, for example, in Krumm & Hinckley (2004) and Soikkeli (2011).

It is not necessarily known where the places detected by CIDs or WLAN fingerprints locate geographically, but the places can be distinguished from each other (by the IDs). Furthermore, it is relatively straightforward to calculate how many times a place is visited, when it is visited and the amount of time spent at the place. This information, together with some time-based heuristics, can be utilized to infer the meaning of a place to a user. The time-based heuristics are based on observations of people’s daily routines and statistical data on how people spend their time (Eurostat, 2004; OSF, 2011). For example, people tend to be at work or school during daytime and at home during nighttime on weekdays. For the work in this thesis three different methods have been used for labeling a place as one of the semantic places described above: *i*) heuristic unsupervised classification (Dataset 1, Publications 2 and 3), *ii*) labeling based on ESM data (Dataset 2, Publications 4 and 6) and *iii*) supervised classification (Datasets 1 and 2, Publications 4 and 6).

In the case of the heuristic unsupervised classification, no ground truth semantic place data are available for classification model training purposes. This was the case when only Dataset 1 was available (Publications 2 and 3). The first step of this classification detects based on MCC whether a certain CID (cluster) is *Abroad* or not (the MCC with the most CIDs is assumed to be the user’s country of residence). After this *Home*, *Office/School*, *Other meaningful place* and *Elsewhere* are associated to CIDs (clusters) based on the user’s time spending behavior. The CID (CID cluster) based classification forms the basis for the semantic place detection as the CID log data is time-wise continuous. Similar classification (excluding *Abroad*) is performed for the places based on WLAN fingerprints. Finally, if the WLAN-based classification for a place disagrees with the CID-based classification the WLAN-based classification is used. This allows semantic place separation within a mobile network cell. This type of a heuristic approach has been used also, for example, in Jimenez (2008), Verkasalo (2009a), Jo et al. (2012b) and Hintze et al. (2014b).

In the labeling based on the ESM data (available for Dataset 2) the user provided semantic place information is time-stamped. At a certain point in time

the user has announced in which semantic place (excluding *Abroad*) she is. Based on the timestamp the answer is associated to a certain CID (cluster). Typically, the users have quite reliably indicated certain cells as homes and certain cells as work or school. Depending on the user, zero or more *Other meaningful places* are provided per user. CIDs not associated to the three other semantic places are finally labeled as *Elsewhere*. The same is done for WLAN-based places and in the case of a conflict WLAN-based label overrides CID-based label. User provided semantic place labeling has been used also, for example, in Bayir et al. (2010) and Do et al. (2011).

Finally, the supervised classification involves training (by machine learning) a classification model utilizing the user provided ESM data as training data. The model training can thus be done only with the data of Dataset 2. However, the model itself is then used also for the data in Dataset 1 as the inherent characteristics of the data are very similar. The features for inferring the semantic place class (excluding *Abroad*) include metrics related to the users' time spending behavior in the places (based on CIDs). More information on the approach can be found in Publication 6. More elaborate approaches of this type include, among others, Zhu et al. (2013), Huang et al. (2012) and Montoliu et al. (2012).

Conceptual perspective

		Personal Context			Environmental Context		
		User	Social Environment	Activity/Task	Conditions	Infrastructure	Location
Operational perspective	Manually Provided Context	Identity (user id) Gender Age Happiness	Surrounding people Strength of ties				Semantic place (home, work, other meaningful place, elsewhere)
	Sensed Context		Surrounding devices Communication links	Using apps Calling Messaging		Battery level Charging status Surrounding devices Form factor (smartphone, tablet)	Network cell IDs WLAN Access Points Bluetooth Access Point GPS
	Derived Context					With or without tablet	Semantic place (abroad, home, work, other meaningful place, elsewhere)

Time

Figure 3 Contextual data acquired during the thesis work placed on the context framework. The red color refers to data actually utilized in the analyses.

4.2 Surveys

In this thesis, surveys are used as a complementary method for the handset-based measurements. Furthermore, the surveys were administered in conjunction with the handset-based measurements. This thesis utilizes three different handset-based datasets and at least one survey was administered for each corresponding user panel. In general, surveys are used for collecting data from people and in many cases about (the same) people. Surveys are one, and traditionally the predominant, method for studying, for instance, beliefs, values, attitudes and motives of individuals. Robson (2011) has identified some of the most typical features of surveys. In a usual setting a survey has a fixed design and the data is collected in a standardized form. The population the survey is

administered to is typically a relatively large group of people, which, in the desired case, is a representative sample of known populations. Because of the aforementioned characteristics, surveys are not very suitable for exploratory research (Robson, 2011). Nowadays, surveys are relatively easy to set up quickly and with low costs using online survey tools, such as LimeSurvey (2015). Online surveys support also more complex survey structures than the more traditional paper-based surveys, and finally, the sending of the surveys and subsequent data collection and storing can be automatized. The data acquired with surveys is susceptible to different types of response biases (see, e.g., Paulhus, 1991). Such biases include, among others, recall bias and social desirability bias. The survey respondents can also misunderstand the questions or take the survey without necessary seriousness. The reliability of a survey is usually evaluated in terms of its external and internal validity (Robson, 2011).

In conjunction with the handset-based datasets utilized in this thesis five different surveys were administered. The user panel of Dataset 1 took a preliminary survey before the start of the actual handset-based measurements and an intermediate survey in September 2010. The user panel of Dataset 2 took a preliminary survey before the start of the handset-based measurements and an end survey after the handset-based measurements. The user panel of Dataset 3 took a preliminary survey before the start of the handset-based measurements. The preliminary survey in conjunction with Dataset 1 was concerned only with basic demographics (age, gender, occupation, etc.) and, for example, the device types the users had. The intermediate survey was additionally concerned with participant attitudes towards the data collection in terms of incentives, privacy and mobile technology adoption. For a detailed report of the intermediate survey results, see Karikoski (2012). The preliminary survey in conjunction with Dataset 2 was concerned with basic demographics, residence area, mobile services charging plans, device type, device battery charging, technology adoption and mobile services usage, for example. The end survey was similar to the preliminary survey. The preliminary survey in conjunction with Dataset 3 was concerned, for example, with demographics and device types owned and in use by the panelists. The demographics were not, however, available for the purposes of this thesis.

In this thesis the explicit quantitative usage of the survey data is limited to the demographic data, including usage in user segmentation (Publication 6) and as model features in semantic place derivation (Publications 4 and 6). The demographic data is also used for describing the used datasets (Publications 2, 3, 4 and 6). Finally, the survey responses provide food for discussion regarding the thesis results, for example, in terms of reliability, validity, representativeness and generalization.

4.3 Network traffic measurements

Network traffic measurements are used in this thesis as a complementary method for the handset-based measurements. While the throughput of handset-based data is high (see section 4.1 of this thesis), the number of users in a

handset-based measurements panel is limited. Network traffic measurements, on the other hand, offer a network-wide view on the usage of online mobile services. Network-wide refers here to all the customers of a mobile network operator that have used their devices online during the measurement period. However, the throughput of the data is relatively low, providing only a limited view on the service usage especially in terms of end user context and observation period (see, e.g., Ud Din (2013) and Kivi (2009)).

The network traffic measurements providing data for this thesis were conducted in an operating Finnish mobile network in January 2012. The measured data consists of two parts: Internet traffic trace and network session trace. The Internet traffic trace was measured from the Gi interface of a GGSN (Gateway GPRS Support Node) in a GPRS (General Packet Radio Service) packet core network of the operator, using modified Tstat⁷ software. The traffic trace data included flow-level information about the IP address (anonymized), start and end time, transferred bytes and packets, used protocols and applications, and selected HTTP header fields. For each flow, the HTTP header fields of the first HTTP request/response pair were recorded, including user agent and the host name of the requested URL. The network session trace was produced separately from the operator's reporting systems. It included all sessions that had started and ended during the six-day measurement period (Mon-Sat). The data consisted of RADIUS server logs, including MSISDN (Mobile Station International Subscriber Directory Number) (anonymized) and IP address (anonymized), session start and end times (time of IP allocation and release), and the number of transferred bytes. The session trace included all sessions via the Internet access point of the operator that started and ended during the measurement period. The Internet traffic trace and the network session trace were mapped together using the time stamps and IP addresses. Then, the HTTP user agent information was used to identify the device type and device model of all the sessions for which Internet traffic traces with user agent information were available. Only mobile phone and smartphone data was utilized in the thesis. More information on the measurement setup and characteristics of data can be found in Ud Din (2013).

In this thesis the usage of network traffic measurement data is limited to Publication 4 where the data is used to complement network traffic data observed through handset-based measurements. While the handset-based data offers some context around the network usage of users, the network traffic measurement data provides a network-wide view on the network usage.

4.4 Methods summary

Figure 4 presents the data collection methods used in the thesis on the framework for analyzing the usage of mobile services by Smura et al. (2009) (see also section 2.3.1 of this thesis). Handset-based measurements, surveys and network traffic measurements were utilized to collect data from end users, their devices and from network nodes. The subsequent mobile services usage

⁷ Tstat: <http://tstat.polito.it/>

analysis (see the next chapter) includes devices, applications, network and content. The different measurement points provide different perspectives for the analysis. However, as indicated by **Figure 4** the usage monitoring systems perspective dominates.

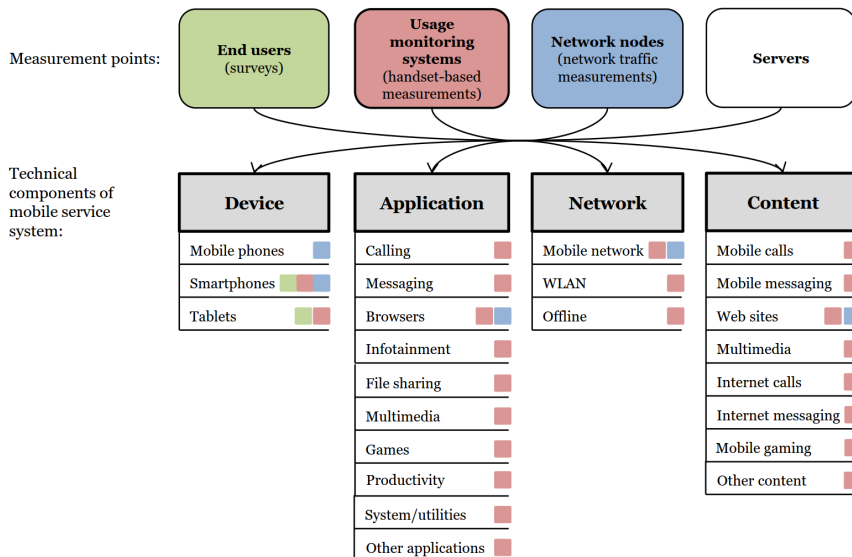


Figure 4 Data collection methods used in the thesis placed on the framework for analyzing the usage of mobile services (adapted and modified from Smura et al. (2009)). The color markings indicate through which methods and measurement points the particular technical components are observed.

