Department of Communications and Networking

Characteristics of mobile technology diffusion

Quantitative research of mobile handset features

Antti Riikonen

Aalto University

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Abstract

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Abstract

Rapid innovation in the mobile industry, and the consequent evolution of mobile handsets from basic phones to advanced multipurpose devices, causes new challenges for the research on mobile technology diffusion. Previous innovation diffusion research has focused on explaining how and why the mobile telephony and mobile handset generations spread. However, these levels of analysis provide limited understanding on the diffusion of individual technologies and product features.

The purpose of this dissertation is to measure, conceptualize, and provide empirical evidence on how new mobile technologies spread. The focus is on mobile handset feature diffusion, and especially on factory-installed software and hardware features. For the research, several quantitative datasets were collected from Finland during 2003-2012. These data provide complementing viewpoints, from mobile handset sales volumes, prices, and device installed base to mobile service usage, enabling holistic analysis of the phenomenon.

The research provides a methodological contribution by creating a framework for measuring the diffusion of complex technological innovations, and by comparing several methods and datasets. The results highlight the importance of using clearly defined measures when analyzing technology diffusion, due to the differences in the available datasets. Theoretical contributions of the research include applying well-known diffusion models to the new dataset and providing empirical evidence on the relationship of mobile handset features and lifetimes.

The dissertation also provides domain-understanding on mobile technology diffusion patterns and their practical implications. Mobile technology diffusion follows an s-shaped pattern, with high variations in the duration of the introduction stage prior to the takeoff with fast growth. The research also found typical price levels for mobile technology and feature takeoff, and associations between mobile handset sales and prices to be relatively linear for the technologies. Overall, the traditional innovation diffusion research methods were found to be applicable for studying mobile technology and product feature diffusion.

Keywords Technological innovation, diffusion, mobile handset, product feature, Internet protocol

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Tekijä
Antti Riikonen

Väitöskirjan nimi
Mobiiliteknologioiden leviämisen ominaispiirteet: Kvantitatiivinen tutkimus matkapuhelinten ominaisuuksista

Julkaisija Sähkötekniikan korkeakoulu

Yksikkö Tietoliikenne- ja tietoverkkotekniikan laitos

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Tutkimusala Tietoverkkotalous

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Tiivistelmä

Nopea innovointi mobiiliteollisuudessa, sekä siitä seurannut kehitys peruspuhelimista edistyneisiin ja monikäyttöisiin laitteisiin, aiheuttaa uudenlaisia haasteita mobiiliteknologioiden leviämisen tutkimiseen. Aikaisempi tutkimus innovaatioiden diffuusiosta on selittänyt kuinka ja miksi matkapuhelimet ja niiden teknologiset sukupolvet leviävät. Tämä analyysin taso tarjoaa kuitenkin rajoitetutusti ymmärrystä yksittäisistä teknologioista ja laiteominaisuuksista.

Tämä väitöskirja mittaa, käsitteellistää ja tuottaa empiiristä aineistoa uusien mobiiliteknologioiden diffuusiosta. Työ keskittyy matkapuhelinteknologioiden ja erityisesti tehdasasennettuihin laitteisto- ja ohjelmisto-ominaisuuksiin. Vuosilta 2003-2012 tutkimusta varten kerätyt aineistot edustavat toisiaan täydentäviä näkökulmia diffuusioilmiöön, matkapuhelinmallikohtaisista myyntitiedoista, -hinnoista, sekä laitekannasta mobiilipalveluiden käyttöön.

Tutkimus tekee menetelmäkontribuution luomalla viitekehyksen kompleksisten teknologisten innovaatioiden leviämisen mittaamiseen sekä vertailemalla metodeja ja aineistoja toisiinsa. Tulokset korostavat selkeästi määriteltyjen mittareiden tärkeyttä saatavilla olevien aineistojen välisistä eroista johtuen. Teoreettiset kontribuutiot sisältävät tunnettujen diffuusiomallien soveltamista uudenlaiseen aineistoon, sekä empiirisiä tuloksia matkapuhelinten tuoteominaisuuksien ja eliniän suhteesta.

Väitöskirja tuottaa myös toimialaymmärrystä mobiiliteknologioiden diffuusiomalleista ja niiden käytännön merkityksestä. Teknologioiden leviäminen noudattavaa s-muotoista kuvaajaa, sisältäen isoja eroja leviämisen alkuvaiheessa ennen nopean kasvun takeoff-pistettä. Tutkimus löysi tyypillisen hintatason mobiiliteknologioiden ja ominaisuuksien takeoff-pisteelle sekä näytti matkapuhelinten hintojen ja myyntimäärien suhteen olevan melko lineaarinen teknologiatasolla. Perinteisten innovaatioiden diffuusiossa käytettyjen tutkimusmetodien näytettiin yleisesti soveltuvan mobiiliteknologioiden ja tuoteominaisuuksien leviämisen tutkimiseen.

Avainsanat Teknologinen innovaatio, leviäminen, matkapuhelin, tuoteominaisuus, Internet-protokolla

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Helsinki, 23 November 2016
Antti Riikonen

Contents

List of Abbreviations and Symbols

AIC	Akaike Information Criteria
EDGE	Enhanced Data rates for GSM Evolution
FM	Frequency Modulation
GPRS	General Packet Radio Service
GPS	Global Positioning System
HTML	Hypertext Mark-up Language
HTTP	Hypertext Transfer Protocol
HSDPA	High-Speed Downlink Packet Access
HW	Hardware
IETF	Internet Engineering Task Force
IP	Internet Protocol
IPv4	Internet Protocol version 4
IPv6	Internet Protocol version 6
Java	A computer programming language
MMS	Multimedia Messaging Service
OLS	Ordinary Least Squares
OS	Operating System
RTP	Real-Time Transport Protocol
RTSP	Real-Time Streaming Protocol
SSE	Sum of Squared Errors
SSL	Secure Sockets Layer
SW	Software
TCP	Transmission Control Protocol
TLS	Transport Layer Security

UDP	User Datagram Protocol
WAP	Wireless Application Protocol
WLAN	Wireless Local Area Network
WCDMA	Wideband Code Division Multiple Access
WWW	World Wide Web

a	Saturation level parameter of a diffusion model
b	First parameter of a diffusion model
B	Bass diffusion model
c	Second parameter of a diffusion model
d	Number of discards
$f(T)$	Probability density function as function of unit lifetime
$F(T)$	Cumulative probability density function as a function of unit lifetime
G	Gompertz diffusion model
L	Simple Logistic diffusion model
m	Handset model
n	Number of units in use
s	Unit sales volume
t	Time
T	Unit lifetime
t^*	Inflection point
t^{**}	Takeoff point
$Y(t)$	Cumulative form of a diffusion model as a function of time

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. Riikonen, Antti; Smura, Timo; Kivi, Antero; Töyli, Juuso. 2013. Diffusion of mobile handset features: Analysis of turning points and stages. Telecommunications Policy, volume 37, issues 6-7, pages 563-572. ISSN: 0308-5961. DOI: 10.1016/j.telpol.2012.07.011.

2. Riikonen, Antti; Smura, Timo; Töyli, Juuso. 2015. Price and sales volume patterns of mobile handsets and technologies. International Journal of Business Data Communications and Networking (IJBDCN), volume 11, issue 2, pages 22-39. ISSN: 1548-0631. DOI: 10.4018/IJBDCN.2015070102.

3. Riikonen, Antti; Smura, Timo; Töyli, Juuso. 2016. The effects of price, popularity, and technological sophistication on mobile handset replacement and unit lifetime. Technological Forecasting and Social Change, volume 103, pages 313-323. ISSN: 0040-1625. DOI: 10.1016/j.techfore.2015.11.017.

4. Levä, Tapio; Riikonen, Antti; Töyli, Juuso; Hämmäinen, Heikki. 2014. A framework for measuring the deployment of Internet protocols. International Journal of IT Standards and Standardization Research (IJITSR), volume 12, issue 1, pages 38-62. ISSN: 1539-3062. DOI: 10.4018/ijitsr.2014010103.

Author's Contribution

Publication 1: Diffusion of mobile handset features: Analysis of turning points and stages

The original idea for the publication was formed jointly with the author, Smura, Kivi, and Töyli. The author assembled the manuscript and was the main author of all Sections. The publication was edited together with Smura and Töyli, while Kivi provided comments.

Publication 2: Price and sales volume patterns of mobile handsets

The original idea for the publication was formed jointly with the author, Smura, and Töyli. The author collected the data, conducted the analysis, assembled the manuscript, and was the main author of all Sections. The author edited the manuscript, while Smura and Töyli provided comments.

Publication 3: The effects of price, popularity, and technological sophistication on mobile handset replacement and unit lifetime

The original idea for the publication was formed jointly with the author, Smura, and Töyli. The author collected the data jointly with Smura, and conducted the analysis. The author assembled the manuscript and was the main author of Sections 1, 2, 3, 5, and 6. Smura and the author edited the manuscript together, while Töyli provided comments.

Publication 4: A framework for measuring the deployment of Internet protocols

The original idea for the publication was formed jointly with the author, Levä, and Hämmäinen. The author and Levä together developed the framework and applied it to the example market. The author was responsible for diffusion data collection and data analysis. The author was the main author of Sections 3 and 5, and edited the rest of the sections together with Levä, while Töyli and Hämmäinen provided comments.

1. Introduction

1.1 Background

Mobile handsets are one of the most widely used technology products globally. The first mobile handsets were introduced in the 1980s, and since then mobile devices have spread fast. There were an estimated 3.4 billion unique mobile subscribers (GSMA, 2014) and 6.7-6.9 billion mobile subscriptions globally in 2013 (ITU, 2013; GSMA, 2014). Over the decades, the mobile handset has evolved from a basic phone to an advanced multi-purpose device with a high number of integrated technological innovations, such as touch-enabled displays, positioning chips, and fast packet data connectivity, enabling the use of different networks and services. Because mobile handsets converge several previously separate products, like cameras and maps, people's time consumption increasingly concentrates around mobile devices. Therefore, better understanding of the evolution of mobile handsets and the spread of mobile technologies is of interest for several industries and academia.

Innovation diffusion literature studies how innovations spread in a market (Peres, Muller, & Mahajan, 2010). Traditional diffusion research often assumes the adoption of an innovation to be a simple binary event, estimated by using, for example, product sales or subscription data of mobile handsets. Previously, literature (see, e.g., Rogers, 2003) has focused on the diffusion of new product categories, such as television or mobile phones, or product generations, such as black and white and color televisions. The diffusion of new products and generations has been shown to follow an s-shaped diffusion pattern. Several studies have also provided explanations for that pattern, such as diffusion of information, as well as adopter, innovation, and market related characteristics. For example, price has been identified as an important determinant of both sales and diffusion, especially in the early stages of diffusion (Peres et al., 2010), and studies have shown that a decreasing price pattern is relatively usual with new product categories (Bayus, 1992).

With mature and fast-developing technology products, such as mobile handsets, several challenges and opportunities arise in the context of innovation diffusion research. For example, the use of traditional data sources is difficult. In maturing markets an increasing share of unit sales consists of replacement purchases (Bayus, 1988). Traditional diffusion models (e.g., Bass, 1969) assume all purchases to be first-purchases and, therefore, do not evaluate the replacement process in other terms than substitution from one generation to another. Therefore, modeling and estimating the replacement timing and unit lifetimes becomes important (e.g., Islam & Meade, 2000). In addition, in mature technology product markets the manufacturers introduce new features into the products with a rapid pace to differentiate from competition and to stimulate device owners to upgrade their existing units. This poses challenges for defining distinct product generations, as the variety in available product feature combinations of the sold product models is high. Therefore, in the case of technology products, like mobile handsets, it becomes potentially beneficial to focus on the level of the product features. However, few empirical studies on replacement and product feature diffusion, especially in the case of mobile handsets, are available (Kivi, Smura, & Töyli, 2012).

Mobile handset features are also a valuable research area due to their varying and complex nature. The features can take the form of hardware features, such as touch screen, or software, such as applications or Internet protocols. Hardware features are often relatively simple factory-installed features, which cannot be notably upgraded or updated once acquired. However, many features are enablers or platforms for other features or applications. For example, touch screen enables the consumption of higher-quality video or new type of games, and Internet protocols provide the basic means to communicate between the device and the network, enabling many services and applications on top of that connection.

1.2 Research questions and scope

Research on product feature diffusion benefits the academia by providing means to better understand how new complex technology products evolve and technologies spread into use. In addition, research on the diffusion of hardware and software features provides tools for practitioners from device vendors to application and protocol developers to do better product planning and development decisions. In this dissertation, a holistic viewpoint on technology diffusion was taken, to provide quantitative empirical evidence on how these new technologies spread, and to conceptualize the complex process and its measurement. For this purpose, three selected research questions are studied:

RQ1. What are the diffusion patterns of mobile handset features?

RQ2. What is the relationship between mobile handset features, prices, and sales volumes, and their effect on handset replacement?

RQ3. How to measure the deployment and diffusion of mobile handset features?

The scope of the research includes the product category of mobile handsets. All research questions are approached by using empirical time series data on mobile handset retail sales, installed base, usage, and features. Research question 3 combines methodological and theoretical contributions by also conceptualizing measurement methods and their suitability for different purposes.

For the research question 3, Internet protocols were selected as an extreme example of complex technologies, also linking devices and networks.

Figure 1 shows the linkages between the research questions and the publications. The arrows indicate how the results of each article were further utilized in other publications. For example, the results of Publication 1 were important input for building the framework in Publication 4. Dashed arrow from Publication 3 to 4 indicates a weaker contribution. Analysis of the installed base provides understanding of the mobile handset feature diffusion patterns for RQ1 (Publication 1). Then, research question 2 is answered by studying, first, handset sales volume and price patterns (Publication 2), and then correlating sales and installed base datasets (Publication 3) to enable detailed analysis on the replacement process. Last, based on the accumulated experiences of the data collection efforts and previous analyses, a conceptual framework is developed and illustrated for Internet protocol diffusion to answer RQ3 (Publication 4).

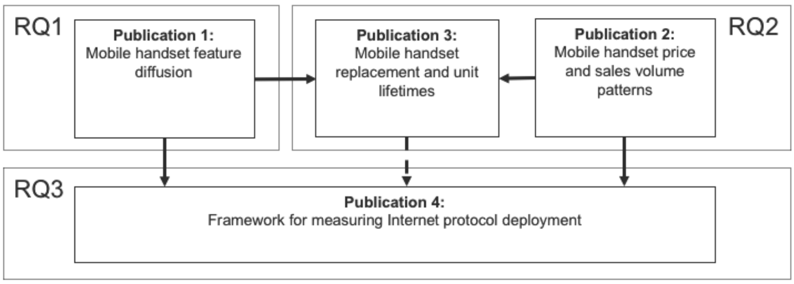

Figure 1. Relations of the publications and research questions.

Four types of research data were collected from Finland over the period of 2003 to 2012. These include feature data on the technologies integrated to mobile handsets, retail sales data on mobile handset sales volumes and prices, installed base data on mobile handsets in use, and usage data on the share of population using different mobile features and services.

The Finnish market is an interesting one to study in the context of this disseration. The use of mobile phones, as well as the quality and coverage of mobile networks in Finland has been traditionally high, representing an early example for emerging markets. The Finnish market also has some peculiarities. During the research period, Nokia was a very popular handset manufacturer in the market, being based in Finland, which could mean that the profile of devices in use in Finland is to some extent different from many other markets. In addition, a large share of mobile handsets in Finland are purchased separately from mobile subscriptions, and bundling of devices and subscriptions was even prohibited before 2006. This means that consumers have a good visibility and understanding on the actual price of the device, as opposed to purchasing a bundle of mobile subscription and the device for a combined monthly fee.

