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Leveraging Mobile and Internet of Things Technologies to Enhance Products with Digital Services

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Dedicated to my family.

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Overview of Contents

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Abbreviations

ANN	Artificial Neural Networks
ANOVA	Analysis of Variance
API	Application Program Interface
AVE	Average Variance Extracted
B2B	Business-to-Business
B2C	Business-to-Consumer
BLE	Bluetooth Low Energy
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CRM	Customer Relationship Management
DTPB	Decomposed Theory of Planned Behavior
ERGM	Exponential Random Graph Model
FFM	Five-Factor Model
G-D	Goods-Dominant
HTTP	Hypertext Transfer Protocol
IDT	Innovation Diffusion Theory
IFI	Incremental Fit Index
IoT	Internet of Things
IP	Internet Protocol
IS	Information System
MANOVA	Multivariate Analysis of Variance
MWTAM	Mobile Wireless Technology Acceptance Model
NFC	Near Field Communication
NFI	Normed Fit Index
Q1	First-Quartile
Q3	Third-Quartile
RFID	Radio-Frequency Identification
RMSEA	Root Mean Square Error of Approximation
S-D	Service-Dominant
SDK	Software Development Kit
SEM	Structural Equation Modeling
SSME	Service Science, Management and Engineering
SVM	Support Vector Machines
TAM	Technology Acceptance Model
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Action
UTAUT	Unified Theory for the Acceptance and Use of Technology
α	Cronbach’s Alpha

Abstract

The difficulty of product differentiation has encouraged machinery manufacturers to transform their business models from selling products towards providing services. On the one hand, services generate more stable revenue and higher profits. On the other hand, services are difficult to imitate and can enhance customer loyalty, thus becoming a sustainable source of competitive advantage. Previous product-centric manufacturers have successfully transformed business to a service-dominant model. Take IBM for example, more than half of the annual revenue comes from its service business units. In a B2B setting, services are typically bundled with products and sold in the form of maintenance contracts. Consequently, manufacturers are able to interact with each individual customer proactively and directly.

Although the service-dominant logic has gained significant success in a B2B setting, applying the logic is not easy for manufacturers in a B2C setting. First, most B2C manufacturers are not able to interact with end-consumers directly to provide services. Second, products in a B2C environment like consumer goods are often of less value. Also, consumers are not used to engaging in a contractual relation when buying a product at a retailer. Consequently, when requiring services for a product, consumers lack support to easily access and consume services. Third, consumers are shown to manufacturers as aggregated sales numbers without additional knowledge about individual characteristics and requirements. Although personalized marketing and recommendations have been proved to be effective, manufacturers in a B2C setting can hardly apply the approaches. The problem of tailoring service offerings to one's individual requirements is called service personalization problem.

The thesis is thus motivated to address these problems based on four empirical studies. The goal is to help manufacturers in a B2C setting to enhance service offerings. First, an online study involving 991 consumers was conducted to identify high potential product-related services that consumers expect manufacturers to offer on mobile. The second study consisted of one laboratory experiment, one field experiment, and one field study. It proposed, compared, and evaluated three mobile Internet of Things solutions to connect non-intelligent physical products with relevant digital services. To address the service personalization problem, the third study was focused on understanding how an individual's personality traits impact her adoption of different mobile services based on two sub-studies. The first sub-study involved 2043 participants; it collected ground-truth about each participant's personality traits and installed mobile apps to examine the impact of personality on mobile service adoption. The second sub-study was based on an online survey with 397 participants; it

further studied how personality interacts with cognitive determinants to impact adoption. Complementing these methods, the last empirical study developed machine-learning models to predict each smartphone user's demographics and personality traits based on her installed apps. The models were evaluated on data points collected from 1531 mobile devices.

The results of the thesis demonstrate that consumers' intention to use product-related services increase by 22% if services are easily accessible on mobile. Such intention is highly dependent on the type of a service as well as the type of the related product. Secondly, the thesis confirms that combining mobile information systems with Internet of Things technologies can significantly reduce service search cost and enhance adoption. By comparing alternative technical implementations and design aspects, the thesis recommends a Bluetooth button solution for manufacturers to enable products as service end-points. Afterwards, it confirms the impact of personality on mobile service adoption and shows how such an impact alters according to service types. It reveals that personality is more powerful in explaining the variance of people's mobile service adoption behavior than demographical differences. Finally, the thesis shows that the proposed machine-learning models are able to predict personality traits 65% better than a random guess in terms of precision while still keep the recall at an acceptable level. Regarding the prediction of demographics, the models can perform 55% better than a random guess in terms of precision and 34% better in terms of recall.