5. Results

The results of the thesis are presented in this chapter. The presentation follows the research questions introduced in Chapter 1. The first section of this chapter contributes to the methods and body of knowledge for acquiring contextual information from handset-based measurements. The two subsequent sections present results of empirical mobile device and service usage studies. This includes the more general mobile device and service usage patterns and related user behavior, as well as, the contextual usage patterns of the devices and services. The second to last section presents the results on how to incorporate contextual information into modeling the usage of mobile devices and services. Finally, the last section summarizes and contemplates the results from the perspective of the research problem.

5.1 Developing contextual information acquisition

Handset-based measurements are a novel method for collecting data regarding mobile device and service usage. Unlike some other methods, handset-based measurements also enable the collection of data regarding the context of the end user of these devices and services. That is, information that can be used to characterize the situation of the end user. The context-rich nature of handset-based measurement data is well identified. However, a gap between theoretical context-awareness research and the handset-based measurements related contextual mobile service usage studies still exists in the literature. The context-awareness literature has put effort in conceptualizing context. Context related studies utilizing handset-based measurements, on the other hand, usually define context very case specifically based on the underlying data available. In other words, these studies have a more practical than a theoretical approach on defining context. Both, the theoretical and practical approaches are, however, important in acquiring real life contextual information.

This section covers an end user context classification framework for handset-based studies (Publication 1) as a result of merging the theoretical practical views on end user context. The combination of the views provides a basis for contextual information acquisition through handset-based measurements. After setting the basis, more case specific results are provided on actual end user context acquisition. This section is closely related to section 4.1.3 of the

methods and data chapter, but focuses on contributions and observations done in the thesis, rather than the methods per se.

5.1.1 End user context framework

The end user context framework has already been utilized in this thesis for mapping related work in terms of context data utilized (section 3.3) and classifying context data collected and utilized for this thesis (section 4.3.1). The framework is a combination of conceptual (theoretical) and operational (practical) perspectives on mobile end user context. It is a result of a literature review and own research work concerning handset-based measurements and context acquisition, and is based on the conceptual analytical research approach (see, Järvinen (2004) and section 1.3 of this thesis).

In the framework, the conceptual perspective on mobile end user context is divided into the personal and environmental context of the end user. Personal context characterizes the personal situation of the user, including the user herself (e.g., age, gender, heart rate), the social environment of the user (e.g., surrounding people) and the activity or task the user is engaged with (e.g., messaging, commuting). Environmental context characterizes the environmental situation around the user, including environmental conditions (e.g., noise and light level), computational infrastructure (e.g., device battery level, mobile network quality) and location (e.g., semantic place, indoors vs. outdoors). The operational perspective on end user context is divided into manually provided, sensed and derived context. Manually provided context comes directly from the user as an explicit input from the user, sensed context is acquired through data available from the sensors of the user's device and derived context is derived from manually provided or sensed context.

Together the conceptual and operational perspectives provide a tool for planning and clarifying the acquisition of contextual data. The conceptual perspective helps in determining *what* is or should be acquired and the operational perspective helps in determining *how* it is or can be acquired. The conceptual perspective covers the notional range of information that *might* be used to characterize the situation of the user. Whether this information is strictly speaking context depends on whether it *can* be used to characterize the situation (see also section 4.3.1 of this thesis). The conceptual perspective helps in perceiving and breaking down the range of possible context and thus considering the most relevant information regarding the usage of a chosen service or application (set). Furthermore, while some information is irrelevant, obviously not all relevant information can be captured with the available methods. The conceptual perspective helps also in perceiving the breadth of the lacking information and its possible impact on the matter under consideration. The operational perspective links the considerations based on the conceptual perspective to practical data acquisition. That is, it helps in determining what means are necessary to acquire the desired information, and on the other hand, given the means available, what information is possible to acquire. The framework additionally has a third axis corresponding to *Time*. This axis

is intended to portray the time-wise dynamic nature of the contextual information – the situation of the user varies over time.

The means to acquiring context (operational perspective) and the type of context (conceptual perspective) have their own particulars concerning the cost of acquisition, Quality of Context (QoC), the usability of the information and privacy issues, to name a few. For example, attitudes towards the ownership of the data can vary depending on the operational means of acquisition and the privacy sensitivity of the data or information can vary depending on the conceptual type (see Publication 1, section 4.1). The framework can also be utilized for mapping existing context related handset-based studies based on the contextual aspects utilized in the studies, or clearly communicating the contextual aspects utilized in a particular study, as already demonstrated.

5.1.2 Context derivation: semantic place

Identifying the significant places in people’s lives has been considered an important problem for a variety of use cases ranging from context-aware services to modeling human mobility. Previous literature suggests that people have only a few important places they spend their time in (see, e.g., Isaacman et al., 2011). Usually, these places include at least the homes and workplaces (or schools) of the people. These types of places are often called the semantic places of people (Laurila et al., 2013) and previous work (see, e.g., Verkasalo, 2009a) along with everyday observations has given evidence that the semantic place indeed has relevance in characterizing the interaction between an end user and at least some mobile service related applications.

In this thesis, the semantic places derived from handset-based data are *Abroad*, *Home*, *Office/School*, *Other meaningful place* and *Elsewhere*, as described in section 4.3.1. Referring to the end user context classification framework described above, semantic place is classified as an Environmental context under Location. It can be acquired manually from users (user matches the meaning of a place to a place identifier) or by derivation. For Dataset 2 semantic place information is acquired manually from users with ESM. Initially, a derivation approach utilizing sensed and time-wise logged data from the antennas of the users’ devices was used for Dataset 1 in Publications 2 and 3, because the manual acquisition option was not available. Later, a derivation approach utilizing both manually provided and sensed data was used for Dataset 1 in Publications 4 and 6 with the help of Dataset 2, as described in section 4.3.1.

Users in Dataset 2 tagged (based on ESM) on average 3.6 places to be significant in their lives. These places refer to *Home*, *Office/School* and *Other meaningful place*. Users in Dataset 1 had on average 3.9 significant places in their lives (based on the heuristic semantic place classification). Furthermore, users in Dataset 1 spend 66 % of time at *Home*, 8 % at *Office/School*, 7 % at *Other*

meaningful place, 17 % *Elsewhere* and 2 % *Abroad* (Publication 2)⁸. This means that on average over 80 % of time is spent in the few significant places.

For the users in Dataset 1, no ground truth semantic place data are available. This means that the quality of the semantic place derivation cannot be directly measured, for example, as accuracy. However, the above reported time spending distribution is similar to other similar studies and general time usage studies (e.g., Eurostat, 2004; OSF, 2011). On the other hand, Dataset 2 can be used for directly evaluating the semantic place derivation approaches, assuming the ground truth data acquired through ESM is accurate enough. I will focus here on three aspects related to the quality of the semantic place derivation by utilizing results from the supervised semantic place classification (Publication 6).

First, I examine the effect of the measurement (data collection) time period on the accuracy of the semantic place classification. The basic idea behind the semantic place derivation methods relies on regularities in the users' time spending behavior, and presumably, over longer time periods, some of the irregularities in this time-spending behavior smooth out. **Figure 5a** shows the change in classification accuracy for a Naïve Bayes classifier⁹ as a function of the amount of data available. The figure shows that as the classifier is provided with more data time-wise on the users' time-spending behavior the more accurately and reliably the classifier is able to classify different places into the semantic place categories (*Abroad* was excluded from the analysis).

Second, I examine the effect of classifier personalization on the accuracy of semantic place classification. As said, the data fed to the classifiers is composed of features related to the users' time spending behavior in different places. On aggregate level people are relatively similar in that they, for example, spend most of the nighttime in one place (home) and go to work or school during daytime. However, the aggregate level hides the individual level differences in daily routines. **Figure 5b** shows the change in accuracy for different levels of classifier personalization. By classifier personalization level I refer to the number of users whose data has been used to train the classifier. The lowest level of personalization refers to using the data of all users to train one classifier, which is then evaluated. The highest level of personalization refers to training one classifier per user (with only that user's data). In the latter case, all the classifiers are evaluated separately and the mean of their accuracy is reported (**Figure 5b**). For the levels in between, the users are clustered into groups of similar users (based, e.g., on demographics) and one classifier is trained per group. The results show that higher level of classifier personalization leads into better classification performance. While observing a single user yields good results for deriving the particular user's semantic places, the single user classification models are obviously not directly applicable to new users. When the model is trained based on the behavior of a particular user, it fits only for users

⁸ The time spending percentages are very similar with Dataset 2, but they are not shown explicitly in any of the publications.

⁹ In this section only accuracy results of a Naïve Bayes classifier are shown for illustration purposes. For the results of other classifiers (and including Area Under Curve evaluation measure) and introduction of the different classifiers refer to Publication 6. Overall, the results are similar with all of the different classifiers.

with the same type of behavior. For a randomly selected new user, an aggregate model (low level of personalization) is likely to work better. Methods such as Nearest Neighbor Search (NNS) can help in matching new users with models of higher levels of personalization. However, in this thesis only an aggregate level model was applied for the new users from Dataset 1 (see Publication 6).