1.3 Definitions

To further position the research, key terms are defined in an alphabetical order as follows:

Deployment: a process during which an innovation advances from a specification into actual use by the potential population of users. The difference between deployment and diffusion is that deployment includes also the implementation and commercialization steps before the actual diffusion of an innovation.

Diffusion: a process during which an innovation spreads within a population of potential users. This dissertation focuses on human users as the main unit of adopters.

Internet protocol: a communication protocol used in the Internet, and in the scope of this dissertation, by mobile handsets. Therefore, Internet protocols are also mobile technologies.

Mobile handset: a wireless and pocket-sized device capable of voice calling via cellular network connectivity. The term “mobile handset” refers to both traditional mobile phones capable of only voice calling and text messaging, as well as to more advanced smartphones with a computer-like operating system.

Mobile technology: a technology integrated into a mobile handset. Referred to also as “mobile handset feature”.

Replacement: a process during which the existing units of a product in use are discarded and replaced with newer ones.

Unit lifetime: the time that a single unit of a product remains in use.

1.4 Structure of the dissertation

The structure of the summary part is as follows. Section 2 provides a literature review by introducing the theoretical background of the dissertation. In Section 3 the research approach, collected datasets, and selected methods are described. Section 4 summarizes the research results. The dissertation closes in Section 5 with a discussion of the main contributions and implications, as well as the limitations and future research suggestions. The publications are included as appendices.

2. Theoretical background

This section presents a selective review of innovation diffusion and related literature, forming the theoretical background of the dissertation. Rogers (2003, original work published 1962) wrote one of the most cited books on the multidisciplinary area of innovation diffusion, summarizing many important concepts. After the seminal works by Rogers, Mansfield (1961), and Bass (1969) among others, the area has been widely researched especially in social sciences, such as economics, marketing, management, and sociology.

2.1 Innovation-development process

According to Rogers (2003), an innovation is generally "an idea, practice, or object that is perceived as new to an individual or another unit of adoption". Following this definition technological innovations are simply innovations that consist of new technology, hardware and software. As technological innovations are usually commercialized as products, the term "new product" is also often used in the innovation diffusion literature (e.g., Peres et al., 2010).

Technological innovations require several activities before they can be taken into use by the adopters. Rogers (2003) calls this process as innovation-development process, and divides it into six high-level steps: 1) need recognition, 2) research, 3) development, 4) commercialization, 5) diffusion and adoption, and 6) consequences. First, recognition of a specific problem or need for the end users leads to the research and development activities. Then, in step three the developed innovation is commercialized, meaning that the developed invention is transformed into a product, product component, or service that is available for customers to purchase in a market. During the diffusion and adoption step the innovation is acquired and adopted by the potential market and, therefore, spreads into use. Last, in the consequences step the adoption (or rejection) decision is re-evaluated, leading to possible changes in the individuals or the social system. According to Rogers, the process can vary in terms of order and overlap of the steps, depending on the innovation. Other closely related process definitions have also been suggested in previous literature (e.g., Tornatzky, Fleischer, & Chakrabarti, 1990; Gopalakrishnan & Damanpour, 1997). Different definitions cover roughly the same high-level activities, but might have differences in the details depending on, for instance, whether the process is linear or more complex with parallel activities, the unit of adoption, and type of innovation.

To better understand the nature of the whole process, different categorizations of innovation have been proposed. For example, separations have been suggested between product and process innovations, incremental and radical innovations, as well as administrative and technical innovations (Gopalakrishnan & Damanpour, 1997). Especially the characteristics related to the newness of the innovation are important in many of the categorizations. The newness of an innovation has been identified, for example, based on newness to the customer, newness to the market, and newness to the world among others (Garcia & Calantone, 2002). The higher the newness of an innovation is, the more discontinuous or extreme change it has on the industry, market, or technology.

The development of new innovations and the consequent diffusion is mainly determined by interplay between providers and end users in terms of technology-push and demand-pull (Zmud, 1984). However, the importance of these two forces fluctuates over time (Prescott & Van Slyke, 1997; van den Ende and Dolfsma, 2005). In addition to technology providers, also governments can be active in pushing technologies to the market by using regulations (Carter Jr., Jambulingam, Gupta, & Melone, 2001).

Different streams of literature focus on a specific part of this process. For example, research on the commercialization step is often related to the competitive strategies of the innovation providers. Examples of competitive producer decisions include ones related to standards (Besen and Farrell, 1994), product versioning (Shapiro & Varian, 1998), product bundling (Bakos & Brynjolfsson, 1999), and pricing (Lehman & Buxmann, 2009). From the diffusion and adoption step, research focuses either on micro-level innovation adoption or on the macro-level phenomenon of innovation diffusion. The individual's innovation adoption decision process can be roughly divided into pre-adoption, adoption, and post-adoption phases. Rogers (2003) calls this process an innovation decision-process, consisting of five different stages, during which an individual first gains knowledge of the innovation, then generates an opinion of the innovation and which leads to an adoption or rejection, implementation, as well as re-evaluation of the made decision. Classical diffusion research, on the other hand, is interested in the system level phenomenon, that is, the rate of adoptions in the market. In this dissertation, the focus is on this system level diffusion, which is introduced next.

2.2 Diffusion of innovations

2.2.1 Definition and determinants of diffusion

Rogers (2003) defines innovation diffusion as a process during which the innovation "is communicated through certain channels over time among the members of a social system". The research traditionally sees adoption as a simple binary event, and the target is to estimate the spread of the innovation over time by using, for instance, data on the number of purchases (e.g. Bass, 1969, Mahajan et al., 1990, Meade & Islam, 2006).

The diffusion, that is, number of cumulative innovation adoptions over time, usually forms an s-shaped curve (Rogers, 2003): initial low diffusion turns into fast growth and then slows down again when the innovation is nearing saturation, that is, the market potential. From the viewpoint of noncumulative adoption rate, the frequency distribution of adoptions follows a bell-shaped curve. However, also other patterns than the basic s-curve, or systematic deviation from the s-curve during specific phases of innovation diffusion, have been identified in the literature. An example of such deviation is the saddle (Goldenberg, Libai, & Muller, 2002), which is a pattern of decreased sales after an initial peak and before the actual larger growth in adoptions takes place.

The s-shaped diffusion pattern is explained by different factors in literature, including diffusion of information, adopter characteristics, innovation characteristics, and the environment. First, according to Bass (1969), the diffusion of information consists of two main sources: advertising and interpersonal communication between the members of the social system. Other types of social interdependencies have also been suggested in literature, such as social signals inferred from adopters and network externalities (Peres et al., 2010). Examples of social signals are status and group identity, which do not necessarily require communication between the members. Network externalities, or effects, are present when the value of an innovation increases as the number of adopters increases (Shapiro & Varian, 1999). Innovations with network externalities usually experience slow diffusion before a certain number of users are reached, after which the diffusion becomes self-sustaining (Rogers, 2003). For example, with communications services, such as text messaging, the value of the service is initially low due to small number of users, but increases fast after the most important communications partners adopt the service. This point is called by different overlapping terms in different streams of literature, such as the critical mass (Markus, 1987), the tipping point (Gladwell, 2000), and the takeoff point (Golder & Tellis, 1997).

Second, adopter characteristics, such as the innovativeness of adopters, have also been used to explain the s-shaped diffusion pattern. Rogers (2003) divides adopters into five adopter categories with varying "degree to which an individual (or other unit of adoption) is relatively earlier in adopting new ideas than other members of the social system". From high to low innovativeness, the categories are named as innovators, early adopters, early majority, and laggards. The categorization of Rogers based on normal distribution has, however, been criticized as too simplistic for many innovations (e.g., Mahajan, Muller, & Bass, 1990; Mahajan, Muller, & Srivastava, 1990). Further, between consequent generations of products, for example, leapfrogging (Goldenberg & Oreg, 2007) can take place. Leapfrogging means that by skipping one generation, the laggards often become innovators in the next one by adopting early.

Third, characteristics of the innovation itself have also an impact on the diffusion. Rogers (2003) divides innovation attributes into five categories, consisting of relative advantage, compatibility, complexity, trialability, and observability, all affecting how adopters experience the innovation, therefore, directly affecting the diffusion rate. Last, the environment where the innovation spreads, and its characteristics, can influence the diffusion. For instance, cultural factors have previously been linked with innovation diffusion (Tellis, Stremersch, & Yin, 2003).

For relatively simple consumer goods the assumption of binary adoption is true: the adopter either adopts or rejects the innovation after he or she has gained enough understanding of it. However, with complex technological innovations the assumption is not always valid (Shih & Venkatesh, 2004), meaning that the adoption decision and usage of the innovation become more continuous. For instance, a gap may emerge between the number of purchases, that is, “adoptions”, and the number of users. In other words, there are a notable number of individuals who acquire the innovation but do not take it into use. This gap was empirically identified in the information systems literature related to innovation adoption and implementation in organizations (e.g., Cooper & Zmud, 1990; Liker, Fleischer, & Arnsdorf, 1992), and is called the assimilation gap (Fichman & Kemerer, 1999).

To extend the traditional innovation diffusion literature, a stream of research has focused on the extending the binary adoption assumption to encompass different aspects of usage in relation to diffusion. Shih & Venkatesh (2004) used two constructs, variety and rate of use, to measure the use of technology products. According Shish & Venkatesh (2004), the nature of use evolves over the course of diffusion, leading to continuous use or disadoption. The usage patterns of the existing product can also affect the adoption of an upgraded or next generation version of the product, therefore, increasing the importance to study also the usage patterns in diffusion literature.

2.2.2 Product life cycle

Product life cycle (PLC) is a concept used especially in marketing and management literature (Golder & Tellis, 2004; Hauser et al., 2006) with a direct linkage to innovation diffusion. Bayus (1994) has defined the product life cycle concept generally as the “description of the evolution of unit sales over the entire lifetime of a product”. Product life cycle research divides the innovation lifecycle into four generic phases of introduction, growth, maturity, and decline, which, assuming all purchases as first-purchases, are relatively closely aligned with the ones used in diffusion research. Several studies on product life cycles have focused on identifying the turning points, especially the takeoff of products. The takeoff can be identified as the discontinuous sudden increase in sales, which follows the period with low or slowly increasing sales after the introduction (Golder & Tellis, 1997; Agarwal & Bayus, 2002; Tellis, Stremersch, & Yin, 2003).

Furthermore, the evolution of prices over the lifecycle of products has been extensively studied, as prices are important determinants of product life cycle sales volume patterns (Golder & Tellis, 1997) and diffusion (Horsky, 1990). Generally, prices and price patterns are determined by factors such as competition, consumer valuations, consumer heterogeneity, costs, and market saturation over time (Hernández-Mireles, 2010). Increased competition usually forces companies to decrease prices to protect their market share (Álvarez et al., 2006). Even without changes in competition, the experience curve effect, which includes learning, technological improvements, and economies of scale (Day & Montgomery, 1983), also enable a decreasing pattern by decreasing costs. Different adopter groups also have heterogeneous willingness to pay, which enables to use of price skimming by the producer. Therefore, theoretical research on optimal pricing often supports a decreasing pattern (e.g., Bayus, 1994b). Diffusion research also argues that often the price sensitivity of innovators and early adopters is lower than that of the other adopter categories (Goldsmith & Newell, 1997), supporting the decreasing pattern. However, in markets with indirect network effects between software and hardware, penetration pricing might be a better alternative to enable an initial buildup of the installed base of hardware devices when there is little software available (Clements & Ohashi, 2005).

Empirical studies on price patterns both model prices directly and include price as an explanatory variable in diffusion models. Several studies have shown that prices - and other marketing mix variables - have an impact on the product category level diffusion (e.g., Simon, 1979; Clements & Ohashi, 2005; Chintaguinta et al., 2009). In addition, depending on the product category and level of analysis, prices have been found to change gradually or with more sudden drops or increases. Golder & Tellis (1997) identified prices at takeoff for products introduced between the Second World War and 1990, showing that prices dropped on average to 63% of the introduction price at takeoff. Hernández-Mireles (2010) modeled price patterns of video games, and found that prices of individual games often experience sudden price decreases at some point during their lifecycle.

2.2.3 Replacement

When a technology or product matures, an increasing share of sales starts to shift from first-purchases, that is, people buying their first unit of the product, to replacement purchases, which mean that the buyer replaces the existing unit with a new one. Therefore, the phenomenon of replacements is important also from the viewpoint of innovation diffusion.

The owners of the existing units replace or upgrade the products for different reasons often other than breaking or wear and tear (Bayus, 1991). For example, manufacturers innovate improved versions or new product features so that there would be benefits from an upgrade for the owners of existing products (Okada, 2006). Therefore, in addition to durability, factors such as price (Bayus, 1988) and quality (Prince, 2009) have been linked with replacement cycles in empirical research. However, often the price and quality of a product are highly correlated and, for instance, Prince (2009) used price directly as a proxy for product quality. On the other hand, the effect of time has contrasting results by previous research. The lifetimes of products are often assumed to decrease due to the higher pace of innovation, supported, for example, by results of Gordon (2009) for personal computers, but also contrasting findings have been made. For example, Bayus (1988) and Kivi et al. (2012) identified relatively stable lifetimes over time for the studied products.

2.3 Modeling diffusion of innovations

Mathematical diffusion models can be estimated on the aggregate data on innovation penetration to parameterize diffusion. Previous research has suggested several methods for modeling innovation diffusion, but there are no generally accepted rules for the selection of the method (Meade & Islam, 2006).

2.3.1 Basic diffusion models

Geroski (2000) divides mathematical diffusion models into epidemic models and probit models. Epidemic models assume that information diffusion drives the diffusion process. In so-called common source models, there is a single information source, which is usually assumed to reach a certain share of non-users per time period. The shape of the diffusion curve, therefore, depends on what the share of non-users reached per period is, but generally leads to an exponential pattern. However, technological innovations often have an initial period of slow diffusion that cannot be modeled with an exponential function. The shape can be reached with so-called word-of-mouth models, for which the information source is the population of users that have already adopted the innovation (e.g., Mansfield, 1961). They assume that an existing user of the innovation reaches out to a non-user with a certain probability, forming a symmetric s-shaped curve. This means that the diffusion rate is slow when the population of users is small in the beginning, then gets maximized in the middle when user and non-user population are equally sized, and then starts to slow down again when the population of non-users gets small and are difficult to find. Because both sources of information exist in the real world, they have been combined into mixed information source models. Depending on the assumptions of the models, the form can become asymmetric in the sense that the maximum diffusion rate comes earlier and the slowing end part of the diffusion curve becomes longer.

The Bass model (Bass, 1969) is one of the most well-known examples of an epidemic model, including both the effect of a common source, that is, advertising, and the effect of word-of-mouth. The Bass model has also been further modified in literature to include, for example, price or other marketing mix variables as determinants (e.g., Kalish, 1985; Horsky, 1990). Many other growth models have also been used when parameterizing diffusion, such as the Gompertz function (Gompertz, 1825), different variants of the logistic function (e.g., Bewley & Fiebig, 1988) and the Fisher-Pry model (Fisher & Pry, 1972). Further, Geroski (2000) identifies another type of diffusion models called probit models. Probit models, also called choice based models, are used more in economics and seek to explain the penetration of the innovation as a function of the characteristics of the individual adopters. Detailed reviews of different diffusion model types and mathematical forms are provided, for example, in

Kumar and Kumar (1992), Geroski (2000), as well as in Meade and Islam (2006).