As a key contribution to theory, this thesis reveals the importance of personality traits in adoption research. It strongly recommends future research to study the impact of personality in addition to that of cognitive determinants. Complementing previous studies which estimated adoption from questionnaires, the thesis provides researchers with a data-driven tool to study adoption based on actual behavioral data in a scalable way. Furthermore, the service science and IoT research has been augmented with key insights developed from field studies, thus going beyond existing technical-driven and design-focused literature.

For practitioners, these results help manufacturers prioritize their service offerings on mobile devices. The proposed IoT solution enables manufacturers to connect consumers in a direct and low-cost way. Alternative implementations of the solution were compared and suggestions were given. Furthermore, the thesis presents actionable knowledge about how to enhance mobile service offerings based on each consumer's personality traits. Finally, it provides manufacturers with powerful machine-learning models to conduct automatic user profiling in the digital world. The models are non-intrusive, low privacy-concern, highly scalable, and can be integrated into any mobile app.

Zusammenfassung

Die Schwierigkeit der Produktdifferenzierung hat Maschinenhersteller dazu bewogen, ihr Geschäftsmodell vom Produktverkauf in Richtung Serviceanbieter zu transformieren. Auf der einen Seite generieren Services einen stabileren Umsatz und höheren Profit. Auf der anderen Seite sind Services schwierig zu imitieren und können die Kundenloyalität verstärken. Damit werden sie zu einer nachhaltigen Quelle für Wettbewerbsvorteile. Ehemals produktorientierte Hersteller haben ihr Geschäft erfolgreich in ein servicedominantes Model transformiert. Zum Beispiel wird bei IBM mehr als die Hälfte des Geschäftsumsatzes von Geschäftseinheiten generiert, die mit Services zu tun haben. In einem B2B Setting sind Services üblicherweise gebündelt mit Produkten und werden als Unterhaltsverträge verkauft. Somit sind Hersteller in der Lage, mit jedem einzelnen Kunden proaktiv und direkt zu interagieren.

Obwohl die servicedominante Logik einen signifikanten Erfolg in B2B Settings zu verzeichnen hat, ist die Logik für Hersteller nicht einfach anwendbar. Erstens, die meisten B2C Hersteller sind nicht fähig zur Interaktion mit Endkunden, um direkt Services anzubieten. Zweitens, Produkte in einem B2C Umfeld, wie zum Beispiel Verbrauchsgüter, sind oft von kleinem Wert und Konsumenten sind sich nicht gewohnt eine vertragliche Beziehung einzugehen, wenn sie ein Produkt bei einem Einzelhändler kaufen. Als Folge leiden Konsumenten an einem Mangel an Unterstützung für den einfachen Zugang und Konsumation von Services, sobald sie einen Produkteservice benötigen. Drittens, Konsumenten werden Herstellern als aggregierte Verkaufszahlen gezeigt, ohne zusätzliches Wissen über die individuellen Eigenschaften und Anforderungen. Hersteller in einem B2C Setting können die Konzepte kaum umsetzen, obwohl personalisiertes Marketing und personalisierte Empfehlungen bewiesenermassen effektiver sind. Das Problem der an individuelle Bedürfnisse angepassten Serviceangebote wird als „Service-Personalisierungsproblem" bezeichnet.

Die Dissertation ist damit motiviert, die genannten Probleme basierend auf vier empirischen Studien zu adressieren. Ziel ist es, Hersteller beim B2C Setting zu helfen und die die Serviceangebote zu stärken. Erstens wurde eine Onlinestudie mit 991 Konsumenten durchgeführt, um das grosse Potential von produktbezogenen Services, welche Konsumenten von Herstellern auf mobilen Plattformen erwarten, zu evaluieren. Die zweite Studie besteht aus einem Laborexperiment, einen Feldexperiment und einer Feldstudie. Es werden drei Lösungen im Bereich „mobiles Internet der Dinge" vorgeschlagen, verglichen und evaluiert. Dabei werden nicht-smarte, physische Produkte mit relevanten, digitalen Services verbunden. Um das Service-Personalisierungsproblem zu adressieren, fokussierte die dritte Studie auf das