Finally, **Figure 5c** provides True Positive Rate (TPR) results for classifying *Home*, *Office/School*, *Other meaningful place* and *Elsewhere*. TPR measures the proportion of positives that are correctly classified as such. Classification accuracy of a classifier is a weighted average of the TPRs. The results show that *Home* and *Elsewhere* are relatively easy to classify correctly followed closely by *Office/School*. *Other meaningful place* proves to be more difficult to classify. The reasons for this might include bigger diversity in the *Other meaningful*-type of places even in the case of a single user, and definitely across different users. Also, the quality of the ground truth might be poorer than in the cases of, e.g., *Home* and *Office/School*. Common nighttime and daytime time-spending patterns of the users contribute to the relatively good performance in the case of *Home* and *Office/School*. *Elsewhere* differentiates relatively easily from the other semantic places in that the time spent in individual *Elsewhere*-type of places is very limited in comparison with the more “meaningful” places.

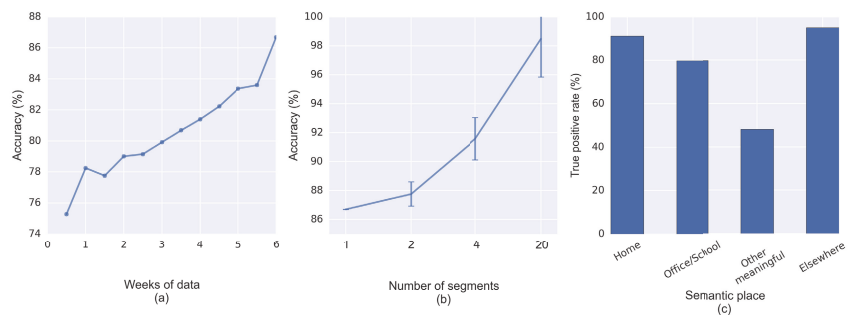


Figure 5 Semantic place classification accuracy of a Naïve Bayes classifier as a function of the amount of data (a) and classifier personalization level (b). (c) shows True Positive Rates of the classification (with Naïve Bayes) of individual semantic places. Results in (a) and (c) are obtained with aggregate classification models, that is, with the lowest classifier personalization level. Adapted and modified from Publication 6 Figures 1, 2 and 3.

5.2 Mobile usage patterns

Handset-based measurements and different handset-based measurement implementations provide their own particulars for capturing different aspects of mobile device and service usage. However, a session (with varying definitions) has become an often used unit of measurement in this type of studies (see section 2.1.2). This section covers first the work done, in the scope of this thesis, for defining and developing session as a unit of mobile service usage measurement. Then the unit of measurement is applied for measuring and studying mobile usage patterns in general and on the mobile application level.

5.2.1 Measuring mobile usage in sessions

The implementations of the handset-based measurement software utilized in this thesis log events on the users' devices with one-second granularity. In short, these events include start and end events related to applications moving to (start) and leaving from (end) the foreground of the user's device. These events enable approximations (in one-second granularity) for when the user started and ended interaction with a particular application. I call this interaction time interval as an *application session*. Allen (1983) provides a framework for describing basic relations between two finite temporal intervals (see also Publication 5 and section 2.1.2 of this thesis). **Figure 6** presents these thirteen relations. For example, if interval A starts and ends before interval B, A *precedes* B. This relationship can be expressed also as a converse: B *precededBy* A. On the temporal axis, application session is equivalent to the finite temporal interval described by Allen (1983). For one user, one device, and application sessions on this device, only sequential relations are applicable. This includes *precedes* and *meets* and their converses. For the purposes of this thesis, *precedes* and its converse are too loosely defined and they are thus replaced with *precedes within time-window* (abbreviated as *precedes within TW*) and *precededBy within time-window* (abbreviated as *precededBy within TW*) (Publication 5). This provides the basis for defining a *single device usage session* as a set of application sessions on a single device where an application session *precedes within TW* or *meets* the next one. However, the time-wise first application session of the set is *precededBy* the previous one *outside* the time-window. A maximum (threshold) value for the time-window needs to be assigned. The single device usage session definition is used in Publications 2, 3, 4, 5 and 6.

For a single user and multiple devices, all of Allen's relations are applicable as the simultaneous usage of the devices is possible. The construction of a *multidevice usage session*¹⁰ follows a two-step process (Publication 5). First, the single device usage session definition is applied separately for each device. Then, the relations of the usage sessions of the multiple devices are examined. If the single device usage sessions are (at least partly) simultaneous, *meet* (are *metBy*) or *precede* (are *precededBy*) *within TW* then they belong to the same multidevice usage session. The multidevice usage session definition is used in Publication 5.

The usage session in general approximates a continuous time period the user is interacting with her device(s). This interaction period as a whole is composed of the usage of one or more applications. As with handset-based measurements the interaction is observed from the perspective of the device, the true impression of the user about the interaction can only be approximated. The maximum allowed time-window between application sessions is the variable which tries to estimate the transition time necessary for the user to change applications or to continue the task at hand. The choice of the maxi-

¹⁰ If also data on background application processes on the devices were available, the multidevice usage session definition could be extended to *multiprocess session*. This is, however, out of the scope of this thesis.

imum time-window evidently affects the interpretation of the session based results. However, no prevailing value has emerged from the previous literature. Analysis on the effect of the maximum time-window value on the change in the number of usage sessions (as the value grows, more application sessions merge into one usage session) was conducted in Publications 4 and 5. The results suggest moderate values of more than 30 s and less than 1000 s for the maximum time-window, but are not conclusive, however. Setting the time-window to 0 s provides comparable base-case results. Analysis of the actual usage session construction process (Publication 5, Dataset 3, smartphone users) reveals that 32 %¹¹ of application sessions *meet* (or are *metBy*) another application session. This indicates that, most of the application to application transitions are very fast.

Finally, a note on the technical measurement perspective related to usage sessions. As illustrated in Publication 4 (Fig. 1), different measurement points can capture only certain kinds of sessions: the network traffic measurements provide view only on network usage sessions and server logs on server sessions, whereas the handset-based measurements provide view on both, online and offline application sessions. From the user behavior perspective, the user’s view on an interaction session with a device would be interesting, but achievable directly only in laboratory settings.

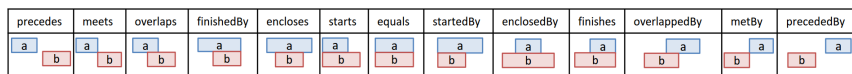


Figure 6 Allen’s thirteen basic relations between finite temporal intervals a and b.

5.2.2 Usage session patterns

This section examines mobile device and service usage on usage session level. The unit of analysis is a single device usage session and the device I focus on is smartphone. Patterns on usage session level provide a general view on the usage, without yet considering the particular services used. **Figure 7** illustrates some basic characteristics of smartphone usage sessions from Dataset 3 (Publication 5). The distributions of inter-session times (**Figure 7a, b**) are dominated by small values, however, also a number of very large values exist (bound by the data collection period). This is characteristic of a long tail distribution observed also in many other human related phenomena. A linear slope of a probability density function (PDF) on a log-log scale indicates, the so called, bursty behavior (Barabasi, 2005), meaning that many activities are executed in a relatively brief time period followed by long inactivity times (see section 2.1.1). The convex shape of the graphs on **Figure 7a** indicate, however, less very large inter-event values than expected by a power-law. This does not still remove the fact that the difference between the observed mean and standard deviation of the inter-session distribution is high, indicating a form of

¹¹ This particular number is not directly presented in Publication 5, however, its calculation from the statistics is trivial. Comparable numbers for Datasets 1 and 2 are 26 % and 28 % respectively.

bursty¹² or cascading (Malmgren et al., 2008) usage, where the inter-session times are just bound more strictly¹³ than suggested, for example, by the “scale-free” nature of the basic power-law. Also, a slight peak around the value corresponding to ~ 8 h ($\sim 30\,000$ s) is likely an indication of the diurnal patterns in human life (that is, no usage during the period of sleep). In the case of the general smartphone usage the processes driving it are presumably quite complex, including the mentioned diurnal patterns and usage of different types of services (with different requirements from the user) in different contexts. Furthermore, a large share of the usage is still communication, which is affected also by the communication patterns of other individuals in the user’s social circles.

The lengths of smartphone usage sessions are also dominated by small values (**Figure 7c**). The median session length over the whole Dataset 3 (smartphone usage, TW=1 s) is 31 s while the mean (207 s) is drawn up by the occasional very long sessions (Publication 5). Corresponding results from (the considerably older) Dataset 1 (Publication 2) are 45 s for median and 207 s for mean. Increasing the maximum time-window the sessions obviously get longer as more application session merge together.

The aggregate numbers presented above hide a considerable diversity among the users. **Figure 8** illustrates this diversity based on Dataset 1 (Publication 2). For example, the range of median session lengths per user (from 5 s to 355 s) is two orders of magnitude. Similar magnitudes in diversity are present also for the number of sessions per day (range from 2.3 to 46, mean: 20) and interaction time with the device per day (range from 9.2 minutes to 276 minutes, mean: 73 minutes). The corresponding numbers from the newer Dataset 3 (Publication 5) are median session length (range from 10 s to 618 s), sessions per day (range from 1.8 to 183, mean: 65), interaction time per day (range from 9.4 minutes to 872 minutes, mean: 227 minutes).

Even though the usage sessions are sets of application sessions, the number of application sessions per usage session is relatively low with moderate maximum time-window values (<100 s) (see, e.g., Publication 5, Figure 2). In this time-window value range one application session per usage session clearly dominates. Based on Dataset 3, 53 %¹⁴ of smartphone usage sessions (with TW = 1 s) have only one session (correspondingly 41 % with TW = 60 s). However, the tail of the distribution is again long, meaning that usage sessions constructed of a very large number of application sessions still exist.

¹² Goh & Barabasi (2008) quantify burstiness B between -1 and 1, where -1 refers to constant inter-event time, 0 to exponentially bound (Poissonian) inter-event distribution and 1 to power-law inter-event distribution with $\alpha = -1$. Furthermore, they observe different human activity to take values of B between 0.2 and 0.7. The inter-session distribution of Dataset 3 (smartphone usage, all users) shows user averaged B of 0.71 (minimum: 0.38, maximum: 0.96), i.e., in the higher levels of burstiness in human activity.

¹³ For example, inter-session times of longer than 24h are nearly non-existent (0.009 % of all inter-session times) in Dataset 3 (smartphone usage).