2.3.2 Diffusion turning points

Turning points between stages of diffusion are often identified to further analyze the characteristics of diffusion and product or technology lifecycles. Similarly to diffusion models, the choice and identification of these turning points depend on the data and used diffusion model. Therefore, there are no generally accepted definitions for the turning points, and several methods have been suggested in the literature.

The introduction or start of sales is usually identified directly from the data, when the penetration of the innovation exceeds zero, or from secondary sources informing the data when the innovation was made commercially available. Some authors also make a distinction between the introduction (e.g., at an exhibition or by a press release), and the actual start of sales when customers can purchase the product (e.g., Kivi et al., 2012). Next, takeoff is the point in time when the diffusion rate experiences fast growth. With s-shaped diffusion models this is often identified as the point when the growth rate of adoptions is highest (e.g., Lim et al., 2003). However, also other definitions have been suggested. For example, in product life cycle literature, which focuses on the unit sales of new products, the takeoff is identified based on sudden increases in sales after the introduction. For instance, Golder & Tellis (1997) compared several methods for identifying takeoff from sales data, and developed a practical threshold rule for the percentage growth in sales of product categories, based on visual inspection, which has later also been used at least in Tellis et al. (2003) and Foster, Golder, & Tellis (2003). Agarwal & Bayus (2002) used a generalized version of discriminant analysis to identify the sales data points that could not be visually interpreted to belong to the pre-takeoff or post-takeoff period. Therefore, when using sales data, the identification often relies on identifying the discontinuities, whereas with diffusion models the definition relies on the point of maximum growth.

2.3.3 Replacement models

The traditional diffusion models, such as the Bass model (Bass, 1969), assume that all the purchases of an innovation or a new product are first-purchases, that is, lead to a new adoption. Because a large share of sales in mature markets consist of replacement purchases, the use of these traditional models especially for explanatory purposes is difficult. For this purpose, Olson & Choi (1985) divided product sales into first-purchases, that is, adoptions, and replacement purchases, and used Rayleigh distribution as the density function for product unit lifetime in their diffusion model. Other distributions have also been used in literature. Kamakura & Ealasubramanian (1987) used the truncated normal distribution by and Islam & Meade (2000) the Gamma distribution. The previously mentioned models assume that the replacement time remains static over the product life cycle. To overcome this restriction, also time-varying replacement models have been proposed in the literature (Steffens, 2001). Most previous research on replacement has focused on product categories, and studies of product model level replacement or other sub-segments of product categories are rare (Gordon, 2009; Kivi et al., 2012).

2.4 Research on the diffusion of mobile technologies

The area of telecommunications and mobile technologies has gained wide interest in the innovation diffusion research. Several studies have modeled and explained the diffusion of mobile telephony as a product category (e.g., Gruber, 2001; Islam et al., 2002; Frank, 2004; Botelho & Pinto, 2004; Rouvinen, 2006; Chu et al., 2009; Gamboa & Otero, 2009; Gupta & Jain, 2012; Mir & Dangerfield, 2013; Yamakawa et al., 2013). In addition, generational studies have analyzed the substitution between analog, second generation, and third generation mobile access technologies (e.g., Michalakelis, 2010). More recently, some studies have also defined smartphones as a new product category or generation (Lee & Lee, 2014), and the s-shaped diffusion curve has been identified for various mobile services and content (Liu et al., 2014).

Research in complementing areas of mobile technology diffusion has focused, for example, fixed-to-mobile substitution for Internet connectivity (Grzybowski, 2014), and multiple subscriptions (Annafari, 2012; Annafari & Bohlin, 2014). Further, some studies have explored the evolution of innovation in the mobile market by trying to identify dominant designs for mobile phones (Koski & Kretschmer, 2007) and smartphones (Cecere et al., 2015). Even though certain patterns in innovation have been identified related to dynamics between the incremental improvement of existing features and introduction of totally new features, these studies have not been able to identify specific dominant designs. This highlights the differentiation in the mobile handset market, visible in the high number and variety of product features included in different handset models.

To better understand how technologies spread in the mobile handset market and to explain the diffusion of the product category, some studies have focused on the diffusion of mobile handset features. Nair et al. (2004) used information on hardware and software features to model brand-level diffusion patterns of personal digital assistants (PDAs). Riikonen, Juntunen, & Smura (2011) analyzed the diffusion of two emerging technologies used in mobile handsets, namely GPS and NFC, and identified reasons for the diffusion patterns, and Kivi, Smura, & Töyli (2009) fitted diffusion models to data on mobile handset feature penetrations. Kivi et al. (2012) developed a forecasting approach, which divides the product category evolution into product category diffusion, product replacement process, and the product feature dissemination among the installed base of devices. They applied the approach to data on the Finnish mobile market, and illustrated how it can be used for evaluating the diffusion of mobile handset features with different scenarios related to supply-decisions. The study emphasized that supply-driven decisions have a major impact on which features are included in handsets on sale and therefore, on the diffusion patterns of the features.

The smaller role of mobile handset features on the demand side is also supported by research on product choice. The main factors in a mobile handset purchase decisions have been identified to include, for example, price and properties, brand, prior experience and size (Karjaluoto et al., 2005; Liu, 2002; Riquelme, 2001). In these studies, the importance of a single specific handset feature is generally small, indicating that there could be a notable gap between the number of device owners and the actual users of those features.

Internet protocols are a special example of mobile handset features, which are especially dependent on the supply-side. Because of protocols are embedded in applications, operating systems, or devices, the impact of them on the end users' decision making is low (Warma, Levä, Tripp, Ford, & Kostopoulos, 2011), and the distributed and loosely regulated nature of control in the Internet means that several stakeholders are required for successful diffusion of protocols into use (Clark et al., 2005). Because of these reasons, authors have asked for more comprehensive diffusion studies, which consider the whole process from development to end user adoption (Lyytinen and Damsgaard, 2001) called protocol deployment (Levä & Suomi, 2013).

In conclusion, literature on diffusion and growth models related to mobile telephony is rich. However, empirical research on the diffusion of individual mobile handset features is rare, and in the case of Internet protocols the focus has been only on the diffusion rate, without expanding the analysis to the whole deployment process.

3. Research methods and data

This section first introduces the general research approach. Then, the collected datasets and analysis methods are described.

3.1 Research approach

According to Järvinen (2004), building on research by March & Smith (1995), research approaches can be divided into mathematical approaches, which do not have a linkage to real-world objects, and approaches studying reality. Approaches studying reality can further be divided into two classes; those that study the utility of human-made artifacts and those that focus on studying what the reality is. Approaches studying reality can further be divided into artifacts-building and artifacts-evaluating, theory-testing and theory-creating, as well as conceptual-analytical approaches. Artifacts-building and artifacts-evaluating approaches stress the utility of artifacts by studying whether it is possible to build them for specific purposes, or to test the effectiveness of existing ones, respectively. Theory-testing and theory-creating are empirical approaches, focusing on creating new theories based on collected data or testing existing models and frameworks. Last, conceptual-analytical approaches focus on theoretical development either by making specific assumptions and premises to see what kind of theories could be derived, or by using theories and frameworks of prior studies, which are then integrated by using logical reasoning.

Using the taxonomy by Järvinen (2004), the research approaches used in this dissertation include both conceptual-analytical approaches and theory-testing approaches. Publications 1, 2, and 3 use the theory-testing and to some extent theory-creating approaches, whereas Publication 4 uses the conceptual-analytical approach. These empirical approaches and conceptualizations are applied to the theoretical area of diffusion of innovations (Rogers, 2003; Peres et al., 2010), and in more detail, to the domain area of mobile handsets and mobile technologies. The research approaches are implemented using quantitative analysis methods, as well as data triangulation in terms of collecting several complementing datasets from different viewpoints of mobile technology diffusion. The data collection and the selected analysis methods are described in the following subsections.

3.2 Data collection

Traditional diffusion research relies on sales data collected directly from the product retailers by third parties, such as market research companies. However, with mobile handsets and services there are several additional measurement points available. According to Smura, Kivi, & Töyli (2009) the main technical components of mobile service systems include devices, applications, network and content. These components can be measured using four main measurement points, namely end-users (e.g., Bouwman et al., 2007), usage monitoring systems (e.g., Verkasalo & Hämmäinen, 2007), network nodes (e.g., Riikonen, 2009; Kitahara, Riikonen, & Hämmäinen, 2010), and web servers. For this dissertation, data collected from retailers, end users, network nodes, and public sources were used. The main datasets were collected in co-operation with industry partners, forming a comprehensive view on the diffusion of mobile technologies in the Finnish mobile market.

Table 1 describes the data sources, research datasets, and their linkage to the publications. In total four separate datasets were collected: *feature data*, *retail sales data*, *installed base data*, and *usage data*. The datasets collected from different sources were partly in different formats. Therefore, the initial data processing harmonized all datasets (except usage data), including the handset model names used by different sources, and they were then mapped together based on the requirements of each individual research publication.

Table 1. Research datasets and publications.

Research dataset	Data source	Data description	Publication
Feature data	Various sources: GfK, device description repositories, manufacturer websites	Pre-installed features and Internet protocols equipped in mobile handset models	1, 2, 3, 4
Retail sales data	Market research company GfK	Monthly retail unit sales volume and mean price of mobile handset models in Finland	2, 3, 4
Installed base data	Finnish mobile network operators: DNA, Elisa, TeliaSonera	Annual device model specific number of units in use in Finnish mobile networks	1, 3, 4
Usage data	Finnish Communications Regulatory Authority (Ficora)	Survey data on the share of population using different mobile services	4

Variety of data sources were used also to ensure the quality of the data used for this research. For example, sales, installed base, and usage data, as well as data collected for other research purposes were compared to ensure the quality. These supporting sources include network traffic data (see, e.g., Soikkeli & Riikonen, 2015), as well as available reports from the regulator and industry stakeholders among others. Quality checks to each dataset revealed some differences or erroneous data points. In cases where better ground truth data was available (e.g. on launch date of a specific handset model) direct corrections were made to the data. If no ground truth data were found, handset models with erroneous data points were removed from the final research data.

3.2.1 Feature data

Feature data were collected from two main sources: manually from public sources, such as device manufacturer websites and device description repositories, as well as from market research company GfK. The data were collected for handset models in use and sold in Finland between 2003 and 2013. The information collected from the different sources were then manually combined and checked to provide information on the technical features of each mobile handset model. The data covers three types of features: hardware features, software features, and Internet protocols. The features were selected to represent a wide variety of feature types and the main functionalities of the mobile handset during the study period.

In total, information on 13 integrated hardware and seven pre-installed software features of mobile handsets were collected. The integrated hardware features included mobile data connectivity features (GPRS, EDGE, WCDMA, HSDPA), features related to input and output methods (Camera, Dual camera, Color display, Touch display, Multi touch display), and four other hardware features (Bluetooth, GPS, FM receiver). The software features covered areas related to messaging (MMS, Email), web browsing (WAP, HTML, Full WWW browser), and application platform related features (Smartphone OS, Java)

Furthermore, information on 11 pre-installed Internet protocols of mobile handsets was collected, covering several layers of the Internet Protocol Suite. From lower to higher layers, the protocols include one network layer protocol (IPV4), two transport layer protocols (TCP and UDP), one presentation layer protocol (TLS), and application layer protocols for email (SMTP, IMAP4, POP3, bundled as EMAIL), web browsing (HTTP), video streaming (RTSP, RTP), and voice over IP (SIP).

Feature data were collected using several sources, which were compared against each other. In addition, one can also infer whether it is possible to have a certain feature based on other features of the device. For example, a mobile handset cannot have MMS feature without any packet data network access technology. After data collection, such cross-checks were made to ensure the quality of the data.

3.2.2 Retail sales data

Retail sales data on mobile handset unit sales volumes and mean retail prices were obtained from GfK. The data were collected monthly on a mobile handset model level for the period of January 2003 to September 2012. The market coverage of the data varied between 70% and 90% over the study period.

The unit sales volumes in *retail sales data* were scaled to full market coverage by using quarterly total retail unit sales volume of the Finnish market. This total retail unit sales volume was obtained from public market reports by KOTEK, the collaboration forum of the Finnish consumer electronics and appliance industry. Further, the mean retail prices were adjusted to inflation for Publication 2.

3.2.3 Installed base data

Installed base data on mobile devices in use in mobile networks were obtained from all three Finnish mobile network operators in the context of research collaboration and several projects. The data were collected annually on a device model level from each operator for the period of September 2005 to September 2012 (Riikonen & Smura, 2013). The device model names of the operator specific datasets were first manually harmonized, and then the datasets were aggregated to form comprehensive market data of the devices in use in Finnish mobile networks. Last, as several types of devices are active in mobile networks, mobile handsets were separated for the research based on device model and manufacturer information. The coverage of the final dataset was between 80% and 98% of the handset base in Finland over the study period.

3.2.4 Usage data

Usage data on the share of Finnish population using mobile services were obtained from Ficora, the Finnish Communications Regulatory Authority. Ficora (2012) collected the data annually for the period of 2006 to 2012 from representative samples of 15-79-year-old Finns. The annual sample sizes increased over time from 1500 to 3000. The results were weighted to represent the 15-79-year-old population in terms of gender, age, and geographical region.

3.3 Analysis methods

The collected datasets were analyzed by using several methods depicted in Table 2. The methods include mathematical diffusion model estimation and identification of diffusion turning points, mobile handset model replacement and unit lifetime estimation, as well as linear regression analysis for the determinants of unit lifetimes and associations between mobile handset feature prices and market shares. Further, a conceptual framework for measuring Internet protocol deployment was developed in this dissertation and it is described in the results in Section 4.4.

Table 2. Analysis methods and publications.

Analysis method	Tested models or functions	Research dataset	Publication
Diffusion model estimation	Simple logistic model, Bass model, Gompertz model	Installed base data	1
Identification of diffusion turning points	Diffusion model based rule, Maximum change in sales rule	Installed base data, Retail sales data	1, 2
Replacement model estimation	Gamma distribution, Rayleigh distribution, Weibull distribution	Installed base data, Retail sales data	3
Linear regression analysis	Effect of price, popularity, and technological sophistication on handset unit lifetimes, Association between sales and prices of handsets equipped with different features	Installed base data, Retail sales data	3, 4

3.3.1 Diffusion model estimation

Mathematical diffusion models were estimated for historical and, in some cases, future diffusion of mobile handset features. This required, first, mapping *installed base data* and *feature data* together and calculating annual penetration of each feature among the installed base of mobile handsets. Then, the selected mathematical diffusion models were fitted to these feature penetration data points. The analysis enabled finding the most suitable models to be used in feature diffusion studies, as well as systematic comparison of the diffusion patterns of different features.

Because several diffusion models have been suggested in previous literature (Kumar & Kumar, 1992; Meade & Islam, 1998) and no commonly accepted criteria exists for model selection, three widely used models were selected for testing: the simple Logistic model (Verhulst, 1845), the extended logistic model, that is, the Bass model (Bass, 1969; Meade & Islam, 2006), and the Gompertz model (Gompertz, 1825). The cumulative forms *Y(t)* of the three models read

$$Y_G(t) = a_G \exp(-c_G \exp(-b_G t)) \, , b_G > 0, c_G > 0, \tag{1}$$

$$Y_L(t) = a_L \, (1/(1 + c_L \exp(-b_L))), \; b_L > 0, c_L > 0, \tag{2}$$

$$Y_B(t) = a_B \frac{1 - \exp(-(b_B + c_B)t)}{1 + (c_B/b_B)\exp(-(b_B + c_B)t)} \; b_L > 0, c_L > 0, \tag{3}$$

where a is the saturation level, b and c are the model parameters, and t is the time variable. Equations 1, 2, and 3 refer to the Gompertz model G, the simple Logistic model L, and the Bass model B, respectively.