Verständnis des Einflusses von persönlichen Charaktereigenschaften auf die Adoption von verschiedenen mobilen Services. Diese Studie gliedert sich in zwei Teilstudien. Die erste involviert 2043 Teilnehmer. Sie sammelt die Ground-Truth über Charaktereigenschaften der Teilnehmer und installierten mobilen Apps, um den Einfluss der Persönlichkeit auf die mobile Serviceadoption zu prüfen. Die zweite Teilstudie basiert auf einem Onlinefragebogen mit 397 Teilnehmern. Sie untersucht, inwiefern die Persönlichkeit mit den kognitiven Faktoren interagiert, um die Adoption zu beeinflussen. Aus der letzten empirischen Studie entstanden Machine-Learning-Modelle welche basierend auf installierten Apps demographische und charakterspezifische Eigenschaften von Smartphone-Benutzern vorhersagen. Die Modelle wurden mit den Datenpunkten von 1531 mobilen Geräten evaluiert.

Die Resultate der Dissertation zeigen, dass die Absicht von Kunden, welche produktorientierte Services zu nutzen, um 22% steigt, falls die Services auf mobilen Geräten einfach zugänglich sind. Eine solche Absicht ist stark abhängig vom Typ des Services und ebenso vom entsprechenden Typ des Produkts. Die Dissertation bestätigt zweitens, dass die Kombination von mobilen Informationssystemen mit Technologien des Internet der Dinge die Service-Suchkosten signifikant reduzieren und die Adoption verstärken. Nach dem Vergleichen von alternativen technischen Implementierungen und Designaspekten empfiehlt die Dissertation eine Lösung mit einem Bluetooth-Knopf. Hersteller können damit Produkte als Service-Endpunkte aktivieren. In der Folge wird der Einfluss der Persönlichkeit auf mobile Serviceadoption bestätigt und gezeigt, wie sich der Einfluss entlang des Servicetyps verändert. Es deckt auf, dass Persönlichkeit mehr Erklärungskraft bezüglich Varianz des Verhaltens in mobiler Serviceadoption aufweist als demographische Eigenschaften. Schliesslich zeigt die Dissertation, dass die vorgeschlagenen Machine-Learning Modelle fähig sind, persönliche Charaktermerkmale mit 65% besserer Präzision vorherzusagen als mit blossem Raten. Gleichzeitig bleibt die Sensitivität auf einem akzeptablen Level. Betrachtet man die Vorhersage von demographischen Eigenschaften, dann sind die Modelle 55% präziser als zufälliges Raten und haben eine 34% höhere Sensitivität.

Die Dissertation zeigt als ein Schlüsselbeitrag zur Theorie die Wichtigkeit von Persönlichkeitsmerkmalen in der Adoptionsforschung. Für zukünftige Forschung wird nachdrücklich empfohlen, neben den kognitiven Faktoren den Einfluss der Persönlichkeit hinzuzuziehen. Bisherige Studien, welche die Adoption aus Fragebögen geschätzt hatten, werden ergänzt durch ein datengesteuertes Werkzeug, um die Adoption basierend auf aktuellem Verhalten auf skalierbare Art und Weise zu studieren. Zudem wird die Service-

Wissenschaft und die IoT-Forschung erweitert mit Schlüsselerkenntnissen, die durch die Feldstudien entwickelt wurden und somit weiter gehen als bisher existierende, technikgetriebene und designfokussierte Literatur.

Aus Sicht von Praktikern helfen die Resultate den Herstellern beim Priorisieren von ihren Serviceangeboten auf mobilen Geräten. Die vorgeschlagenen IoT Lösung ermöglicht den Herstellern die Kunden direkt und günstig zu verbinden. Alternative Implementierungen der Lösung wurden verglichen und Vorschläge gegeben. Darüber hinaus präsentiert die Dissertation verwertbare Kenntnisse, wie mobile Serviceangebote dank den Persönlichkeitsmerkmalen von Konsumenten verbessert werden können. Schliesslich bietet sie den Herstellern leistungsfähige Machine-Learning Modelle, um automatische Benutzerprofilerstellung in der digitalen Welt durchzuführen. Die Modelle sind nicht aufdringlich, verursachen wenig Bedenken bezüglich Privatsphäre, sind hoch skalierbar und können in jede mobile App integriert werden.