¹⁴ Corresponding number for Dataset 1 is 72 % (Publication 2)

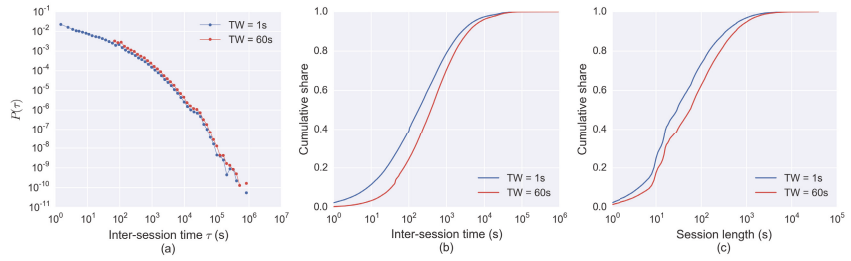


Figure 7 Probability density functions (a) and cumulative distribution functions of inter-session times, and cumulative distribution functions for session length with 1s and 60s maximum time-window values. CDF of TW=60s is shifted 60s to the left for better readability on log scale. Adapted and modified from Publication 5, Figure 4.

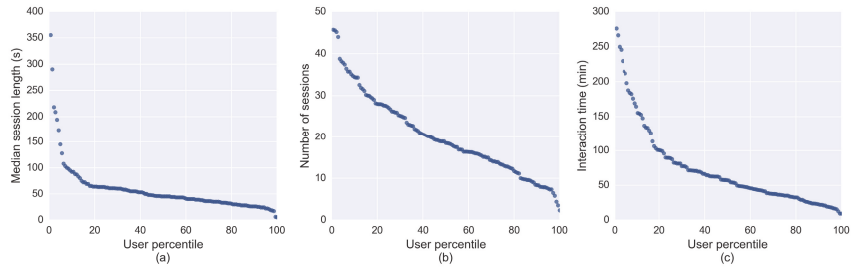


Figure 8 Median usage session lengths (a), number of usage sessions per day (b) and interaction time per day (c) per user. Adapted and modified from Publication 2, Figures 2 and 3.

5.2.3 Application session patterns

Smartphone usage consists mainly of using different applications from the messaging applications to games and much more. In the case of Dataset 1, an average user at least tried 50 different applications during the data collection period while the corresponding number for Dataset 3 is 58. Again, diversity across users is noticeable (Dataset 1: 15-118 different applications tried, Dataset 3: 10-310 different applications tried).¹⁵ **Table 6** summarizes part of the smartphone application usage of the users in Dataset 1 (Publication 2) and Dataset 3 (Publication 5)¹⁶. The table is used here to illustrate some basic patterns in smartphone application usage. Usage recorded in Dataset 1 is dominated by some of the more traditional smartphone usage, such as, Messaging and Browsing. These are in a rather dominant position also in Dataset 3. However, Dataset 3 reflects the more modern smartphone usage, showing increased gaming, social media and video usage. Furthermore, the more modern smartphone usage results in a very long tail of various other applications. While in Dataset 1 the other applications not shown on **Table 6** constitute 27

¹⁵ Direct comparison between the datasets is not feasible here, because of the large difference in the data collection period. The explosion of the number of applications available during the past years is visible in unique applications observed in the two datasets: 508 for Dataset 1 and 5860 for Dataset 3.

¹⁶ The statistics for Dataset 1 are directly from Publication 2, Table 3. The corresponding statistics for Dataset 3 do not appear directly in Publication 5; they are a result of applying the same calculations to Dataset 3 than for Dataset 1 above, and are shown for high-level comparison purposes between the datasets.

% of all interaction time (calculated over the whole dataset), the corresponding figure for Dataset 3 is 49 %. In addition to applications or application classes shown on the table, traditional voice calls are still an important part of smartphone usage. Due to technical limitations¹⁷ in the measurement setups, showing statistics exactly similar to **Table 6** for the voice calls is not feasible. However, the percentage shares of launches, compared with other usage, for voice-calls (both, incoming and outgoing) can be reported. The shares are 9.80 % and 10.60 % for Dataset 1 and Dataset 3, respectively. This shows that voice calls are indeed an implicit part of the communication bundle dominating smartphone usage. Finally, considerable diversity across users is present in the usage of individual applications. For most of the popular applications, the diversity in the number of application launches and interaction time is around two orders of magnitude, as already reflected by the results on usage session level.

Table 6 Descriptive statistics of smartphone application usage. The statistics are calculated on user level and then averaged. This means that only the users that have used the particular application are considered. Adapted and modified from Publication 2 Table 5 for Dataset 1.

	Users	% of launches	% of interaction time	Launches per day	Minutes used per day	Mean app session length (s)
Dataset 1						
Messaging	140	21.01 %	23.10 %	7.05	17.21	188.92
Browsing	140	11.71 %	15.99 %	4.11	11.65	161.50
Contacts	140	14.82 %	14.95 %	4.68	10.03	156.24
Calendar	139	3.98 %	4.63 %	1.32	3.96	162.32
Clock	138	4.68 %	5.51 %	1.50	5.83	284.79
Photos/Gallery	135	1.33 %	1.29 %	0.46	0.83	109.72
Camera	132	1.89 %	1.69 %	0.61	1.03	136.26
Maps and Navigation	125	2.24 %	3.70 %	0.74	2.25	193.69
Games	71	0.78 %	2.37 %	0.25	1.44	371.28
Dataset 3						
Messaging	553	16.02 %	12.50 %	23.11	23.29	80.29
Browsing	555	8.03 %	12.50 %	11.69	29.46	143.90
Contacts	481	4.64 %	1.56 %	6.04	2.73	31.46
Calendar	437	0.61 %	0.42 %	0.87	0.71	73.14
Photos/Gallery	511	1.89 %	0.95 %	2.57	1.72	61.98
Camera	486	1.00 %	0.54 %	1.27	0.93	48.67
Maps and Navigation	380	0.39 %	0.69 %	0.55	1.34	147.00
Games	435	4.67 %	12.18 %	5.91	28.13	334.04
Facebook	419	6.16 %	10.97 %	9.55	24.18	171.74
YouTube	371	0.67 %	2.44 %	1.00	6.45	293.95

5.3 Contextual usage patterns

As discussed earlier, handset-based measurements enable the acquisition of various contextual information. Furthermore, this information can be collected in conjunction with the device usage data. This means that the contextual

¹⁷ The application usage is measured as foreground usage. In most devices the screen shuts down during a voice call, moving the phone application to the “background”. Thus the usage duration measurements are not always reliable. Counting the number of launches is, however, possible.

information can be linked with the device usage data to examine contextual device and service usage. In this section, I examine the results of linking selected contextual information to mobile device and service usage data. The main focus is on temporal and semantic place information, but also mobile device form factor and battery level are briefly covered.

5.3.1 Time and semantic place

Temporal information is an integral part of the handset-based measurement data logs, as every measurement event is coupled with the timestamp of the event's occurrence. Thus, the linkage between time and mobile device and service usage is built-in in the handset-based data. **Figure 9a** shows aggregate level hourly distributions of different types of mobile usage sessions. Smartphone usage does not have any clearly identifiable peaks during the presumed awake hours – it stays relatively constant from the late morning to early evening. This, not surprisingly, applies also for mobile network usage associated to application usage. On the other hand, network sessions generated by the device without direct user interaction (Publication 4) follow a more uniform hourly distribution. Finally, the tablet device is associated to evening use, having a usage peak at 8 PM.

The temporal usage patterns of mobile devices and services are closely related to semantic place related usage patterns. On aggregate level people follow relatively stable spatiotemporal routines. **Figure 9b** shows how the shares of the identified semantic places (excluding *Abroad*) vary per hour of day. *Home* dominates regardless the hour of day, having the highest share during nighttime and the lowest around midday. *Office/School* peaks during daytime, and *Other meaningful place* and *Elsewhere* peak in the late afternoon and early evening, respectively. Considering overall smartphone usage in interaction time with the device (Publication 2) it is divided among *Home*, *Office/School*, *Other meaningful place*, *Elsewhere* and *Abroad* as 53 %, 12 %, 8 %, 24 % and 3 %, respectively. This reflects the distribution of time spent in the semantic places (66 %, 8 %, 7 %, 17 % and 2 %, in the same order). However, as the device usage is daytime and evening oriented, the share of *Home* drops as the others increase when comparing device usage with time spent. The differences follow from different usage intensities in different semantic places (shown here as usage minutes per hour spent in a semantic place). Including nighttime, the intensities are 2.6 min/h, 4.0 min/h, 3.4 min/h, 4.1 min/h and 5.9 min/h for *Home*, *Office/School*, *Other meaningful place*, *Elsewhere* and *Abroad*, respectively. If presumed sleeping hours (1AM-7AM) are removed, the *Home* intensity rises to 3.4 min/h while the rise is only marginal for the other semantic places. If usage intensity is measured in the number of usage sessions per hour, differences between the semantic places stand out more. This originates from the underlying pattern of longer, but relatively fewer sessions at *Home* and shorter, but relatively higher number of sessions in the other semantic places, and especially *Elsewhere* (see Publication 2).

Results

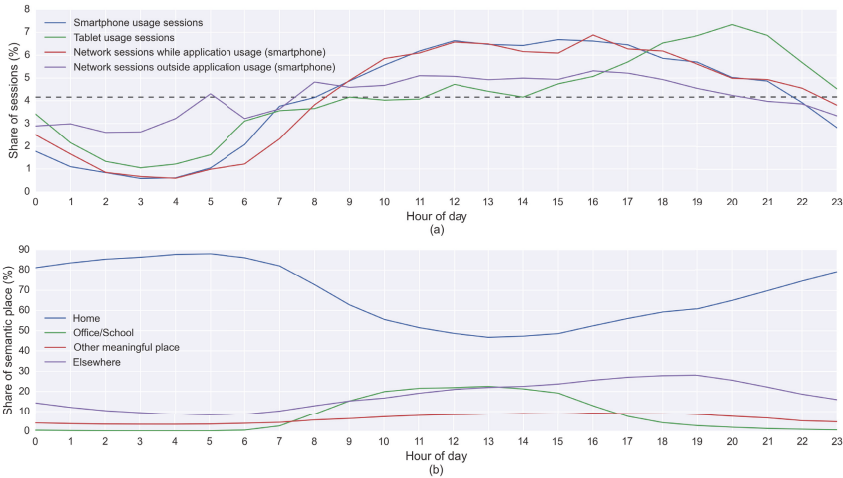


Figure 9 Share of different types of sessions per hour of day (a). Share of identified semantic places per hour of day (b). Adapted and modified from Publication 3 Figure 2, Publication 4 Figure 5 and Publication 5 Figure 5.