Two types of estimations were conducted. Three-parameter estimations (a, b, and c) were fitted when sufficient data on the saturation level was available. Two-parameter estimations (b and c) were fitted for features with data only from initial diffusion, and the saturation level was taken as the average of the estimated a of the three-parameter models.

3.3.2 Diffusion turning point identification

Different methods were used for the identification of handset feature diffusion turning points. The identification was conducted for the estimated diffusion models of subsection 3.2.1, that is, for the *installed base data*, as well as directly for the raw *retail sales data*. This enabled systematic analysis and comparison of the diffusion patterns of different handset features, and provided understanding on the suitability of the different datasets and methods for mobile handset features.

Three turning points of diffusion were identified, namely the start of sales, the takeoff point, and the inflection point. The start of sales is the point in time when the first unit of a specific product, or a product with a specific feature, is sold in the studied market. Then, the takeoff point is the point in time when the initial low sales turn into fast growth. The inflection point refers to the time when the increasing growth in adoptions or sales turns in to decreasing growth, that is, when the number of adoptions is at its highest. Two stages of diffusion were identified between the three turning points. The introduction stage was calculated as the time from the start of sales to the takeoff point, and the growth stage was identified from the takeoff point to the inflection point.

Two rules for turning point identification were selected: diffusion model based rule and maximum absolute change rule, using *installed base* and *retail sales data*, respectively. First, the start of sales was identified for handset features from public sources and *retail sales data*. Then, for the diffusion model based method the takeoff was defined as the point when the noncumulative growth rate is maximized. For the cumulative function this is the maximum of the second derivative, and for the Gompertz function (equation 1) the takeoff t_G^{**} is can be calculated as

$$t_G^{**} = (\ln(1/2(3c_G - \sqrt{5})))/b_G, \tag{4}$$

where b_G and c_G are the model parameters. Similarly, the inflection point t_G^{*} can be calculated as the maximum of the first derivative, which for the Gompertz function is

$$t_G^{*} = \ln(c_G)/b_G. \tag{5}$$

Because no commonly accepted definition for the takeoff exists in the literature, the takeoff point was also identified directly from the *retail sales data*. Based on other sales data based methods (e.g., Golder & Tellis, 1997) and visual interpretation of the sales patterns, a maximum absolute change rule based takeoff point was defined as the point in time (month) when the maximum absolute change in feature market share took place.

3.3.3 Replacement model estimation

Replacement models were used for the estimation of mobile handset unit lifetimes at the level of product models. This required, first, calculation of unit discards by mapping *retail sales data* and *installed base data* together. Then, selected mathematical replacement distributions were estimated to the data on the annual discards. The analysis enabled finding the most suitable models to be used in handset replacement studies and practical estimation exercises, as well as provided input for the analysis of unit lifetime determinants.

The product model level unit discards can be calculated using the product model life cycle formulation (Kivi et al., 2012). According to this formulation, the number of units of product model m in use at the end of a time period t is given by

$$n_{m,t} = \sum_{i=0}^{t} (s_{m,i} - d_{m,i}), \qquad (6)$$

where $n_{m,t}$ is the cumulative sum of unit sales volume $s_{m,i}$ and discards $n_{m,i}$ for the time period from 0 to t. By modifying equation 4 we get the number of product units of model m discarded in the time period between t_1 and t_2 as

$$\sum_{t=t_1}^{t_2} d_{m,t} = \left(n_{m,t_1} - n_{m,t_1}\right) + \sum_{t=t_1}^{t_2} s_{m,t} + \varepsilon, \qquad (7)$$

where ε is the error. The sources of error in practical measurements include units entering the installed base without being recorded to unit sales (such as purchases from abroad) and units recorded to unit sales but not entering the installed base (such as purchases to abroad).

Replacement models were estimated to the handset model specific unit discards $d_{m,t}$ calculated according to equation 5. Replacement models typically use different distributions for the probability density function $f(T)$ of unit lifetime T. The four commonly used lifetime distributions $F_m(T)$ selected for testing were Gamma, Rayleigh, and Weibull (see, e.g., Islam & Meade, 2000).

Assuming the same lifetime distribution for all sold units, the number of discards during time period t can be calculated as

$$d_{m,t} = \sum_{i=0}^{t} s_{m,i}[F_m(t-i) - F_m(t-i-1)], \qquad (8)$$

where $F_m(T)$ is the cumulative probability distribution for the discards of model m. For this dissertation, the *installed base data* were on an annual level, so also the discard data points were calculated as the sum of 12 monthly discards:

$$\sum_{t_1}^{t_2} d_{m,t} = \sum_{t=t_1}^{t_2} \sum_{i=0}^{t} s_{m,i}[F_m(t-i) - F_m(t-i-1)], \tag{9}$$

where t_1 and $t_2 = t_1 + 11$ are the first and last month in *retail sales data,* preceding each annual *installed base data* point. The resulting number of discard data points for each handset model was between three and seven, depending on the first sales month of the model.

3.3.4 Linear regression analysis

Linear regression –based estimation were used for the identification of the effect of different factors on handset model specific unit lifetimes, and for estimating the associations between mobile sales and prices of handsets equipped with the studied features. These analyses enabled to better understand possible determinants of mobile handset replacement and feature diffusion, as well as to do initial evaluation on the usefulness of price as a variable for feature diffusion models.

Linear regression is a statistical analysis method (e.g., Kutner et al., 2005), which can be used for studying the associations of a dependent variable and one or more independent variables. Both continuous and nominal variables can be studied, if the nominal variables are coded as dummy variables in the regression model. In more detail, ordinary least squares (OLS) regression with multiple independent variables with both continuous and dummy variables was used in this dissertation. A matrix form of such a linear model reads

$$Y = \alpha + X\beta + \gamma D + \varepsilon, \tag{10}$$

where Y is the matrix for dependent variables, α is the intercept, X and γ are the model matrixes for continuous and dummy variables, respectively, β and D are the vectors of parameters for continuous and dummy variables, respectively, and ε includes the residuals.

The regressions on unit lifetimes were based on handset model specific unit lifetime estimates described in the previous subsection 3.2.4. The associations between feature market shares and prices were estimated with *retail sales data* preprocessed to represent the total market shares and mean prices of the handset models equipped with each selected handset feature, respectively. The detailed initial and final models in are presented in Publication 3.

4. Results

This section summarizes the main results of the dissertation. First, subsection 4.1 provides empirical evidence on the diffusion patterns of mobile handset features. Subsection 4.2 shows the associations between prices, unit sales, and features by analyzing product model and product feature specific price and sales volume patterns. Subsection 4.3 further analyses the effect of prices, sales volumes, and features on mobile handset replacement. Last, subsection 4.4 summarizes the earlier findings into a conceptual framework on measuring Internet protocol deployment, and the framework is applied to an example mobile market.

4.1 Mobile handset feature diffusion

To provide empirical evidence on the diffusion patterns of mobile technologies, mobile handset feature diffusion models were estimated and main diffusion turning points were identified.

4.1.1 Diffusion model estimation

Two- and three-parameter diffusion model estimates were fitted to the data on mobile handset feature penetrations in the installed base. For mobile handset features with data from later diffusion, three parameter estimates were used, meaning that also the saturation level was estimated. For features with data points only from the initial diffusion, the saturation level was taken as the average of the three-parameter fits.

Table 3 presents the three-parameter estimates for the Bass, Gompertz, and simple Logistic models fitted the annual feature penetrations derived from combining the *installed base data* and *feature data*. The Gompertz model was chosen to be used in further analysis, because of it provided the best goodness-of-fit for two out of five features, had visually good fits for all features, as well as because the Bass model provided unrealistic results due to the data-truncation bias (Jiang, Bass, & Bass, 2006). The average saturation level from the three-parameter Gompertz fits was identified as 87% of the total size of the handset base. Further, Table 4 presents the two-parameter fits for the rest of the selected features with the saturation level taken from the three-parameter Gompertz fits. All two-parameter fits had an r-squared value over 0.99, indicating that the model fits the data reasonably well.

Table 3. Three-parameter estimates for a) the Bass, b) Gompertz, and c) Logistic models (modified from Publication 1).

a)

Feature*	b_B	c_B	a_B	SSE_B	$RMSE_B$	R_B^2
GPRS	0.007	0.033	4 589 236	**8.5E+09**	**4.6E+04**	**0.9994**
Color display	0.002	0.054	4 725 274	8.4E+09	4.6E+04	0.9995
WAP browser	0.007	0.023	4 675 584	**4.7E+09**	**3.4E+04**	**0.9996**
Java	0.009	0.037	4 458 538	**1.1E+10**	**5.3E+04**	**0.9991**
MMS	4	0.051	4 323 975	1.1E+10	5.3E+04	0.9991

b)

Feature*	b_G	c_G	a_G	SSE_G	$RMSE_G$	R_G^2
GPRS	0.040	4.697	4 537 437	1.11E+10	5.26E+04	0.9992
Color display	0.045	9.846	4 815 597	**3.68E+09**	**3.03E+04**	**0.9998**
WAP browser	0.034	4.834	4 534 800	9.30E+09	4.82E+04	0.9993
Java	0.046	4.441	4 399 318	1.58E+10	6.29E+04	0.9988
MMS	0.045	6.594	4 387 691	**6.83E+09**	**4.13E+04**	**0.9995**

c)

Feature*	b_L	c_L	m_L	SSE_L	$RMSE_L$	R_L^2
GPRS	0.066	23.35	4 273 751	8.54E+10	1.46E+05	0.9936
Color display	0.063	41.27	4 636 493	2.77E+10	8.33E+04	0.9982
WAP browser	0.058	30.90	4 275 435	6.30E+10	1.25E+05	0.9953
Java	0.074	19.95	4 176 984	1.08E+11	1.64E+05	0.9919
MMS	0.069	29.08	4 189 557	4.77E+10	1.09E+05	0.9964

** Seven observations were available for each model and feature*

*Note: Relatively better performing model for each feature marked in **bold***

Table 4. Two-parameter estimates for the Gompertz model (Publication 1).

Feature	b_G	c_G	a_G	SSE_G	$RMSE_G$	R_G^2
EDGE*	0.040	5.502	4 534 968	2.73E+10	7.39E+04	0.9977
WCDMA*	0.024	5.506	4 534 968	5.32E+10	1.03E+05	0.9868
WLAN*	0.017	5.460	4 534 968	5.93E+09	3.44E+04	0.9927
HSDPA**	0.029	5.497	4 534 968	3.21E+09	2.83E+04	0.9975
Camera*	0.035	6.509	4 534 968	1.30E+10	5.11E+04	0.9988
FM receiver*	0.035	11.346	4 534 968	6.85E+10	1.17E+05	0.9937
Bluetooth*	0.038	13.759	4 534 968	2.37E+10	6.88E+04	0.9979
GPS*	0.032	51.493	4 534 968	5.97E+09	3.46E+04	0.9950
Email*	0.042	49.756	4 534 968	3.03E+10	7.79E+04	0.9977
HTML browser*	0.025	12.660	4 534 968	2.91E+10	7.62E+04	0.9940

** Seven observations were available for the feature*

*** Six observations were available for the feature (HSDPA)*

Figure 2 shows the data and the fitted Gompertz functions from both, three-parameter (solid line) and two-parameter (dashed line) fits. The fast uptake and slow saturation of the Gompertz model fit to the data also by visual inspection, and further validate the use of an asymmetric function for modeling feature diffusion. The diffusion patterns also visually support the finding that the saturation levels of the studied features are below 100%. This phenomenon is mainly explained by the slowly diminishing population of low-end handsets, which only have the basic voice-calling and text-messaging functions.

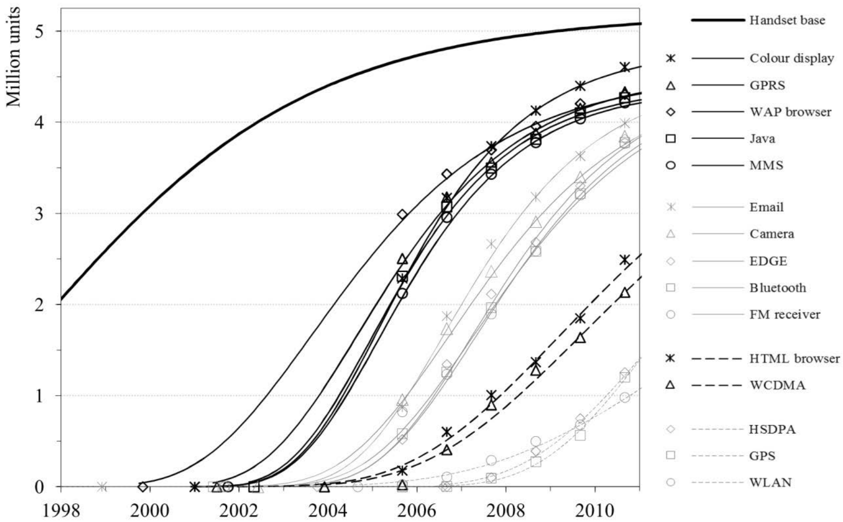

Figure 2. Data and the Gompertz model fits for mobile handset feature penetrations in Finland, shown with the size of the total handset base (Publication 1).

Based on the diffusion patterns, four general groups of features can be identified with internally relatively similar diffusion. These groups are marked with different color and line combinations in Figure 2. The features in each group seem to have relatively similar diffusion patterns due to their introduction times and functional similarities. For example, GPRS feature was an enabler for WAP browser feature and, therefore, it is naturally that their diffusion patterns follow each other closely. However, there are notable differences in the diffusion patterns of different groups and individual handset features. For example, for color display two million units in use were reached in three years, whereas for WLAN the same spread was reached only after nine years. To enable better comparison of individual features, the turning points (takeoff and inflection point) and the related diffusion stages (introduction and growth) were identified for the fitted Gompertz models.

4.1.2 Turning points of diffusion

Figure 3 shows the start of sales month, as well as the durations of the diffusion stages for each studied feature identified from the fitted Gompertz models. The results show that the introduction stage (0-7%) explains the temporal differences in diffusion better than the growth stage (7%-37%). The average duration of the introduction stage (three years) is longer than the growth stage (two years), and the variation is high. The shortest estimated introduction stage for Java feature was 10 months, whereas for GPS this delay from start of sales to takeoff took 90 months. On the other hand, even though the duration of the growth stage for GPS was also longer, the difference is notably smaller. This is confirmed when looking also at other features: long introduction stage does not seem to indicate similarly slow growth phase. This could mean that different factors affect the diffusion during the two stages.