1 Introduction

The trend of focusing on services as a key revenue stream in addition to selling products started in the manufacturing industry. Machinery manufacturers realized that in most markets competing products became too similar and room for product differentiation was limited (Joseph Pine and Gilmore 1999). Management literature thus suggested a transition from product manufacturing towards service provision due to financial, marketing and strategic opportunities (Gebauer et al. 2006). On the financial side, services generate more stable revenue and higher margins (Lay and Erceg 2002); Marketing opportunities can be generated as "better services for selling more products (Mathe and Shapiro 1993)". Strategically, services can become a sustainable source of competitive advantage because they are difficult to imitate and can meet complex customer needs (Simon 1993).

Following the suggestion, some manufacturers have successfully transformed from selling products towards providing services (Tukker 2013). Take IBM for example, the previous hardware-manufacturing giant is now mainly a global service provider and software company. More than half of the company's $90 billion revenue in 2006 came from its service business (Chesbrough 2007; IfM and IBM 2008). Other leading-edge manufacturing companies such as General Electric, Toyota Industries and ABB have increasingly shifted their strategic focus from selling goods to providing services to serve consumers in new ways (Gebauer and Friedli 2005; Mathieu 2001; Oliva and Kallenberg 2003; Saarijärvi et al. 2014).

For these Business-to-Business (B2B) manufacturers, selling services is relatively easy because they are able to interact with customers proactively and directly (Oliva and Kallenberg 2003). In addition, information about each customer's purchased products, service history, preference and contract detail is available, which makes it possible to tailor service offerings according to customer demands. In this context, services are typically bundled with products and sold in the form of maintenance contracts (Stremersch and Frambach 2001).

While more companies in a B2B setting have achieved successful transformations to service-dominant business models, such transformations are not easy to achieve for companies in a Business-to-Consumer (B2C) environment (Day 2006; Saarijärvi et al. 2013). First, most B2C companies do not interact directly with end-consumers. Consumers are shown to them as aggregated sales numbers without any knowledge about each individual's demographics, preferences, previous behavior, etc. This prevents manufacturers from customizing service offerings according to individual needs thereby enhancing long-term relationships. Also, manufacturers are not able to proactively sell services to consumers because they do not know where consumers are and how to contact them directly. Second, products in a B2C setting are often of less value and consumers are, except for phones, not used to engaging in a contractual relation when buying a product at a retailer (Marceau 2002). Even for simple services such as free warranty extensions, manufacturers often rely on old-fashioned mail-in coupons and have to encourage consumers to reach out to them over inefficient channels. Some manufacturers try to overcome this problem by producing intelligent products represented as an integrated product-service bundle. However, intelligent products are expensive to manufacture and typically require changes in the production lines. As a result, nowadays 99% of products are still non-intelligent and disconnected (Cisco Systems 2013). Consumers thus have to find product-related services manually for the majority of products they own, which is cumbersome thus reducing consumers' intention to use services.

With the increasing ubiquity and connectivity of mobile Information Systems (IS) like smartphones and tablets, it becomes for the first time technologically and economically feasible for manufacturers to offer services directly to end-consumers. On the one hand, mobile IS can serve as a service broker to connect consumers to different physical products through Internet of Things (IoT) technologies. Widely used examples are barcodes and short-range communication technologies like Radio-Frequency Identification (RFID), Near Field Communication (NFC), and Bluetooth. Instead of connecting products directly to the Internet, which is costly, manufacturers can attach cheap IoT identifiers to products to enable them as services end-points (Deordica and Alexandru 2014; Lorenzi et al. 2014; Mu et al. 2009). Consequently, consumers can access digital services of physical products easily on mobile with a simple action such as scanning a barcode or attaching an NFC tag. On the other hand, mobile devices are the most personal devices consumers own and carry around with them all day (Scornavacca and Barnes 2006). The personal nature of mobile devices makes it possible for manufacturers to gain knowledge about each consumer's demographics, personality, and interest based on how the user interacts with her smartphone (Montjoye et al. 2013; Pan et al. 2011). Such benefits that were not reachable in a B2C environment become possible for manufacturers to obtain with the help of mobile IS and IoT. Consequently, B2C manufacturers are able to conduct timely personalized marketing, accurate customer segmentation, relevant service recommendation, etc.

1.1 The Service Provision Problems & Research Questions

Although mobile IS has a potential to help B2C manufacturers tap into the huge market of product-related services, four main questions have to be answered to maximize benefits for both consumers and manufacturers.