The above reported contextual differences in the overall mobile device usage naturally originate from the contextual usage patterns of individual applications. **Figure 10** displays semantic place related usage patterns on application level (from Publication 2 supplemented by email and outgoing voice calls from Publication 3 and network usage sessions from Publication 4). The numbers on the heat map cells show the number of application launches per one hour of interaction with the device. The heat map color indicates the distribution of application specific launches in the different semantic places. For example, the total number of Maps and Navigation launches per device interaction hour is 3.43, of which 55 % occur *Elsewhere*, 20 % at *Other meaningful place*, 14 % at *Home* and 10 % at *Office/School*. In other words, Maps and Navigation applications are, quite understandably, highly *Elsewhere* oriented. Also other applications show a degree of semantic place sensitivity. For example, Camera is used the most intensively *Elsewhere* and the least intensively at *Home*, while Calendar is used the most intensively at *Office/School*. Overall, the results suggest that semantic place and its underlying characteristics are a factor affecting mobile device usage. However, some of the individual applications (or application types) are clearly more semantic place sensitive than the others.

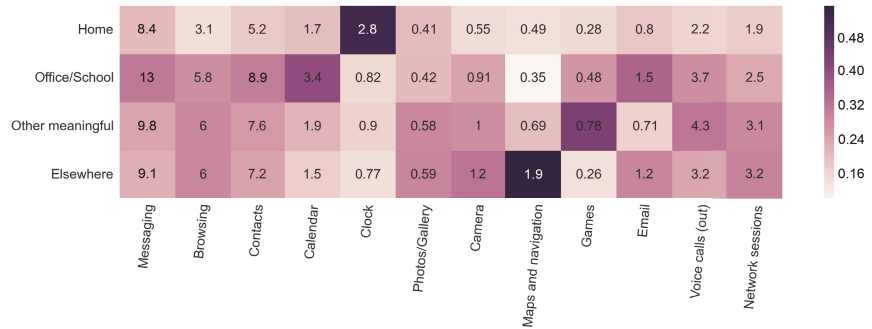


Figure 10 Smartphone usage intensities on application level per semantic place. The numbers indicate the number of application launches per device interaction hour and the color indicates the distribution of application specific launches in the different semantic places. Adapted and modified from Publication 2 Table 5, Publication 3 Figures 4a, 5b and Publication 4 Figure 7b.

5.3.2 Other contextual information

A significant portion of the empirical part of examining contextual mobile device and service usage patterns in this thesis is based on semantic place information. However, also a few other types of contextual information were available and examined during the thesis process. Here I will briefly cover the results of examining mobile device and service usage in the light of different device form factors (smartphone and tablet) and device battery level. Also, results on smartphone usage in the light of location based tablet availability (available vs. not available) and simultaneous tablet usage (simultaneous usage vs. no simultaneous usage) are presented. Form factor and battery level information belong conceptually to computational infrastructure (in environmental context) and operationally to sensed context since the information is readily available through the device monitoring software. Information on tablet availability and simultaneous tablet usage belong conceptually to computational infrastructure and operationally to derived (see Publication 5) context.

In Publication 4 (with a combination of Datasets 1 and 2) smartphone generated mobile network usage is studied, among a few other topics, on different device battery levels¹⁸. On the aggregate level the smartphones of the users stay 8 % of time on level low, 15 % on low-mid, 17 % on mid-high and 60 % on high. Foreground application related network sessions have overall relatively similar patterns to the actual foreground application sessions. Based on the number of these network sessions 4 % of them occur on battery level low, 12 % on low-mid, 19 % on mid-high and 65 % on high. Finally, the relative network usage intensity¹⁹ is divided among the battery levels as 15 %, 23 %, 31, % and 31 % for low, low-mid, mid-high and high, respectively. The results imply that the users prefer to keep their devices on higher than lower battery levels. Furthermore, foreground application related network usage is somewhat more

¹⁸ The battery levels are: low (0-25 %), low-mid (25-50 %), mid-high (50-75 %), high (75-100 %)

¹⁹ The relative usage intensity measure utilized in Publication 4 divides first the number of (foreground application related) network sessions per battery level with the total time “spent” on the particular battery level. The result is then divided by the total time “spent” on all battery levels.

intensive on higher battery levels than lower battery levels, possibly reflecting the user preferences of cutting down usage when the battery appears to be low.

The modern smartphone and a tablet computer are similar devices in a sense that they use the same (or very similar) operating systems, have access to the same services and applications and have similar user interfaces. However, the tablet is considerably larger in its dimensions parallel to the screen. Based on Dataset 3 (Publication 5), tablet usage sessions are longer (including, however, the same number of application sessions), occur less frequently and are more evening time oriented in comparison to the smartphone usage sessions of the same users. In device interaction time, however, smartphone (56 %) and tablet (44 %) are fairly equal. Tablet usage concentrates on browsing, gaming and video activities, whereas smartphone is more communication and social networking oriented. Based on results in Publication 5, smartphone usage does not differ significantly between the two options of location based tablet availability (i.e., tablet in the same or different location than the smartphone, based on GPS readings). On the other hand, the users do utilize their smartphones differently if simultaneous²⁰ tablet usage is detected. This is the most visible in the relatively less intensive usage of photos and gallery, video and email related applications during the simultaneous usage.

The results on device availability and simultaneous usage provide a glimpse at the concepts of device substitution and complementarity. For example, some of the smartphone usage might shift to the tablet or some of the tablet usage might induce more smartphone usage. Device substitution (e.g., from smartphone to tablet or PC), among other underlying factors, could be partially behind the less intensive usage of smartphone at home, for instance. Publication 5 studies also device substitution between multidevice (smartphone and tablet) and smartphone only users. Based on the results, on aggregate level 48 % of tablet usage is classified as substituted from smartphone usage (mainly from gaming applications) and the rest is classified as novel usage (mainly due to applications related to browsing, video and email). This does not, however, tell much about the ongoing substitution patterns of multidevice users; it rather depicts the behavior related to the binary state of owning vs. not owning a tablet device.

5.4 Contextual user modeling

Identifying contextual patterns in mobile device and service usage serves for the purpose of understanding the context related particulars of mobile usage and providing the basis for modeling better mobile user behavior with the help of the contextual information. Thus, one purpose of this thesis is also to examine how to incorporate the contextual information into modeling the usage of mobile devices and services (Publication 6). This is realized by empirically examining and evaluating three different approaches for incorporating semantic place information into mobile user behavior models. The semantic place in-

²⁰ Simultaneous usage refers here to a multidevice usage session. For reference see Publication 5 and section 5.2.1 of this thesis.

formation consists of the already familiar classes of *Home*, *Office/School*, *Other meaningful place* and *Elsewhere*. The incorporation approaches for the semantic place (or any other contextual) information are called: *Pre-filtering*, *Contextual modeling* and *Post-filtering*.

In *Pre-filtering* the contextual information is used for filtering other usage data for modeling the usage in the particular context. For example, if modeling mobile service usage at *Home*, only service usage data generated at *Home* are utilized. In *Contextual modeling* the contextual information is used as an independent variable alongside the other usage data for inferring the dependent variable under interest. Finally, in *Post-filtering* the contextual information is used for modifying the output of a model which is based on the other usage data (without the particular contextual information). Taking a very simple example case, a base model might recommend particular mobile content to a user. However, if the user is at *Office/School* and according to contextual information based a priori knowledge the user never consumes the particular type of content when at *Office/School* the final model might switch to the next best option of the base model, if applicable. For more formal definitions of the approaches see Publication 6, section 3.3.

The experimental setup for comparing and evaluating the three approaches includes two datasets (Dataset 1 and Dataset 2), five mobile service usage related dependent variables (each in turn being the variable under interest) and three types of machine learning models for building the (base) user behavior models. Additionally, the models were built for different levels of user segmentation, that is, from aggregate level models to user level models. Finally, the outputs of the models were evaluated with two different performance metrics (see Publication 6, chapter 4). The different combinations arising from the experimental setup resulted in thousands of individual models for each of the three approaches. Additionally, for each model, a semantic place-ignorant (no semantic place information utilized) counterpart was constructed, allowing a comparison between semantic place-powered vs. semantic place-ignorant models, in addition to comparing models between the three (semantic place-powered) approaches.

The results demonstrate that none of the three considered approaches dominate across all the experimental settings. Instead, they show circumstance-specific differences when modeling the examined aspects of mobile user behavior. This means that while one approach performs well for modeling one aspect of mobile user behavior, it might perform poorly for modeling some other aspect. For example, the *Pre-filtering* approach models relatively well time of day and day of week related aspects of mobile usage, especially for *Office/School* context. However, in other cases, and especially for the *Other meaningful place* it performs poorly²¹. One reason for this is that *Pre-filtering* is subject to the so-called data homogeneity versus data sparsity bias. The pre-filtered semantic place specific data are more homogenous, contributing positively to the model performance, but, on the other hand, fewer data are available, contributing negatively to the model performance. If the data homogeneity

²¹ See Figures 4 and 5 of Publication 6.

increases only marginally while the amount of data is significantly reduced by the filtering (e.g., the case of *Other meaningful place*) the performance is poor. The *Post-filtering* approach performs relatively well for *Other meaningful place* and is overall rather consistent across the experimental settings. Furthermore, it increases its performance relatively more than the other approaches when moving towards more personalized models²². One reason for this is the post-filtering process. It can be used to drop unnecessary (for a certain semantic place, for a certain user) dependent variable values, while retaining all of the valuable predictive data. The *Contextual modeling* approach is at its best with the time of day and day of week related aspects of mobile usage, but contrary to *Pre-filtering* does not strongly underperform in the other aspects²³.