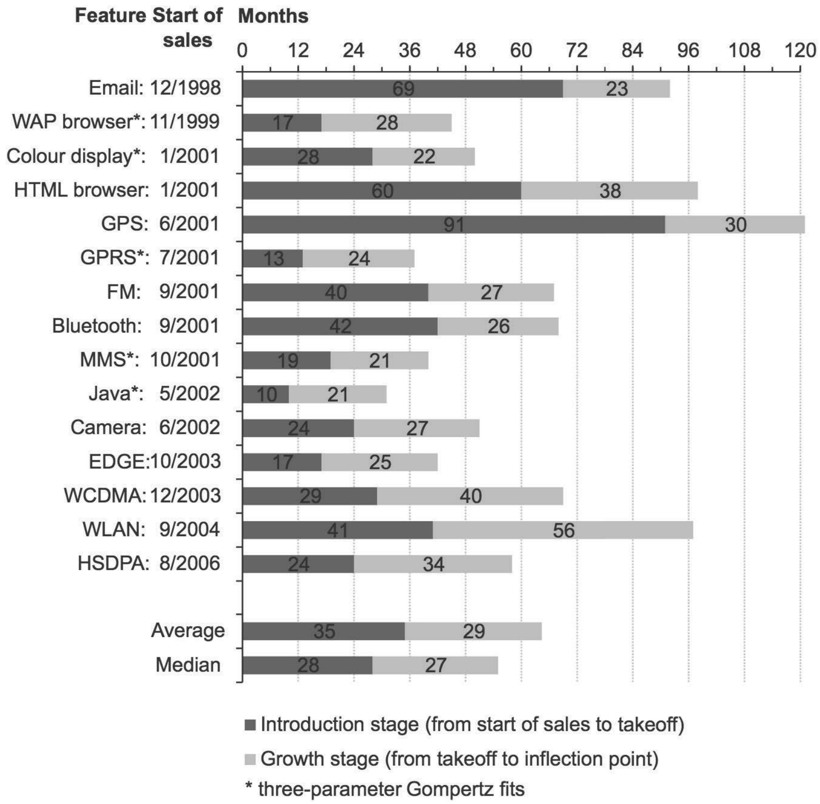

Figure 3. Durations of introduction and growth stages for mobile handset features in Finland (Publication 1).

The duration of the introduction stage can be partly explained by technology immaturity of the features when they were first introduced in handset models. Further, because of the high component and integration costs, as well as low performance of these features of complementing features explain the low interest by manufacturers to include the feature more widely on their handset models. In some cases, also individual handset models and vendors explain the pattern. For example, GPS, HTML, and Email features were initially introduced in functionally experimental handset models – namely Benefon Esc!, Nokia 9110 Communicator, and Nokia 9210 Communicator, respectively – which were relatively different from the popular models at their introduction.

Even though most differences are explained by the introduction stage, there are also differences in the durations of the growth stage. The results indicate that the faster diffusing features were introduced earlier, that is, they are from the first two temporal groups. A general explanation could be that the increase in the size of the installed handset base made the diffusion faster, whereas the other features have spread mainly due to replacement purchases. Example of a feature with an especially slow growth stage is WLAN. Specific reasons for the slow of diffusion include WLAN's inclusion only in business segment smartphones, which were relatively expensive. Other data connectivity technologies also provided basic data connectivity, meaning that WLAN was only needed for applications requiring fast connectivity. In comparison to, for instance, display technologies, the color display provided a visible performance upgrade over black and white displays, and was important for any content and advanced applications. Therefore, color display spread faster to all sub-segments leading to faster overall diffusion.

4.2 Mobile handset price and sales volume patterns

Analysis of the retail sales data provided a complementing viewpoint on mobile technology diffusion. First, handset model sales and price patterns were identified, and then feature diffusion patterns and turning points were studied.

4.2.1 Product category level

During the study period the total sales volumes in Finland grew notably, from 1.3 Million units in 2003 to 2.5 Million in 2012. On a yearly level, mobile handset sales have a clear seasonal pattern with December the peak sales month and lowest sales between January and March. Another seasonal peak was identified between August and September, explained by the start of the school year during these months. There were changes also in the mean mobile handset prices during the study period, which generally decreased. However, the increasing demand for advanced smartphones affected the trend, and the unit-sales weighted mean price of mobile handsets started to increase in 2011. The product category sales and price patterns, as well as handset model introduction dynamics are described with more details in Publication 3.

4.2.2 Product model level

For the mobile handset model level analysis, only the models with at least two sales months and full lifecycle coverage were included in the sample. The handset model lifecycle was defined as the period from first sales month to the month when 99% cumulative sales are reached, providing a sample of 798 handset models introduced during 2003-2009.

Figure 4 shows the median unit sales distribution over the handset model lifecycle. The handset models were divided into three categories based in the duration of the lifecycle, that is, the sales period: 1-11 months, 12-23 months, and 24 months or more. The peak sales month of a typical handset model takes place after four or five months of sales, after which the sales start to slowly decline. Another common sales pattern is one where the peak sales takes place already during the first two months, and starts to decline immediately after that, as is in the case of handsets sold for less than 12 months.

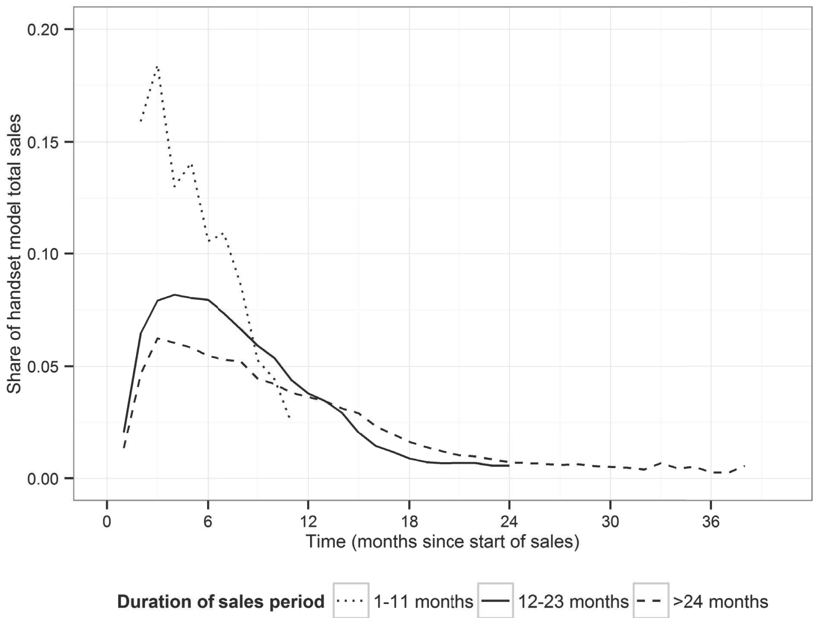

Figure 4. Median distribution of sales for product models with varying lifetimes (Publication 2).

For the analysis of price patterns, the prices were calculated relative to the introduction price of each model. Figure 5 shows the median of these prices for the previously used three lifecycle-categories. The results indicate that there are only small differences in the price patterns, independent of the category. The median prices decline relatively linearly: the price of a typical handset model decreases to 72% of the introduction price after one year, and to 47% after two years. The only exceptions with a nonlinear pattern are handset models with shorter sales period than one year. For those models, there is an abrupt increase in median prices after 9 months. Similarly, higher variation can be identified for handset models with longer sales period than 30 months. These anomalies are, to some extent, explained by the small number of handset models sold during the end of each studied period.

When comparing the sales and price patterns, the results show most mobile handset units are sold with a price relatively close to the introduction price. For the peak sales month, the median price is 89% of the introduction price, and for the month when 50% cumulative sales are reached, the price drops to 85%. This could indicate that manufacturers do not use aggressive price skimming in the mobile handset market.

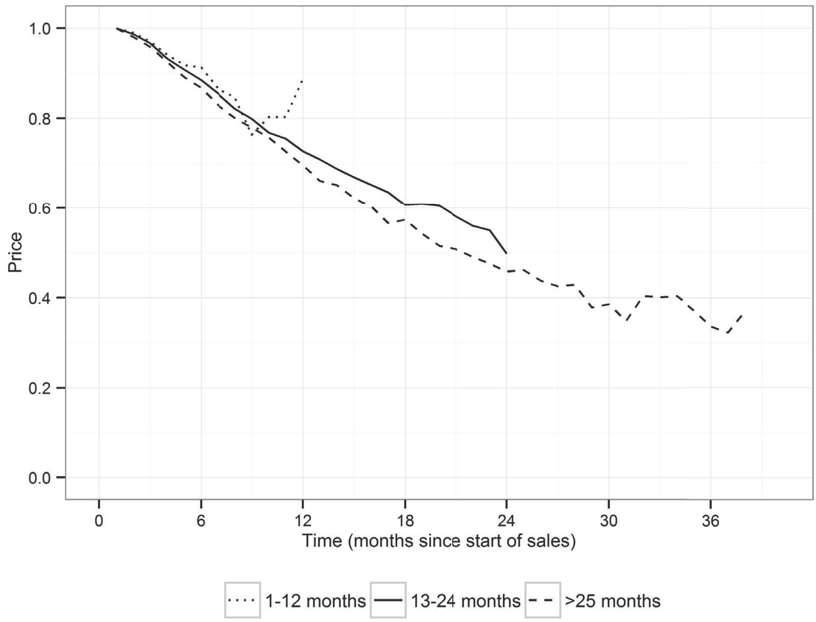

Figure 5. Median price patterns of mobile handset models with varying lifetimes (Publication 2).

4.2.3 Product feature level

The association between the diffusion and prices of mobile handset features was analyzed indirectly, by using mobile handset sales and mean prices of handset models equipped with the features. Therefore, price calculated this way is different from what the direct producer cost (often bilaterally negotiated between component vendor and device manufacturer) or implicit price (estimated using hedonic price models; see, e.g., Rosen, 1974; Triplett, 2004) for the feature would be, but reflects the actual cost for the end user to acquire a device with the feature.

For new feature introductions, the absolute mean prices of the handset models are generally high, starting from more than 400 Euros. This supports the idea that most features are first introduced in the high-end handsets, and then as the cost of the feature decreases and possibly demand increases, spreads into a larger number of cheaper models. Feature market shares seem to follow similar growth patterns as shown with installed base, but there is high variation. For some features the market share increases fast after the introduction, whereas other experience long periods with low market shares in the beginning. The factual price and sales patterns are described with more details in Publication 2.

Figure 6 shows these mean prices of the models equipped with each analyzed feature (from now on feature price), and the inverse market shares (from now feature market share) of the same models. The time axis is normalized to the first sales month of the feature, or to January 2003 for features that started selling already before 2003, to enable the comparison of the features. Further, the features that were introduced before 2003 are in the bottom part of the figure, separated by a horizontal line.

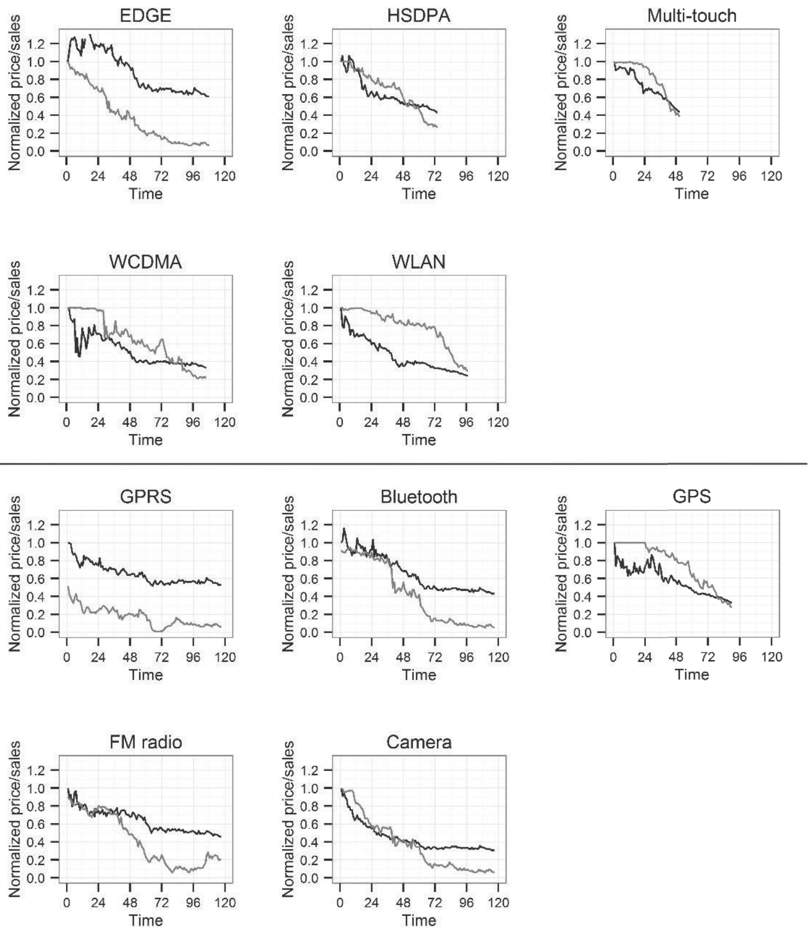

Figure 6. Normalized mean prices (black line) and inverse market shares (gray line) of mobile handset features. Time variable is in months from the first sales month of the feature (Publication 2).

The results indicate a relatively strong association between feature prices and market shares for many features, but also opposite examples were found. For example, WLAN experienced large price decreases while the market share did not increase notably for a long period. WCDMA had large variations in price during the first sales months. Last, EDGE is an example with an increase in the price after the first sales months, and it took long time before the price decreased below the introduction price, while market share rose notably also during that period. These examples with high variation and increasing initial prices can to some extent be explained by a small number of experimental handset models that generate the initial sales. These models can, for example, have lower profit margins with purpose to test the market and get feedback of the new feature.

The explanation of experimental models is further supported by Figure 7, which shows the association of feature prices and market shares as a scatter plot. There is a lot of variation and differences between features with market shares below 10%, highlighting that during the introduction stage the manufacturers test with different feature and price combinations to see how the market responds. However, after the 10% market share is reached, the relationship seems to be relatively linear. To enable comparison between features, linear regression lines were fitted to the data for market shares over 10%.

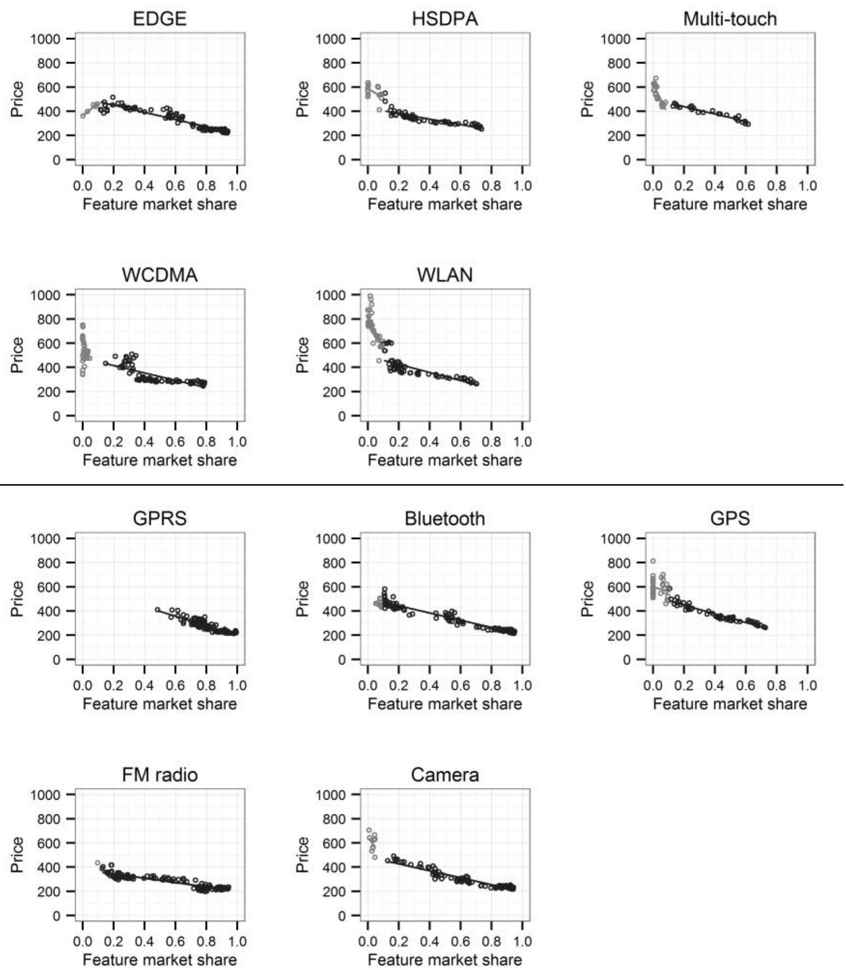

Figure 7. Association between mean prices and market shares of mobile handset features (Publication 2).

Table 5 presents the linear regression estimates for different features, including the intercept, SALES_SHARE (share of total unit sales) coefficients, and

R-squared values. Modeling price as a function of the share of total sales seems to provide relatively good results, except for WLAN and WCDMA. These results show the association of the market share with price to be on average a decrease of 30 Euros per 10% market share increase, with an intercept of 489 Euros. The result could indicate for a relatively common absolute price level, after which the feature becomes attractive also for the mass market. To further confirm this, the takeoff point was identified and the prices at takeoff were calculated.

Table 5. Linear regression estimates of feature prices for market shares 10%-100% (Publication 2).

	Feature	Intercept	SALES_SHARE (Coef.)	r^2
Full sales period available	EDGE	511	-298	0.902
	WCDMA	477	-305	0.576
	HSDPA	427	-228	0.716
	WLAN	492	-335	0.628
	MULTI_TOUCH	499	-304	0.928
Full sales period not available*	GPRS	594	-393	0.807
	FMRADIO	379	-178	0.841
	BLUETOOTH	503	-299	0.939
	CAMERA	485	-287	0.917
	GPS	521	-360	0.899

* "Full sales period not available" means that the diffusion of the feature started before the data collection period started (2003), i.e., research data does not include all data points from early diffusion.

Three different methods for takeoff identification were tested: Maximum percentage growth, maximum absolute growth, and diffusion model based rule. Maximum percentage growth measures the relative growth of market share to the previous month, maximum absolute growth measures the absolute market share change between two months, and diffusion model base rule uses the identified takeoff point from the Gompertz diffusion models, calculated by Equation 4. Out of the three tested methods, maximum percentage growth was excluded from further analysis, because of its tendency to identify too early points from the first few sales months.

Table 6 presents the estimates for the duration of the time to takeoff, that is, the introduction stage, and the prices at takeoff for all features with full sales data available. For other features than EDGE both methods provide relatively similar takeoff estimates. Generally, takeoff identification requires the initial period with low sales, but with EDGE the growth in unit sales was almost linear from the first sales month (see Figure 6). This makes the takeoff identification for EDGE more sensitive to the selected method. For other features, the results are similar with both methods, the average time to takeoff being 34 months with the maximum absolute growth rule. At takeoff the feature price is on average 430 Euros, that is, 58% of the introduction price. These results further support the previous results, indicating that an absolute price level of 400-500 Euros must be reached before the feature starts to spread fast among the installed base of devices. Therefore, the use of price as a support variable for estimating feature diffusion is worth further research.

Table 6. Takeoff points and prices at takeoff for mobile handset features (modified from Publication 2).

		Maximum absolute growth rule			Diffusion model based rule		
		Time to takeoff	Relative price at takeoff	Absolute price at takeoff	Time to takeoff	Relative price at takeoff	Absolute price at takeoff
Full sales period available	EDGE	34	1.18	425	17	1.29	466
	WCDMA	30	0.66	490	29	0.64	478
	HSDPA	19	0.74	437	24	0.67	395
	WLAN	42	0.42	458	41	0.41	452
	Multi-touch	45	0.51	345	NA*	NA*	NA*

** Takeoff point was not estimated for Multi-touch screen in Publication 2*

4.3 Mobile handset replacement and unit lifetimes

The replacement of mobile handset models was analyzed by fitting replacement distributions as the probability density functions for mobile handset unit lifetime, and by estimating linear regressions on unit lifetimes.

4.3.1 Replacement model estimation

For the probability density function $F_m(T)$ of mobile handset unit lifetime, three distributions were tested: Gamma, Rayleigh, and Weibull. Table 7 shows the estimation results with descriptive statistics on handset unit lifetime. Both two-parameter functions, Gamma and Weibull, converged with most handset models, and Gamma provided the highest number of best fits (228) using sum of squared errors (SSE) as criterion. The estimated unit lifetimes with Gamma and Weibull were relatively similar: both median and mean lifetimes were about 20 months with a standard deviation of 8 months. The Gamma function, with a sample of 343 handset models with converged estimations, was selected as the estimate of mobile handset model unit lifetime for further analysis.

Table 7. Comparison of replacement model fitting results (Publication 3).

Replacement distribution	Converged (total=359*)	Best fit (total=359)	Median of median lifetimes	Mean of median lifetimes	Standard deviation
Gamma	343	228	20.1	19.7	8.4
Weibull	341	115	20.2	19.8	8.2
Rayleigh	288	16	12.4	13.5	11.2

** Number of handset models for which at least one of the three functions converged*

4.3.2 Conceptual model and construct operationalization

To understand the determinants of mobile handset replacement and unit lifetimes, a conceptual model and a set of hypothesis were constructed. Figure 8 shows the model and the related hypothesis.

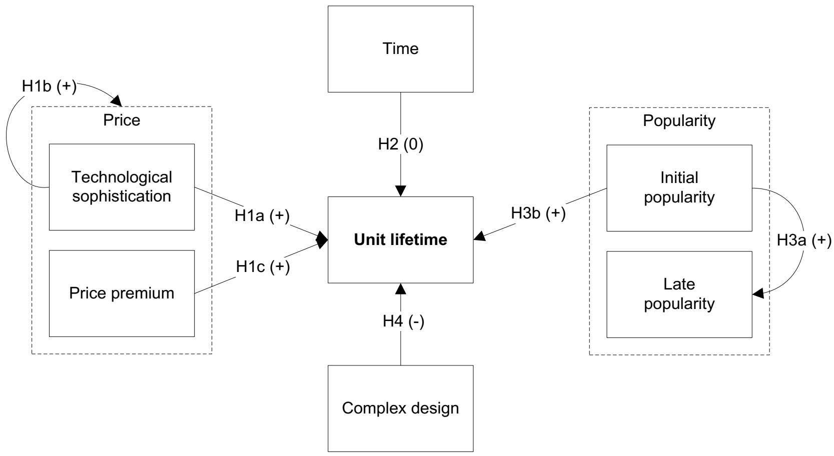

Figure 8. Model constructs and hypotheses for mobile handset unit lifetime.

In total seven hypotheses were selected for testing based on previous literature and domain understanding of the mobile handset market. In the case of H1 and H3 where the main hypothesis is divided into three and two sub-hypotheses, respectively, the sub-hypotheses were tested. The hypotheses are as follows:

- *H1. Price and technological sophistication are associated with longer unit lifetimes*
    - *H1a. Higher technological sophistication is associated with longer unit lifetimes*
    - *H1b. Higher technological sophistication is associated with higher price*
    - *H1c. Higher price premium is associated with longer unit lifetimes*
- *H2. Unit lifetimes are stable over time*
- *H3. Higher popularity is associated with longer lifetimes*
    - *H3a. Higher initial popularity is associated with higher late popularity*
    - *H3b. Higher initial popularity is associated with longer unit lifetimes*
- *H4. Complex product designs are associated with shorter lifetimes*

Based on the hypotheses and the conceptual model, the constructs were operationalized as nine variables. The variables are presented in Table 8, and are described with more details in Publication 3.

Table 8. Description of the variables (Publication 3).

Construct	Description
LIFETIME	Continuous. Median unit lifetime of a handset model calculated from the fitted replacement distribution.
TIME	Continuous. First sales month of a handset model, measured in months since January 2003.
INITIAL_POPULARITY	Continuous. Natural logarithm of the unit sales volume from the first three sales months relative to the total sales from the same time period.
LATE_POPULARITY	Continuous. Natural logarithm of the unit sales volume from the sales period not covered by INITIAL_POPULARITY, i.e., from months 4…m, where m is the last sales month of the model.
PRICE	Continuous. Natural logarithm of the unit sales weighted average price of a handset from the first three sales months.
PRICE_PREMIUM	Continuous. Residuals from a model regressing PRICE with SOPHISTICATION.
SOPHISTICATION	Continuous. Centered and standardized measure of the number of features included in the handset model, i.e., technological sophistication.
DESIGN	Categorical. Categories = Block, Flip, Slider. Coded as two dummy variables, DESIGN_FLIP and DESIGN_SLIDER, i.e., block as reference.

4.3.3 Hypothesis testing results

The associations between mobile handset unit lifetime and the other variables were analyzed by using sequential multiple regression. First, ordinary least squares (OLS) regression model on PRICE was estimated, showing the association between technological sophistication and prices. It was found that the features explain 71%-76% of variation in the mobile handset model introduction price (Table 9). During the second half of the study period, from July 2006 to December 2009, sophistication explained introduction price slightly better than during the first half.

Table 9. Mobile handset price (PRICE) regression estimates (Publication 3).

	1st half		2nd half		Whole time period	
	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)
Intercept	5.467	***	5.12998	***	5.26994	***
SOPHISTICATION	0.50229	***	0.5829	***	0.55009	***
R-SQUARED	0.7252		0.7572		0.7083	

*Significance codes: * < 0.05, ** < 0.01, *** < 0.001*

Next, the part of price not explained by sophistication was included in the model on unit lifetime as PRICE_PREMIUM with the original SOPHISTICA-

TION accounting for both, its individual effect and the shared effect of price and sophistication. This unit lifetime model reads as

$$LIFETIME_m = \alpha + \beta_1 SOPHISTICATION_m + \beta_2 PRICE\_PREMIUM_m + \beta_3 POPULARITY_m + \beta_4 TIME_m + \beta_5 DESIGN\_FLIP_m + \beta_6 DESIGN\_SLIDER_m, \quad (11)$$

where $LIFETIME_m$ is the unit lifetime of handset model m, α is the intercept, and β_1 to β_6 are the parameters. Both, the full starting model, and stepwise regression with Akaike information criteria (AIC) and bidirectional elimination, were estimated. The data were further split into two halves – January 2003 to June 2006 and July 2006 to December 2009 – because a possible structural break was identified based on visual inspection of the unit lifetimes. The regression models were estimated separately for the two halves and the whole time period. The structural break was tested statistically by using the Chow test (Chow, 1960).

Table 10 shows the parameter estimates for the unit lifetime regressions. The full model had an intercept and six parameters, whereas the stepwise models had intercepts and two to three parameters. Chow test (p-value < 0.01) supported the use of separate regressions for the two time periods.

The models explain 14%-24% of the variation in handset unit lifetimes. Based on the stepwise regression, only SOPHISTICATION was statistically significant for both time periods. This result indicates longer lifetimes for device models with higher technological sophistication, with the assumption that the shared effect of price and sophistication is all accounted for the features. PRICE_PREMIUM was not identified to have explanatory power on lifetimes. TIME variable was statistically significant only on the second time period, indicating that lifetimes were stable during the first half, but started to decrease after that. Last, mobile handset models with flip design were identified to be associated with shorted unit lifetimes, and initial popularity with longer lifetimes during the first time period.

Table 10. Regression model parameter estimates (Publication 3).

	1st half				2nd half				Whole time period			
	Full model		Stepwise		Full model		Stepwise		Full model		Stepwise	
Intercept	30.352	***	29.491	***	26.346	***	26.333	***	25.321	***	25.425	***
TIME	-0.011		-		-0.134	**	-0.137	***	-0.059	*	-0.051	**
POPULARITY	1.791	***	1.703	***	0.088		-		0.705	*	0.864	**
PRICE_PREMIUM	1.652		-		-1.393		-		-1.170		-	
SOPHISTICATION	3.137	***	3.125	***	2.443	***	2.211	***	2.677	***	2.673	***
DESIGN_FLIP	-4.284	*	-4.031	**	1.680		-		-0.963		-	
DESIGN_SLIDER	-2.846		-2.604		-0.559		-		-1.038		-	
R2	0.241		0.238		0.152		0.135		0.150		0.144	

*Significance codes: * < 0.05, ** < 0.01, *** < 0.001*

Table 11 summarizes the results of the regression model based hypothesis testing. For the first time period from January 2003 to June 2006, five out of eight hypotheses were supported. For the second half, only two hypotheses were supported, highlighting the structural break. Hypothesis 3a was separately tested with a simple linear regression in Publication 4, and showed a statistically significant association between initial and late popularity.

Table 11. Summary of the hypothesis testing results (Publication 3).

Hypothesis	1st half (1/2003-6/2006)	2nd half (7/2006-12/2009)
H1a. Higher technological sophistication is associated with longer unit lifetimes	Supported	Supported
H1b. Higher technological sophistication is associated with higher price	Supported	Supported
H1c. Higher price premium is associated with longer unit lifetimes	*Not supported*	*Not supported*
H2. Unit lifetimes are stable over time	Supported	*Decreasing trend (Not supported)*
H3a. Initial popularity is associated with late popularity	Supported	Supported
H3b. Higher initial popularity is associated with longer unit lifetimes	Supported	*Not supported*
H4. Complex product designs are associated with shorter lifetimes (FLIP/SLIDER design)	Supported / *Not supported*	*Not supported / Not supported*

4.4 Framework for measuring Internet protocol deployment

Based on previous literature and experiences from the research data collection, a framework for measuring Internet protocol deployment was developed. The framework helps to better understand Internet protocol deployment, and to measure the process. First, subsection 4.4.1 describes the framework with examples. The framework is then applied to the Finnish mobile market for illustrative purposes in subsection 4.4.2.

4.4.1 Framework

The framework divides the temporal deployment process into distinct steps loosely linked to the commercialization and diffusion phases of the innovation-development process by Rogers (2003). During the deployment steps the actions that the stakeholders take depend on the chosen protocol deployment model. Depending on the deployment step and model in question, the framework identifies the main deployment measures and data sources, which can be used to estimate the protocol deployment level and diffusion rate.

Deployment steps

The deployment steps of an Internet protocol include 1) implementation, 2) commercialization, 3) acquisition, and 4) adoption.

First, during the implementation step the provider of a protocol implement the protocol according the specifications. For an Internet protocol, the specifications are usually developed and standardized by IETF (Internet Engineering Task Force), whereas for other software features the standardization organization can differ depending on the type of software in question. Three implementation locations are available for protocols and other software features. The locations include different layers in software hierarchy from low to high: 1) kernel of an operating system, 2) middleware, and 3) application. Examples of protocols implemented at these respective three layers include TCP/IP protocols, OpenSSL for SSL/TLS, and BitTorrent.

Second, during the commercialization step the provider includes the protocol in one or more products, therefore, making it available for end users and customers to acquire. Depending on the implementation location, the commercial product can be software (application or middleware), an operating system with the protocol, or a hardware device with an operating system and the higher-level software included.

Third, during the acquisition step the end user achieves the ownership of the protocol. Because of the modularity in software hierarchy, the acquisition consists of the product, which contains the protocol, and the platform, where the product is installed after the acquisition. When the product and platform are bundled together, such as in the case of a smartphone and its operating system, the two acquisitions occur simultaneously.

Last, during the adoption step the end user starts to use the protocol and to generate traffic directly or indirectly. In some cases, the user generates traffic directly by using an application with the protocol. On the other hand, in the case of operating system services the protocol is often turned on automatically, and does not require direct user interactions.

Deployment models

Three protocol deployment models are identified: pre-installation, post-installation, and update installation.