In short, *Pre-filtering* offers a “high risk, high reward” approach, and thus, cannot be applied blindly without knowing the properties of the underlying data. *Contextual modeling* offers a relatively reliable “safe bet” which, in general, does not fall behind semantic place-ignorant approaches, but rather outperforms them at least slightly. *Post-filtering* has potential for the “best of breed” approach on condition that suitable a priori knowledge is available through the contextual information.

Generalized over all the experimental settings, models built with the semantic place-powered approaches outperform the semantic place-ignorant models. However, when examining the results with finer granularity, it becomes visible that semantic place information is able to contribute positively only to the modeling of certain aspects of mobile usage. The relatively good performance of the semantic place-powered models related, for example, to temporal aspects (e.g., time of use) of mobile user behavior partly reflects the earlier results regarding the strong diurnal patterns in human behavior. The increasing model performance while moving towards more personalized models reflects the diversity in user behavior across users. The observed semantic place sensitivity of different applications materializes rather inconsistently in modeling the usage in terms of usage frequencies, durations and applications used. However, according to the earlier results, *Home* related mobile usage is probably the most distinguishable from the others, and indeed modeling of the foregoing aspects of mobile usage are in general the easiest for the *Home* context.

5.5 Results summary

The results of this thesis are derived based on literature review combined with own experiences from handset based measurements, surveys, network traffic measurements and handset-based measurements of mobile device and service usage. **Table 7** shows the research questions of the thesis, relates the individual publications to the research questions and summarizes the main results of the thesis. These results together answer the research problem: ‘*How to char-*

²² See Figures 4 and 7 of Publication 6.

²³ See Figures 4 and 6 of Publication 6.

acterize, analyze and model contextual usage of mobile devices and services utilizing handset-based measurements?

Mobile end user context is a central concept in the thesis. For this reason existing research from the domains of ubiquitous computing and context-awareness was studied and reflected on own experiences in acquiring mobile end user related contextual information from handset-based measurements. The concrete results of this conceptual analytical approach to mobile end user context include a context classification framework that maps together the conceptual and operational perspectives of mobile end user context. The framework synthesizes the theoretical definitions of context with the practical approaches of context acquisition from mobile end users. It helps in planning and communicating mobile end user context related data and information acquisition and research efforts. In this thesis semantic place is the most utilized contextual information. It was acquired manually from users with the help of the Experience Sampling Method and also derived from the combination of manually provided and sensed base information. The derivation itself benefits from time-wise longer datasets and user personalized derivation models.

To utilize the acquired contextual information in identifying patterns and modeling mobile device and service usage, the contextual information was linked with actual mobile device and service usage data collected with the handset-based measurements. The mobile device and service usage was measured predominantly in application and usage sessions. These units of measurements are based on a definition presented in the thesis. On the high level the mobile device and service usage occurs in bursts of activity and the usage is dominated by relatively short sessions. Mobile devices are used mainly for communication and web browsing purposes. However, the long tail of a myriad of other use purposes has been growing during the past few years. Partly because of this also the pervasiveness of the devices is growing. An overarching theme in the usage of the devices is the considerable diversity across different users. In most aspects of the usage, roughly two orders of magnitude differences can be observed between light and heavy users.

The contextual usage patterns of mobile device and service usage show that the usage varies between certain contexts. A major part of the thesis examines the usage in different semantic places. For example, the intensity of overall usage is the lowest at *Home* and highest *Elsewhere* (excluding *Abroad*). On the other hand, the usage sessions are the longest at *Home*. Of individual applications, some are clearly more context (semantic place) sensitive than others. For example, the usage intensity of Maps and Navigation is clearly the highest *Elsewhere*, while for example the intensity of Web browsing is relatively uniform across other semantic places and somewhat lower at *Home*. The usage is also observed to vary across time, battery level, device form factor (smartphone vs. tablet) and simultaneous usage of multiple devices (also using the tablet while using smartphone).

After understanding better the contextual usage patterns of mobile device and service usage the final purpose of the thesis is to examine how the contextual information can be utilized in modeling the usage of the devices and ser-

vices. This is done by studying and evaluating, under multiple experimental settings, three different approaches for incorporating contextual information (semantic place) into mobile user behavior models. The results imply that none of the approaches dominate, but show circumstance specific differences. That is, the model types perform differently while modeling different types of mobile user behavior. For example, *Pre-filtering* based models performed well with the temporal aspects of usage while underperforming with other aspects. In general, semantic place-powered models outperformed semantic place-ignorant models and user personalized models outperformed aggregate level models.

Table 7 Research questions, publications and the main results of the thesis

Research question			
RQ1: How to define and categorize mobile end user context as a synthesis of theoretical and practical viewpoints and acquire contextual information utilizing handset-based measurements?	RQ2: How to measure mobile device and service usage from handset-based data, and what types of mobile usage patterns do the measurements reveal?	RQ3: How are mobile devices and services used depending on certain use contexts of the mobile end user?	RQ4: How to incorporate contextual information into modeling the usage of mobile devices and services?
Publication			
1 & 6	2, 4 & 5	2, 3, 4 & 5	6
Main result			
- An end user context classification framework that maps conceptual and operational perspectives of mobile end user context. - Case example of acquiring contextual information: semantic place can be provided manually, sensed and/or derived. The derivation benefits from time-wise longer datasets and user personalized derivation models	- Application and usage session defined as units of measurement. - Mobile device and service usage occurs in bursts of activity, dominated by relatively short sessions and is communication and web browsing oriented. - Considerable diversity is observed across users.	- Mobile device and service usage varies between certain contexts (time, semantic place, battery level, device form factor, simultaneous usage of multiple devices)	- Three different incorporation approaches were studied and evaluated (in terms of the accuracy of modeling mobile user behavior). - None of the approaches dominate, but show circumstance specific differences. - In general, semantic place-powered models outperform semantic place-ignorant models.

6. Discussion

This chapter discusses and interprets the results introduced in the previous chapter. This is done from a few different points of view. First, the results are discussed from the academic research point of view. This includes especially the domains of context-awareness, user (human) behavior and mobile service usage research. Then, the results are discussed from the point of view of mobile service providers, by contemplating the practical implications of the results and the thesis topic area. Also, methodological and user privacy related implications are discussed because of their importance related to measuring and analyzing the behavior of individual people. Finally, the thesis is concluded with a discussion on research limitations and future research.

6.1 Research implications

The end user context framework (Publication 1) is an answer to the problem of merging the theoretical and practical perspectives of mobile end user context, especially for empirical and quantitative end user context related studies. Previous work on context-awareness has provided conceptual definitions and categorizations of context (e.g., Dey, 2001; Schmidt et al. 1999). These do not, however, discuss the approaches for acquiring context in any systematic way, because the purpose is to provide more general definitions and frameworks applicable in a range of target applications. In practical context acquisition efforts based on, for example, handset-based measurements, the possible context acquisition approaches become a relevant part of the process from the planning phase to communicating what was done. Some of the previous work (e.g., Henriksen & Indulska, 2004) has focused on the practical acquisition approach perspective of context, with lack of linkage to the theoretical and conceptual definitions, however. Finally, empirical handset-based studies observing contextual mobile device and service usage (e.g., Verkasalo, 2009a; Liang et al., 2011; Do et al., 2011; Böhmer et al., 2011) rarely position themselves in terms of either of the two perspectives. This does not mean that the studies do not communicate the data collection methods or the contextual information considered, but they do not link themselves to the broader picture.

The context framework proposed in this thesis is a tool for positioning individual context related studies within the broader picture of context, both conceptually and operationally. The approach taken towards the end user context

in this thesis leans against the general definition of Dey (2001) and can be described as representational rather than interactional (Dourish, 2004). The representational approach has its limitations regarding its pre-set type of nature and neglect of how activity affects other context and vice versa. However, the implementations of current context measurement methods, including the handset-based measurements, rely in any case on pre-set assumptions and data items to collect, making it difficult to adopt the interactional approach.

As mentioned in the introductory chapter of the thesis, the handset-based measurement approach utilized in this thesis falls into the realm of computational social science. Studying mobile user behavior on individual user level with a large number of users produces its own input into understanding some of the more general patterns in human behavior (Raento et al., 2009; Eagle & Pentland, 2009; Miller, 2012). On the high level, the bursty or cascading nature of mobile device usage observed in this thesis resembles many other human activity patterns from email and letter correspondence (Barabasi, 2005; Malmgren et al., 2008) to broker trades (Vazquez et al., 2006). Some authors (e.g., Barabasi, 2005; Karsai et al., 2012) are seeking universality in these patterns, while others (e.g., Stumpf & Porter, 2012) question the universality claims and emphasize the quest for the processes causing the patterns.

Overall, mobile device usage is relatively bursty, meaning that when usage occurs, it is likely to be followed by other usage in short intervals. On the other hand, the usage of modern mobile devices is daily, meaning that breaks on usage longer than, for example, one day are extremely rare. Furthermore, the natural daily rhythm of human life can be observed in the usage patterns. For example, breaks in usage corresponding to the sleeping time are evident. These considerations lead to similar implications to Malmgren et al. (2008) and Jo et al. (2012a) for separating the diurnal (daily, weekly, etc.) usage patterns to their own processes. In the case of mobile device and service usage the remaining processes are likely very complex, including the effects of a variety of contextual attributes, from the activity of communication partners and places of usage to social situations, and much more. Thus, the usage is difficult to explain with any universal models. It is also very likely that different processes drive the usage of different applications. For example, the usage of calling and messaging applications depends also on how others communicate through these channels, whereas the usage of maps and navigation applications depends more on the whereabouts of the user. This calls for dividing the analysis into different services and service classes, and utilizing a variety of contextual information.