The pre-installation model is a bundled model, where the end user acquires hardware (e.g., a mobile handset), which has pre-installed software (e.g., an application) containing the protocol. Therefore, the producers' decisions have an impact on the diffusion of the protocol into the installed base of devices. On the other hand, the pre-installation as the only deployment model can lead to slow diffusion, because of the long unit lifetimes of hardware.

The post-installation model is an unbundled model, where the end user acquires the software (product) and the hardware (platform) separately, and installs the software to the hardware by herself. An example of the post-installation model is the application store for smartphones. Therefore, as the diffusion process is not bound to the unit lifetimes of hardware, the protocol could spread faster than in the pre-installation model if the existing installed base of devices can use the protocol.

The update installation is also an unbundled model, where the end user acquires the protocol via a SW update (product) for existing HW (platform). Examples are web browsers, smart phone applications, and operating systems, which are all updated regularly. Therefore, this model is similar to the post-installation model, with the exception that an update decision might not require any end user action. If automatic updates are used in the existing installed base of devices, this model could enable fast diffusion of new protocols, as the examples of Apple's iOS operating system updates have shown.

Deployment measures and data sources

For each deployment step, there is a separate deployment measure. On the provider side, the protocol spreads into the commercial products available to the end users. On the end user side, the measures are related to the ownership and usage of the devices.

The implementation step can be measured with the implementation level, that is, the number of implementations of a protocol. Because a protocol can be implemented in several layers, the definition of the target population for the measure is not straightforward. One option is, for example, to calculate the share of operating systems or relevant applications for which the protocol is implemented. Data for the implementation level can be collected from product specifications, device description repositories[1] or using source code analysis (e.g., Komu, Varjonen, Gurtov, & Tarkoma, 2012).

The commercialization step can be measured with the availability level, that is, the share of all commercially available products that contain the protocol. For the pre-installation model, the share of device models on sale containing the protocol is calculated. For the post-installation and update installation models the measure is the share of available software products, such as operating systems or application types. Possible data sources include online and offline product catalogs, as well as market research companies collecting information on retail product sales. Another measure for the commercialization step is the acquisition rate, which can be calculated by weighting the availability with unit sales volumes. The acquisition rate is a link between the provider and end user measures, and provides information for evaluating the success of the provider commercialization strategies. Data collection requires access directly to the stores selling the products, or to market research companies focusing on retail sales.

The end user side measures focus on the diffusion of the protocol and, therefore, the measures are relative to the potential population of users or devices in the market. Figure 9 illustrates the end user measures (levels) with the deployment gaps and delays.

[1] e.g., ScientiaMobile (https://www.scientiamobile.com/)

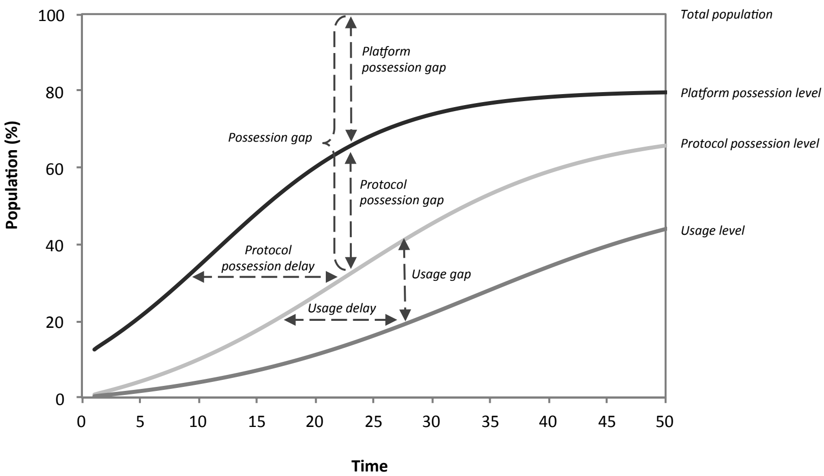

Figure 9. End user side deployment measures, gaps, and delays (Publication 4).

The acquisition step can be measured with platform and protocol possession levels. Platform possession level is the share of population with ownership of the platform, that is, users who could acquire and install the protocol into their devices. The measure, therefore, describes the short-term user population potential, where the total population is the long-term potential. Platform possession is only valid for the post-installation and update installation models, in which the platform and protocol are acquired separately. In comparison, the protocol possession level is the share of population, which have the protocol acquired and installed, that is, can use the protocol. Both measures can be estimated from data on cumulative sales, installed base of devices, or network traffic measurements, which are then correlated with the information on the protocols installed in each device.

The adoption step can be measured with the usage level. The measure can be measured both on binary (user or non-user) and continuous scale (for example, the amount of generated network traffic). Data on usage level can be collected by utilizing several methods and measurement points (Smura, Kivi, & Töyli, 2009), such as end user surveys, usage monitoring systems, and network measurements.

Figure 9 also shows the gaps and delays, which can be calculated directly from the end user measures. As stated in Publication 4, deployment gap refers to the "relative or absolute difference between two measures at time *t*", and deployment delay is defined as the "timely difference between two deployment steps reaching a specific deployment level". The gaps and delays are called as platform possession gap and delay, protocol possession gap and delay, as well as usage gap and delay.

Framework

Figure 10 links the deployment step and models, as well as the deployment measures and data sources into a conceptual framework. The deployment steps in the framework go in a temporal order from top to bottom, and are divided into the provider and end user sides. The three deployment models are presented horizontally, as they can occur at the same time depending on the chosen deployment strategies. The right-hand side of the framework maps the measures and data sources to the steps and models. When using the framework, is important to identify the population that is measured in each step, and then identify the most appropriate data sources based on the used deployment model. The analysis of the deployment levels can be complemented by analyzing also the deployment rates, that is, the change in the size of the population over time. Other practicalities related to the usage of the framework are described in detail in Publication 4.

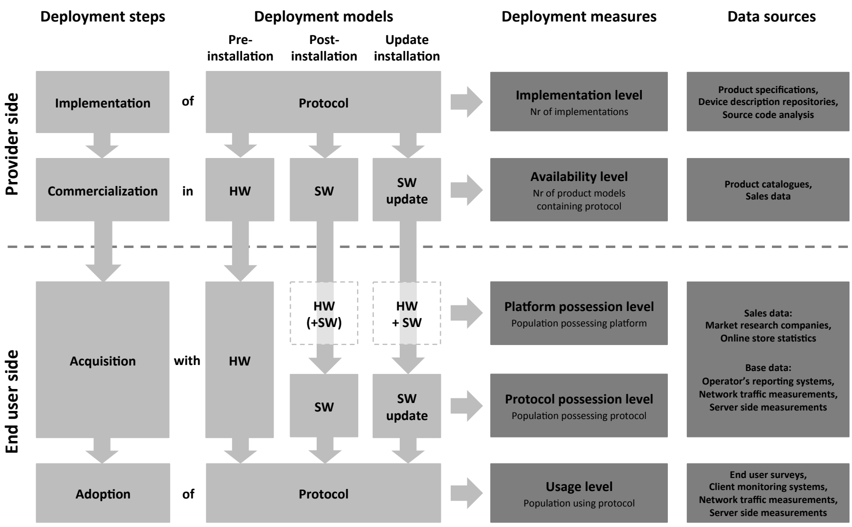

Figure 10. Framework for measuring the deployment of Internet protocols (Publication 4).

4.4.2 Application of the framework to the mobile market

The framework was applied to the Finnish mobile handset market with data from 2003-2012. In total 11 protocols were selected for the analysis, as described in Section 3.2.1. The analysis focused on the end user side, because the protocols are widely deployed in the personal computer market and server-side. The scope was further limited to the pre-installation model, because it was the predominant one in the Finnish mobile market during the study period, and the effect of other deployment models were estimated to be negligent.

Figure 11 maps the research datasets to the deployment measures of the framework. The protocol information from the feature dataset was correlated with the handset model specific retail sales and installed base datasets. This enabled the calculation of the availability level, acquisition rate, and possession level of the protocols. Further, usage data provided the usage levels for two protocols: HTTP and EMAIL.

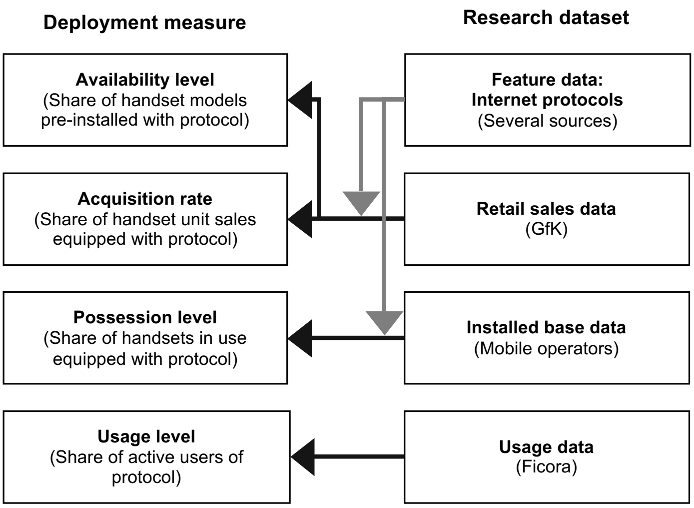

Figure 11. Linkage between the deployment measures and the research datasets (modified from Publication 4).

Figure 12 shows the a) availability level, b) acquisition rate, c) possession level, and d) usage level for the protocols from 2003-2012. Four general protocol groups, marked with different colors in the figure, can be identified based on visual inspection. These groups are related to the diffusion of specific mobile services: 1) WAP browsing (IPv4 and UDP), 2) HTML browsing (TCP and HTTP), 3) email (TLS and EMAIL), and 4) real-time communications (RTP, RTSP, and SIP). TLS protocol is also important for the security in HTTP browsing, but the results indicate that TLS diffusion was primarily email-driven. Because real-time communications protocols include two functions, streaming and voice over IP, the diffusion patterns are not as close to each other, as in the other three groups.

Figure 12a and Figure 12b depict the provider side measures, showing that the deployment of most protocols was relatively successful during the first two steps. Most protocols of groups 1, 2, and 3 reached availability levels and acquisition rates of 80-90%, and were included in a large share of all handset models, including the most popular ones. On the other hand, the intense competition with alternative proprietary protocols (e.g., Skype for SIP), explains the drops in deployment curves for group 4 (RTP, RTSP, SIP). These protocols are more demand-driven, so there is higher variation in the acquisition rates. There are also some differences in both measures between the protocol groups. For example, the availability levels of IPv4 (group 1) were between 78% and 96% during 2003-2012, whereas SIP (group 4) remained below 51% level during the same period. The comparison of availability levels and acquisition rates shows that for many protocols the availability levels were higher than the acquisition rates during initial diffusion. This pattern changes later, as the models equipped with the protocols become more popular, enabling the acquisition rates to reach or surpass the availability levels. This happens because new protocols are often introduced first in high-end or experimental models, meaning low number of acquisitions due to high price or niche status. The general popularity of mobile handsets with advanced features also increased during the study period, explaining partly these dynamics.

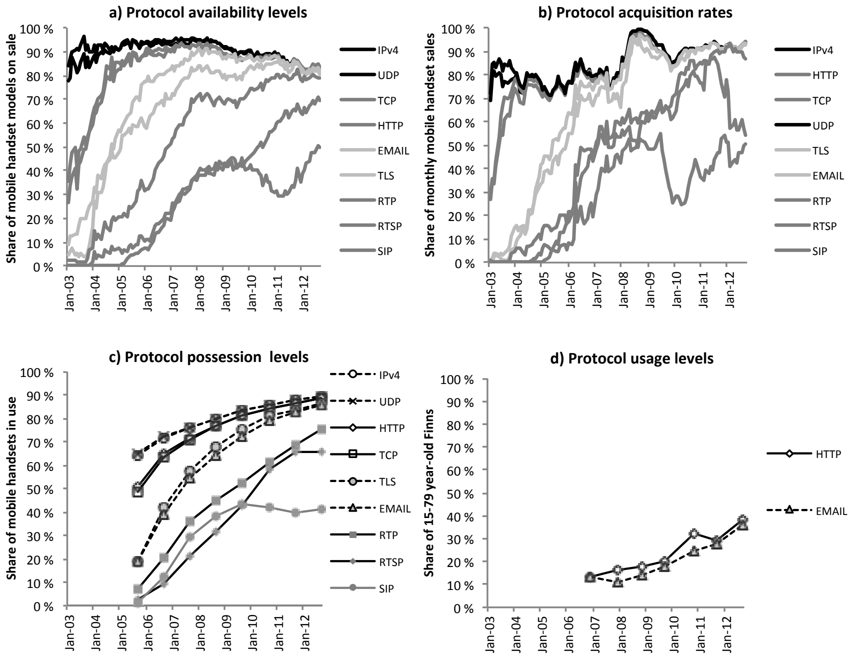

Figure 12. Protocol a) availability levels, b) acquisition rates, c) possession levels, and d) usage levels (Publication 4).

Figure 12c and Figure 12d show the end user side measures. For possession levels, SIP is again a clear exception from other protocols. One reason for the drop with the diffusion of SIP in 2009 is the discards of Nokia Symbian S60 devices, which had SIP pre-installed. These S60 handsets were probably replaced with Apple iPhone and Google Android devices, which did not have SIP during that period. The usage levels of Figure 12d were obtained only for HTTP and EMAIL. There seem to be large differences between possession levels and usage levels. The usage levels of EMAIL and HTTP followed closely each other and increased slowly from 10-15% to 30-40% during the study period, whereas the possession levels of these two and several other protocols started to already reach saturation.

To enable further comparison of the end user side measures, the possession and usage levels of HTTP and EMAIL were plotted together in Figure 13. The strong technology-push that was visible on the provider side is also visible with the possession levels of the protocols, which increased notably during the study period. However, the patterns also show the typical slowness of the pre-installation model due to long unit lifetimes. For example, for EMAIL the delay from 80% availability level and acquisition rate to the same possession level was about three years.

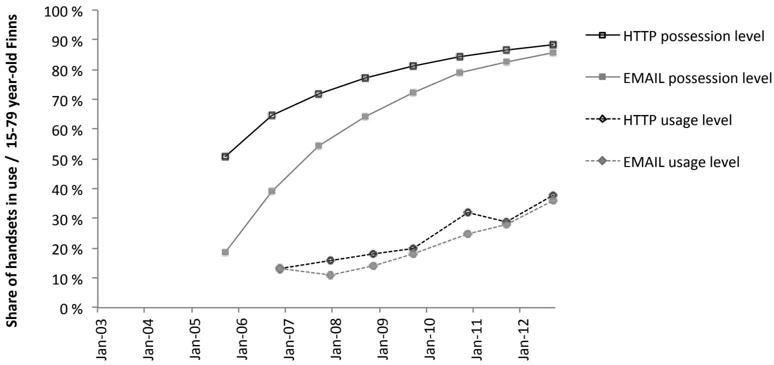

Figure 13. End user side measures – possession level and usage level – for HTTP and EMAIL (Publication 4).

The comparison shows the small effect of the technology push on the usage levels. Large usage gaps and delays were identified for both, HTTP and EMAIL. The possession levels of the protocols increased from 39% to 86% (HTTP) and from 65% to 89% (EMAIL) during the period of September 2006 to September 2012. For HTTP, the usage gap was rather stable 50-55%, while for EMAIL the gap increased notably from 26% to 50%. For EMAIL this translates into about six-year usage delay at the 30% level. This means that either there is a large existing non-user population of the protocol who continue as non-users even, or new protocol acquirers do not start using the protocol.
The findings indicate that HTTP and EMAIL are examples of protocols with unsuccessful deployment during the study period. Providers did push the protocols into the device models and these models were also commercially successful, but the capability to use the protocols did not translate into a high share of users. According to Ficora (2012), web browsing and email services had only a small impact on handset purchase decisions before 2010, explaining the large usage gap. Other explanations for the usage gap include data pricing and usability of mobile handsets at that time.

5. Conclusions and discussion

This section summarizes the contributions of this dissertation, and discusses their significance and limitations. Recommendations for future work are also provided.

5.1 Summary and contributions

This dissertation contributes mainly to the diffusion of innovations theories (Rogers, 2003; Peres et al., 2010) in terms of new data collection, method-development, theory-testing, and theory-creation. The contributions are realized in more detail in the analysis related to the three research questions. The first research question (RQ1) – "What are the diffusion patterns of mobile handset features?" – was studied by fitting traditional diffusion models on diffusion data of mobile handset features. The second research question (RQ2) – "What is the relationship between mobile handset features, prices, and sales volumes, and their effect on handset replacement?" – was studied by first analyzing mobile handset retail sales data, and then correlating the retail sales data to the installed base data on mobile handsets to enable further analysis of the replacement process. For the third research question (RQ3) – "How to measure the deployment and diffusion of complex mobile technologies?" – a generic framework for measuring Internet protocol deployment was developed and applied to the Finnish mobile market by using several research datasets.

To summarize the results, Publications 1, 2, and 3 fitted mathematical models to the data on the diffusion of mobile technologies on several levels. Publications 1 and 2 did explorative analysis and tested diffusion theories on the data on mobile handset features. Publication 3 extended theory-testing to replacement models and theory-creation, by analyzing determinants of replacement. Last, Publication 4 synthesized selected parts from the other publications, and provided a conceptualization on how technology diffusion can be measured during the different stages of diffusion.

Table 12. Summary of contributions, research questions, data, and analysis methods.

	Publication 1	Publication 2	Publication 3	Publication 4
Research topic	Diffusion of mobile handset features	Price and sales volume patterns of mobile handsets	Replacement and unit lifetimes of mobile handsets	Deployment of Internet protocols
Research question	RQ1	RQ2	RQ2	RQ3
Analysis methods	Diffusion model estimation Diffusion turning point identification	Descriptive statistics Diffusion turning point identification Linear regression analysis	Replacement model estimation Linear regression analysis	Literature review Developed framework for measuring protocol deployment
Data	Feature data Installed base data	Feature data Retail sales data	Feature data Retail sales data Installed base data	Feature data Retail sales data Installed base data Usage data
Domain-specific contributions	Empirical evidence on mobile handset feature diffusion patterns and durations of diffusion stages in Finland	Empirical evidence on mobile handset model lifecycle price and sales patterns from Finland Empirical evidence on the sales and prices of models equipped with selected features	Empirical evidence on mobile handset replacement and unit lifetime patterns in Finland Estimation of the effect of price, sales volume, and features on mobile handset unit lifetimes	Empirical evidence on deployment patterns of 11 Internet protocols in Finland Confirmation of the important role of supply-side in the deployment of Internet protocols
Theory and method contributions	Confirmation of an asymmetric s-shaped diffusion pattern for mobile handset features Model estimates for practical forecasting	Estimation of linear models on the association between handset feature prices and sales volumes	Confirmation of suitable unit lifetime distributions for mobile handsets A developed measure for technological sophistication	A framework for measuring protocol deployment Identification of three deployment models: pre-installation, post-installation, and upgrade installation Identification of deployment gaps and delays
Practical and managerial implications	Traditional growth models are suitable for modeling feature diffusion Separation and identification of introduction and growth stages is beneficial for practical forecasting purposes	Association between prices and sales are relatively systematic	Product features can be used to improve unit lifetime estimates	Both possession and usage levels should be measured when analyzing protocol deployment Deployment model selection is important in deployment planning

Table 12 summarizes the specific contributions and implications of each publication, and links them to the research questions, data, and used analysis methods. The unique characteristics and combination of the collected empirical time-series data are one contribution of the dissertation. Mobile handsets enable data collection on mobile technology diffusion from different viewpoints, but due to, for example, business sensitivity issues obtaining market level data is often difficult. The data studied in this dissertation enabled studying and explaining the characteristics of mobile technology diffusion on several levels of product markets (Bayus, 1994a), from product category to product models and product features. Further combining the datasets made possible analysis of the replacement process of mobile handsets in Finland, and more generally comparing the benefits the different datasets.

The number of new mobile technology innovations, in terms of mobile handset feature introductions, has been high after the late 1990s. This dissertation suggests that one should analyze the development of the product category by looking at the detailed level of product feature diffusion, in addition to product generations. This dissertation extends previous research on product feature and mobile technology diffusion (e.g., Kivi et al., 2012), by parameterizing the diffusion of several mobile handset features and quantifying the durations of diffusion stages, using triangulation of several methods and datasets.

Diffusion of mobile handset features has similarities with general innovation diffusion patterns. The results show that mobile handset features follow an s-shaped pattern, identified previously for mobile telephony diffusion (e.g., Michalakelis et al., 2008). The pattern was also identified to be asymmetric: an initial period of slow growth is followed by a fast uptake and growth, which then turns into a long period of slowing diffusion close to the saturation level. Therefore, traditional asymmetric growth models, such as the Gompertz model, provide a reasonable fit when modeling mobile handset feature diffusion. However, an assumption of 100% saturation level for mobile handset features is not often valid, so expert opinions or analogies from other technologies might be needed for practical estimation purposes.

The results indicated large differences in the durations of the introduction stage. The large variation in takeoff times is explained by several factors, such as technology maturity, network effects, and prices. The prices of mobile handsets equipped with the studied features were generally shown to follow a decreasing pattern, supporting previous product category level literature (e.g., Golder & Tellis, 1997). The absolute price level at feature takeoff was identified to be roughly 400-500 Euros, a price level after which the handsets with these features seem to become more appealing to the mass market. In addition, a relatively linear association between prices and market shares was identified for several features after a 10% market share is reached. These results indicate that price could be a useful variable in feature diffusion models or identification of the feature takeoff point.

To better understand the diffusion of new mobile technologies, it is important to study the replacement process of mobile handsets, as the effect of replacement purchases on new technology diffusion is high in the mature mobile market. By correlating installed base and retail sales data to obtain data on mobile handset discards, as well as by conducting handset model level analysis to understand the possible variation in lifetimes of units with different capabilities, this dissertation contributes to the research on replacement (e.g., Islam & Meade, 2000). The results support earlier findings (Kivi et al., 2012) that Gamma and Weibull distributions both provide reasonable results for parameterizing the mobile handset unit lifetime distributions. A relatively simple way of calculating the technological sophistication of handset models was also illustrated, enabling the analysis of associations between the sophistication, popularity, prices, and unit lifetimes of mobile handsets. It was shown that technological sophistication is associated with longer unit lifetimes, and that price is a relatively good proxy for technological sophistication. Therefore, in practical estimations, one should consider using product category subsegments based on technological sophistication.

Diffusion and deployment of mobile technologies is complex. As the results highlight, the number of available deployment models further complicate the picture in the case of software features and Internet protocols. The identification of the three protocol deployment models – pre-installation, post-installation, and upgrade installation – contributes to the innovation diffusion literature (Rogers, 2003). It is important for a protocol developer to consider all deployment models when planning the deployment strategy.

Quantitative measures of the diffusion dynamics and bottlenecks are needed, to better understand the deployment process of Internet protocols. This dissertation developed a framework, which combines protocol deployment steps adapted from previous literature (Rogers, 2003) to the identified deployment models and links these to quantitative measures and data sources. The measures include protocol availability, possession, and usage levels, as well as the deployment gaps and delays that can be quantified between the deployment levels. The deployment gaps and delays support and extend the original idea of assimilation gaps by Fichman & Kemerer (1999). Even though the measurement framework was developed specifically for Internet protocols, it can also be useful with other technologies. For example, the deployment models are generalizable for most software features, and could also be applied to other product categories such as personal computers, tablets, and other emerging device types.

The application of the developed framework to the Finnish mobile market illustrates the general slowness of the pre-installation deployment model. Generally, protocol diffusion is driven by applications, such as the examples of web browsing, email, and video streaming show. The results also illustrate the strong impact of the supply side in deployment of Internet protocols. With the pre-installation model, this is especially visible in the large deployment gaps between the possession and usage levels. For example, differences of 26%-55% were identified between the possession of the selected protocols and the number of actual users. This result supports the idea by Warma et al. (2013) that protocols are often acquired unintentionally along the device purchase. Due to this, the technology-push strategy realized in the pre-installation model may not always provide a successful result. These findings emphasize the need to involve both the deployment levels and gaps into the analysis of protocol deployment. The levels provide information about the general success of deployment at different steps, and the gaps provide understanding on the possible bottlenecks, as was shown for web browsing and email related protocols in this dissertation. Further, for measuring adoptions, the findings highlight the need to use actual usage data instead of the traditional purchase information.

In conclusion, the dissertation emphasizes the need to include the product feature level when studying the diffusion of complex technology products. Relatively simple models were shown to provide meaningful estimates of mobile technology diffusion on a feature level, even though the complexity in the overall phenomena is high. Because such technology products have a variety of features and capabilities, the measurement of the diffusion should also consider usage; while many features are acquired, the use may concentrate on relatively few key features, leading into gaps between ownership and actual usage.

The results do not only apply mobile handsets. An increasing number of product categories have Internet connectivity, which may lead to similar high-paced innovation as with mobile handsets. Once the products have Internet connectivity, and the features also utilize Internet, also the number of available measurement methods increases. While collecting behavioral data on offline usage requires often direct access to the device or the individual, online usage data can also be collected from several points in the networks. Similar studies focusing the adoption process of product features could benefit from the detailed level of data available from device-based measurements, whereas with macro-level diffusion studies network-based measurements can provide enough detail on a census level. Many other new product categories will go through similar evolution as mobile handsets, where the increased processing power enables to start equipping the devices with also increasingly complex features, from basic hardware features to software applications.

The results have practical implications for several stakeholders. First, better understanding of the mobile technology diffusion enables regulator to influence the diffusion of specific features. This dissertation covered a period during which a major regulatory change in the Finnish market was made. The change enabled the previously prohibited bundling of third generation subscriptions and devices, and had short-term effects in the diffusion of third generation handsets. Second, mobile operators, device manufacturers, as well as application, content, and accessory providers may need estimates of the device installed base. For instance, device manufactures need to understand the lifetime dynamics for after sales purposes, mobile network operators need to estimate the evolution of their device base for planning the uptake and rundown of network technologies, and third party providers need to estimate their potential customer population. The estimated models and distributions of the dissertation can be useful for the forecasting purposes of these stakeholders. Last, the framework for measuring protocol deployment aids researchers when planning quantitative studies on the diffusion of such innovations, and protocol developers when doing more practical analysis of their protocols.

5.2 Limitations

There are some limitations in the research of this dissertation. First, the research concentrated on one technology product category of mobile handsets, therefore, possibly limiting the generalizability of the results. Despite Publication 4 conceptualizing protocol deployment more generally, most of the work focused on mobile handsets. The distinction and definition of mobile handsets, personal computers, tablet devices, and other emerging product categories, such as wearable devices, is becoming increasingly difficult make.

Second, the analysis focused on pre-installed product features. Features retrofitted physically (hardware features) or by installation (software features) were not included in the empirical research. However, the developed conceptualization of protocol deployment includes all the three deployment models and discussed the possible differences between pre-installed and retrofitted features. Furthermore, even though a wide variety of features were selected for research, some functional areas were better covered than others. For example, features related to the performance of the devices, such as processor type and the amount of memory were not included due to limited data.

Last, the research concentrated on one geographical market of Finland. The main conceptualizations of the dissertation are generalizable to also other markets, but some of the empirical observations could be market-specific. On the one hand, the Finnish market has some peculiarities, such as the high impact of Nokia as a manufacturer and regulation related to subsidization, as subsidization of mobile handsets and subscriptions was forbidden for a part of the study period in Finland. On the other hand, the results can show examples on diffusion patterns for new emerging countries, where the regulator follows similar decisions as in the Finnish market. The general diffusion patterns could also be speculated to be applicable more widely, for instance, in the emerging markets where the diffusion of mobile handsets and advanced features is still at a lower level. In addition, this research provides an example for other studies to replicate the study in other markets in terms of data collection and analysis.

5.3 Future research

The dissertation provides several avenues for future research. First, the measurement of several deployment steps seems worth more attention. Future research should study the identified gap between technology possession and usage, for instance, by implementing larger scale quantitative measurements on mobile technology usage levels. Qualitative studies could also seek to better understand the reasons for these gaps. The research of pre-installed features in this dissertation could also be extended to cover retrofitted software features, to understand the dynamics between the diffusion steps also for these deployment models. However, the measurement setup for this research would probably require more extensive user-level network traffic measurements or handset based measurements with a sample of users.

This research also did some initial evaluation on the determinants of diffusion and lifetimes, but these factors were not included in the diffusion models. Next step could be to test further whether the price information would be useful when estimating mobile handset feature diffusion. In addition, the way of estimating feature price as such could be improved. For this dissertation, the price was simply calculated as the mean price of devices equipped with the features, therefore, not directly describing the marginal cost or price of the feature on the total price of a handset. Estimation methods, such as hedonic price modeling (Rosen, 1974), or data collection on real components prices could be utilized to provide complementing views on feature prices.

Extending the analysis to other product categories and geographical markets could further verify the results of this dissertation. For example, studying the evolution of other emerging and relatively standardized product categories would be relatively straightforward to replicate, such as tablets and wearable products like smart watches. Further, as these products are also linked to mobile handsets with a complementing or substituting relationship, the association of these products should be studied in more detail.

Generally, research should focus on understanding the post-adoption usage. The concept and identification of an active user is generally somewhat ambiguous, and is worth further research to better understand the dynamics of product adoption and usage. This area is important, because in the digital world devices have increasing computing power, which means that products can be altered or refined notably after they have been manufactured (Yoo, Henfridsson, & Lyytinen, 2010). In addition, installation (retro-fitting) of new applications is becoming increasingly common, and has an important role in how people use their mobile devices (De Reuver, Bouwman, & Nikou, 2016). The analysis of usage in this dissertation continued the traditional definition of a two-stage adoption, without considering, for instance, the rate and variety of use (Shih & Venkatesh, 2004). However, especially in the case of Internet protocols, use patterns could be analyzed in more detail by using, for example, network traffic measurements (e.g., Riikonen, 2009). However, the challenge for user-level network traffic measurements is that all network traffic in one network needs to be measured, in practice requiring close collaboration with the network operators. However, with such collaboration the research of this dissertation could be extended to better understand the different user segments. An interrelated topic is multi-device ownership, which is increasingly common, as people own several devices with roughly the same capabilities, such as a mobile handset, tablet, and personal computer.

Finally, one avenue for future research on mobile handset replacement and unit lifetimes would be to test whether the lifetime distribution should be allowed to vary over time for individual handset models (see, e.g., Steffens, 2001). In this dissertation, the lifetimes of each model were assumed to be stable, but it could be that for some models there is variation between the units bought at different points of the product lifecycle.

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Rapid innovation in mobile technologies and good measurement possibilities related to mobile handsets enable novel contributions to previous research. This dissertation draws on the methods from innovation diffusion literature and provides empirical evidence on the determinants and diffusion patterns of mobile technology diffusion, by measuring and modeling the phenomenon from complementing viewpoints. Further, a conceptual framework is developed for measuring diffusion dynamics and is applied to the case of Internet protocols, a special example of mobile technologies.

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