With the above said, the results of this thesis imply that possibly the most important factor in describing mobile device usage is the user herself and her individual usage habits. While the usage varies, for example, in different semantic places and along different device battery levels, the largest variation is observed between users. Similar magnitudes of user diversity have been observed also in other studies, such as Falaki et al. (2010b) and Hintze et al. (2014b). This diversity emphasizes the need for user level methods in collecting and analyzing the usage data, and considering possible caveats in reporting

aggregate level results. With this in mind, the aggregate level results can be used, for example, in comparing some of the higher level usage measures between similar mobile device usage studies. For instance, the number of usage sessions per time unit, session lengths and device interaction time per time unit are on the same magnitude level in different studies (e.g., Rahmati & Zhong, 2009; Falaki et al., 2010b; Oliver, 2010; Hintze et al., 2014a; Hintze et al., 2014b), keeping in mind the differences in session definitions and including the results of this thesis. However, the more recent studies show somewhat higher levels for the measures, including a higher number of sessions, longer sessions and consequently higher interaction times. This indicates the increasing pervasiveness of mobile devices (even in the case of one device, such as smartphone), visible also in the constantly rising number of applications and services available for these devices. However, while the mobile application and service landscape is getting more fragmented in terms of what is available for use, several studies (e.g., Rahmati & Zhong, 2009; Shepard et al., 2011; Böhrner et al., 2011) still report that smartphone usage is communication oriented. The results of this thesis agree with this, but also recognize the growing number of other services. The traditional communication channels, such as mobile network voice calls and SMSs, are however facing big challenge from instant messaging, IP based calls and the variety of social network services. It is still, however, safe to say that the need for communication between people is not disappearing anywhere.

Of the myriad of different contextual aspects possibly affecting the usage of mobile devices and services, this thesis focuses mostly on the semantic place. The semantic place information was acquired through handset-based measurements with heuristics (Publications 2 and 3) and machine learning (Publications 4 and 6) based derivation approaches. The heuristic type approaches have been successfully utilized by several authors, including Verkasalo (2009a), Jo et al. (2012b) and Hintze et al. (2014b), while the examples of elaborate machine learning approaches include work, such as Zhu et al. (2013), Huang et al. (2012) and Montoliu et al. (2012). In the light of this thesis, both the simple heuristic and (relatively simple) machine learning approaches are able to identify places like *Home*, *Office/School* and *Elsewhere* relatively well. *Other meaningful places* prove to be somewhat more difficult. Similar results are provided also by Montoliu et al. (2012) (with an ensemble machine learning method), reporting high accuracy for home, workplace and “transport related”, while lower accuracies for the home and work of a friend, sports places, etc. This thesis reports results additionally on the effect of the amount (time-wise) of data for and the personalization level of the semantic place derivation models. Especially the personalization level results encourage for seeking, for example, nearest neighbor and collaborative filtering based methods for applying more user-specific models to previously unseen data.

The empirical observations of mobile device and service usage in the different semantic places of this thesis imply that the devices and services are used differently in different semantic places. For instance, the usage intensities at *Home* are in general lower than in other semantic places. Only part of this is

explained by the sleeping time. Other explanations can include the availability and requirements of other activities (house work, etc.) and usage substitution to other devices (TV for entertainment, PC for Web, etc.). The results of this thesis (Publication 5) suggest substitution from smartphones to tablets, and based on the evening oriented usage patterns of tablets, it can be hypothesized that this includes a good amount of *Home* usage. Usage in the other semantic places (more intensive, but shorter sessions), such as *Office/School* and *Elsewhere* might be reflected by the supposedly more hectic and time-table oriented nature of activities in these places. Other work, such as Verkasalo (2009a) and Hintze (2014b), report also the longest sessions occurring at home. Finally, however, all of the studies report the most overall usage occurring at home, simply because people spend the most time at home.

Analysis on individual application level shows differences in the semantic place sensitivity of different applications. While the most used applications related to calling, messaging and web browsing reflect, quite expectedly, the high level patterns of relatively low *Home* intensity and more uniform intensity between other semantic places, applications with more focused purposes (e.g., alarm clock and maps and navigation) relate more specifically to some certain semantic place. Also, for example, Do et al. (2011) report that certain applications appear more often in certain semantic places. Finally, this thesis reports varying usage also in different device battery levels and between smartphone and tablet devices. For example, in a survey conducted by Karikoski & Mäkinen (2012) users state that the device battery level indeed affects their usage (usage cut down when battery low). Hintze et al. (2014b) (along with Publication 5 of this thesis) provide one of the few empirical measurement results comparing smartphone and tablet usage. The results show, for example, that tablet sessions occur less often, but are longer than smartphone sessions. Additionally, Publication 5 is one of the first, if not the first work, to define and construct empirical measurement based multidevice usage sessions and characterize time-wise linked multidevice (smartphone and tablet) usage.

The variety between different mobile applications and services and their varying sensitivity to different contexts call for seeking different approaches for modeling the usage of mobile devices and services. This thesis examines different approaches for incorporating the semantic place (or other contextual) information into mobile user behavior models (Publication 6). Additionally, these models are compared with models without any semantic place information. The results reflect the complex nature of the overall mobile device usage in a sense that different incorporation approaches produce models of good performance under different circumstances (such as dependent usage variables). Similar circumstance specificity has been observed also in the domain of recommender systems (Panniello et al., 2014). The strengths and weaknesses of the approaches are found in different places, and the better mapping of them requires different experimental settings with different datasets and other contextual information.

6.2 Practical implications for mobile service providers

As already described in the introductory chapter of this thesis, the proliferation of mobile networks, devices and services has been rapid in the past few years and shows no signs of slowing down any time soon. On the contrary, for example if realized, the IoT (Internet of Things) paradigm will bring out more and more connected sensors and mobile devices and enhance the possibilities for new types of mobile services. Even the current smartphone era has pushed new types of services to the mobile domain, making an increasing amount of service providers to become also mobile service providers. Contextual information is seen as a central component in mobile services. The hypothesis is that this information helps the services to better adapt to the capabilities and needs of the user.

Mobile service providers offering their services through mobile applications (e.g., via the different app stores) are capable of collecting user level data related to the usage of the service through the application. Indicated by the terms of agreement displayed in conjunction with the application downloading processes, it is also very likely that most of the service providers are collecting at least some of this data. This type of data is similar to data collected via the handset-based measurements and provides similar possibilities. The end user context framework introduced in Publication 1 can thus work as a guiding tool also in the service development. The production implementations of mobile services can be restricted, for example, by computation, data storage and user privacy issues. The framework can help in identifying what contextual information is available, can be collected effectively and by what means, and even in identifying relevant reference material from the academic research.

Through the modern smartphone and tablet applications mobile service providers have access to the usage data of the particular application (on user level from the application side and on aggregate level from the server side). Even though some applications request access to additional data, this is still limited, for example, by privacy concerns. Work such as this thesis can provide a wider (in terms of applications and services used) view on the overall mobile device usage. This can be useful for benchmarking, for instance. Also, usage session level analysis can provide insight on the “application bundles” where certain applications and services are used. This might lead into considerations of bundling these services already on the service provider side. Adding the multidevice session and multidevice usage into the picture, considerations, for example, on transitions between the same service and different available devices can be done on a more informed basis.

On the actual result level, several items of this thesis provide practical implications for mobile service providers. For example, the general level usage results demonstrate that human generated mobile device and service usage displays some recognizable characteristics, including burstiness and diurnal patterns. As demonstrated in Publication 4, the human generated patterns are relatively easily recognizable from the more regular device (machine) generated patterns. Separating the two enables a more accurate analysis of both of them. This can include the behavioral analysis of human usage and mobile

network and other computational infrastructure optimizations regarding the non-human patterns. Another important result for mobile service providers is the diversity across users. This is visible on all levels of mobile device and service usage, meaning that it involves all types of mobile services intended for human use. This diversity implies that averaged measures describe only a small portion of users and that the services need to be personalized to bring better value to the users. The diversity also questions flat rate pricing of mobile services. If one user uses a service (e.g., voice calls, data for Web browsing or a music streaming service) one hundred times more than another user, it is questionable to charge both the same amount. In this case the light user subsidizes the heavy user. On an individual level, one can view this as the subsidizer's problem (if she notices or cares), but if the pricing is seen unfair, these users might change their service providers (see, e.g., Courcoubetis & Weber, 2003, Chapter 7).

In the mobile domain one viable option for moving towards more personalized services is indeed the utilization of contextual information (see, e.g., Zimmermann et al., 2005). As described above, the acquisition of this information is easier than ever in this era of smartphones, tablets and sophisticated data collection systems. On higher level the results of this thesis show that most of the contextual aspects (such as time and semantic place) examined can characterize some of the mobile usage. This is, however, only a good basis for further investigation towards actionable practical implications. Application level contextual usage patterns imply that different services have different dependencies related to contextual usage (even in the case of such high level contexts as the semantic place). For individual mobile service providers, the situation simplifies to investigating and applying the particular information relevant for the particular service. However, the large-scale studies conducted especially in the academia can help in locating this particular information. The results regarding the different approaches for modeling the contextual usage of mobile devices and services further promote the case-specificity of utilizing contextual information in mobile services. This means application or service level implementations with as user-specific models as possible if granular enough data is available.

Finally, let us reflect the results of this thesis on the considerations of business models for context-aware mobile services by de Reuver & Haaker (2009) (introduced also in section 2.3.2 of this thesis). In the *Service domain* targeting, value creation through personalization and generation of trust is seen important. As said, in the light of the user diversity observed, personalization is important. This thesis investigates only post-adoption usage, rendering the results inconclusive for commenting the targeting claim. However, the user diversity definitely justifies the identification of the heavy users as the main target. User level data and personalization are very privacy sensitive issues and thus the importance of generating trust is evident. In the *Technology domain* security, system integration for personalization intelligence and management for user profiles are emphasized. The system integration concerns, for example, the acquisition of user level data. As mentioned, collecting data similar to

those collected with handset-based measurements is possible to some degree through the mobile applications. For example, Google Android has developer APIs²⁴ for acquiring sensed context from the sensors of the device. Apple iOS also provides some derived context based on location data available through its APIs²⁵. The further derivation can be performed either locally on the device or on the service provider's servers, depending for example, on computational restrictions. Additionally, the signing up process for the services and configuration options available for the user can be used to request manually provided context. Security and proper user profile management are required enablers for personalization and trust generation. In the *Organizational domain* the division of roles and network openness and government are emphasized. In the light of this thesis, this relates to the division of roles mainly again in acquiring the contextual information. For example, a service provider can implement the acquisition internally, or use some third party context mediators. In the *Financial domain* pricing and cost and revenue division is seen important. Referring again to user diversity and the earlier discussion on flat rate pricing, user level and contextual information can also enable more personalized pricing schemes that reflect the actual usage, including for example, pricing that adapts to a place (e.g., calls at home cheaper) and time of use (cf. peak load pricing (e.g., in Courcoubetis & Weber, 2003, Chapter 5)). Also, contextual information is hypothesized to enable a more targeted and efficient advertisement, making the advertisement based pricing models more attractive.

6.3 Methodological and privacy implications

The characteristics which make the handset-based measurements an attractive method for studying the contextual usage of mobile devices and services pose also several issues regarding user privacy. For example, the main device utilized in this thesis is the smartphone which is regarded as a highly personal device. This combined with the fact that the data is collected on individual device level means that relatively personal information on a granular level can be acquired. According to Ackerman (1999) information privacy is bound with control, referring in this case to the entity owning the information. Additionally, users' concerns for privacy depend on what information they are asked to give up (Ackerman, 2001). Publication 1 discusses the end users' sense of ownership and control from the *Operational perspective* of the end user context framework (see also World Economic Forum, 2011). In short, the users likely feel the highest sense of ownership and control towards manually provided information, since they have produced it themselves. In the case of sensed information the sense of ownership and control can move away from the user towards the party or organization enabling the sensing and data collection. Finally, in the case of derived information the sense of ownership and control

²⁴ <http://developer.android.com/guide/topics/sensors/index.html>

²⁵

https://developer.apple.com/library/prerelease/ios/documentation/CoreLocation/Reference/CoreLocation_Framework/index.html#//apple_ref/doc/uid/TP40007123

moves even further from the user to the party or organization that has conducted the derivation. For example, the derivation methods can be regarded as proprietary assets. Paradoxically, the user is most likely the least aware of the particulars of the derived type of information, even though it might reveal surprisingly personal things about her and her habits. Additionally, some differences are observed in the users' willingness to disclose personal and contextual information depending on the conceptual type of the information (Publication 1). For example, the willingness to disclose the exact location can be lower for the user, than disclosing the type of mobile device used. Willingness to disclose information, however, boils down to the trust between the user and the data collecting entity.

The introduction of and rising interest towards device monitoring as a research method has, rightfully so, spurred discussion on the topic of personal data ownership also in the academia. For example, Pentland (2009) has proposed that individuals should have the ownership of the personal data they have produced. This means that they should be able to access and remove the data at any time. Moiso & Minerva (2012) have, consequently, proposed that a new third party actor is needed for managing the personal data. The idea is similar to banks providing monetary management services. However, as the users' ownership and control over the data increases, the possibilities for diverse research might be restricted. For example, the control exercised by users' might lead into more partial datasets. Also, the reproducibility of results diminishes if some data is deleted after the research.

In the academic setting, no prevailing solutions on how to conduct device monitoring measurements and preserve the users' privacy exist. Usually the approaches are quite case specific and individual studies provide guidelines for conducting similar data collection and research efforts. The actual data collection effort conducted for Dataset 1 utilized in this thesis is depicted in detail in Karikoski (2012). A very similar approach was followed also collecting Dataset 2²⁶. In terms of preserving user privacy the principles of Langheinrich (2001) were followed closely. For instance, the data was anonymized by a person different to those analyzing the data. However, as discussed, for example, by Ohm (2010), sophisticated de-anonymization methods might render current anonymization techniques infeasible as trusted privacy preservation measures. Finally, it needs to be noted that privacy overall is a complex construct reflected through technological, social and legal domains and as observed in the past people's conceptions of their personal privacy change as the times change.

6.4 Limitations

Contemporary mobile services, which are often used over the Internet, can be regarded as part of the new media. Already Livingstone & Bovill (1999) described the research of new media as a research of a moving target, because

²⁶ In the case of Dataset 3 the data collection was part of regular user panels managed by a private company (Verto Analytics) and thus the process follows the company's privacy guidelines.

new media is evolving constantly. It is also fair to say that the whole mobile ecosystem has evolved considerably even during this thesis research. In this light, empirically studying the usage patterns of mobile devices and services evidently has a snapshot type of nature. Consequently, it is difficult to assess which of the patterns represent some more underlying and long-term aspects and which are more short-term, as pointed out, for example, by Haddon (2005). In this thesis more than one dataset were utilized, leading to a few snapshots. Additionally, some of the more underlying aspects were investigated. These include the nature of contextual information, different approaches for contextual user modeling and the more high-level patterns of the mobile user behavior, including usage session definitions and linking the usage patterns to other human behavior research. The relevance of different contextual information might also change over time. However, the basic semantic places can be seen relevant to many aspects of mobile user behavior as long as people are still moving around. In any case, the results should not be regarded as truth, but rather as descriptive observations.

Handset-based measurements are an emerging and versatile method for studying human and user behavior. However, as Church et al. (2015) point out the method has limitations concerning especially the replicability and generalizability of results. Properly describing the datasets in terms of participants, collection dates and time, collection methods, incentive schemes, etc. and the analysis itself provides good means for reproducibility. Replicability, on the other hand, is a different issue. As described by Church et al. (2015) this type of a data collection effort is a “one-shot” operation in a dynamic environment. A new setup of exactly the same research setting is not possible. Also the generalizability of results gained from certain user populations during a certain time period using certain devices is highly questionable. A Finnish Symbian user university student panel cannot be claimed to generalize to much wider populations than that. However, as Church et al. (2015) emphasize, there is still great value in studying these individual populations at specific points in time. The favoring argument is that the individual researchers and the community as a whole can contrast results and experiences based on different populations, form a better understanding about the different types of mobile users and their user behaviors, and finally identify aspects that separate the users and aspects that tie them together.

This thesis utilizes three different handset-based datasets. Dataset 1 consists mainly of Finnish male university students that at the time used Symbian smartphones. These users were identified as early adopters of mobile services (Karikoski, 2012) and one can speculate that the usage of early adopters might be similar to the later usage of the later adopters. Dataset 2 is similar to Dataset 1. However, the population is considerably smaller but the variety in devices is larger. One notable issue regarding the student-heavy populations and semantic places is that the mobility and diurnal patterns of students might differ, for example, from a regular office worker’s patterns to some degree. Dataset 3 is a considerably more recent dataset than the first two. Additionally, the number of participants is relatively large and the participants come from

the US. These participants are, however, paid for participation. This alone is expected to bias the sample. Despite the clear limitations of the individual populations, even the descriptive results of this thesis can be seen as a valuable part of the community wide effort, in the spirit of Church et al. (2015), to understand the complexities in mobile device and service usage.

Some additional limitations of the thesis include the limited contextual information used, usage session definitions, identification and classifications of mobile services and applications and assumptions of the personal nature of the devices. Under technical and resource limitations and in adopting the representational approach to context, some contextual information is available and some is not. This means that only a part of the user's situation is characterized. This thesis has, however, intentionally taken the approach to call even this partial information context (encouraged by Dey (2001)) and additionally taken an effort to position this information within the larger frame of "acquirable" contextual information (hence, the end user context framework of Publication 1). Filling in the framework with individual studies goes again with the spirit of Church et al. (2015). The time-window based definition of a mobile usage session is limited because a numerical threshold obviously cannot grasp the true intentions of the user. In any case, this type of an approach is prevailing in the literature with the lack of agreement on the actual threshold value, however. This thesis conceptually formalizes the definition based on Allen's temporal interval relations. In a forward-looking manner, the definition also supports multidevice usage. Deciding which mobile service or an application belongs to which category introduces subjectivity to the analysis. This subjectivity is alleviated by utilizing the service classification framework of Smura et al. (2009) as much as possible. Finally, the assumption that smartphones and especially tablets are personal devices predominantly used by one person can be questioned. However, the panel participants stated in the pre-questionnaires that they regard the devices as their own.

6.5 Future research

As already discussed related to the research limitations, future research should include more similar studies to map out a more comprehensive picture of the dynamic mobile device and service usage research area. This should obviously include different combinations of research settings, data collected, methods used and research question. More specific to this thesis, one obvious future research direction is to include a bigger variety of contextual information in the analysis, starting, for example, from higher granularity in the semantic places. Also, one highly important element of contextual information, however outside the scope of this thesis due to technical limitations, is social context (e.g., the nearby people and social network structures of the users). New emerging technologies can substantially help in acquiring the more diverse data. Smartphones and tablets are by no means the only devices the device monitoring type of measurements can be extended to. Smartwatches, activity bracelets and all kinds of external sensors envisioned related to the IoT para-

digm could be utilized in characterizing the mobile users' situations more comprehensively. This, however, requires better guidelines regarding the privacy issues. For studying especially the semantic place related usage of mobile devices and services, the bigger diversity in devices monitored could warrant, for instance, seeking explanations for the varying usage from device substitution. Furthermore, with additional sensors also substitution between mobile device usage and other activities could be investigated. The above means also that the contextual information acquisition and modeling approaches are in need of constant development. Finally, as Church et al. (2015) mention, in this type of research a topic is definitely not fully studied with a one or two "one-shot" studies conducted with certain populations in certain cultures. New studies with varying populations, even with the same research questions, are needed.

On the more general level, the difficulties arising from the snapshot type of nature of device monitoring based usage studies could be alleviated with more continuous data collection efforts. Currently, the longest spanning academic data collection efforts have been limited to less than two years. Advancements in databases, big data frameworks and analysis tools enable the efforts technically. The bottleneck is in participant recruitment and in legal data management issues. However, the current trend towards higher levels of digitalization and more pervasive measurement of everything will require more systematic approaches (e.g., the "banks" of personal data) for data management on the level of the whole society. Research wise the promotion of open datasets is also desirable. This would increase transparency, cross-disciplinary research and comparison of different datasets for the more comprehensive picture.

The mentioned cross-disciplinary research does not mean only that the different datasets are utilized independently in different domains. For example, Willinger et al. (2009) argues that even the most rigorous mathematical analyses can be rendered useless without a deeper understanding about the domain the data collection was conducted in. Thus, the system level scientists with versatile mathematical skills should collaborate with domain experts for the most fruitful results. For example, the quest for identifying the underlying mechanisms behind human action patterns, emphasized by Stumpf & Porter (2012), should be more achievable in this type of collaborations.

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