1.1.1 Taxonomy of Mobile Product Services

Driven by the wide spread of the Internet, manufacturers have provided online access to product services, thus helping consumers find them easily. However, even if a product service is available online, accessing the service is still cumbersome. For consumers, it represents a two-fold search and match problem. In most of the cases, consumers have to open a Web browser, type in some key words on a search engine, find out a Web page that provides the service, and then check its authenticity themselves. Thus, the service search cost (defined as the cost for a consumer to initiate a service transaction) remains high, which reduces consumers' intention to use services.

The ubiquitous and personal nature of mobile devices makes it possible to significantly reduce search cost, thus addressing consumers' unmet service needs. However, consumers' intention to use services on mobile could be strongly affected by the type of a service. For instance, checking the authenticity of a product might be preferred on mobile because consumers can use smartphones to directly interact with the product, while managing invoice after purchase might not be preferred because digital invoices have not been regarded as eligible by many manufacturers and retailers. Lacking feedbacks from consumers, B2C manufacturers have limited knowledge about what services consumers would prefer to use on mobile. Hence, an exploratory study was conducted to understand consumers' unmet needs for product services.

> ***RQ1:*** *Which are the key product-related services that consumers intend to use when mobile devices can serve as service brokers?*

1.1.2 Technical Design Challenges for IS Solutions

Recent studies have indicated that digital services could be bundled to physical products by leveraging IoT technologies and mobile IS (Deordica and Alexandru 2014; Lorenzi et al. 2014; Mu et al. 2009). In practice, HP has attached QR codes to consumer goods to help consumers easily verify the authenticity of a product on mobile. SHIPSU has attached QR codes to maritime products, therefore, consumers can reorder the same product directly. In addition to QR codes, Bluetooth beacons can also be used to link physical products with digital services. Deordica and Alexandru (2014) proposed to leverage low-energy Bluetooth beacons to provide consumers with location-based product recommendations to improve offline shopping experiences.

However, existing research mainly focused on conceptual and architecture-related aspects of the proposed IoT solutions but lacked comprehensive user evaluations. Also, facing alternative design options, previous literature failed to compare the pros and cons of different solutions to providing practitioners with the best practices. Both deficiencies make it difficult to understand key factors for designing a mobile solution to enabling product as service end-points. To address the research gaps, a field experiment was conducted to address the following research question:

> ***RQ2:*** *What factors are critical for consumers to adopt a mobile solution that enables physical products as digital service end-points?*

1.1.3 Personalized Mobile Service Offerings

The Innovation Diffusion Theory (IDT) (Rogers 1995) has concluded that the process of adoption over time follows an S-Curve. In the early stage of an innovation, it requires a huge amount of investment but small performance improvements are observed. As the knowledge about the innovation accumulates, early adopters start to use the innovation, which accelerates the speed of innovation diffusion. After overcoming major obstacles, the innovation reaches an inflection point where an exponential growth will take place. In the end, the innovation saturates and the diffusion speed stops growing or even decreases. Most of the new products and services follow the S-Curve framework but with different slopes (i.e., rate of adoption), inflection points, and saturation points. Researchers argued that diffusion speed could be accelerated along the whole product life cycle through personalization (Datta and Coondoo 2005). Consequently, understanding key factors in personalization benefits manufacturers for reaching quick wins thereby going beyond the typical adoption curve.

However, the impact of personalization on adoption was not well addressed in previous research. Existing individual level adoption research focused on understanding the impact of cognitive determinants like perceived usefulness and perceived ease of use. However, recent studies have showed that personality traits are equally important in impacting an individual's adoption behavior, thus should be focused in the future (Devaraj et al. 2008; McElroy et al. 2007). Empirical research also found evidence between an individual's personality and her use of the Internet (Landers and Lounsbury 2006; McElroy et al. 2007) and some specific mobile apps like Facebook (Ryan and Xenos 2011) and Foursquare (Chorley et al. 2015).

Consequently, personality is hypothesized to have a significant impact on consumers' adoption of mobile services. Due to the diversity of mobile services, such an impact could differ according to service types. Hence, the research question becomes:

> ***RQ3:*** *How can personality traits impact an individual's adoption of different types of mobile services?*

Although understanding the impact of personality traits has attracted more attention in adoption and diffusion research recently, it is difficult for practitioners to apply the knowledge to support their business decisions because an individual's personality traits remain unknown until being measured by lengthy survey. Answering such a survey takes five to fifteen minutes (Gosling et al. 2003), which is costly and not scalable (Montjoye et al. 2013).

Recent advances in machine-learning techniques have drawn the attention to automatic data-driven approaches to overcome the limitations of the traditional survey-based approach. Researchers have started to predict an individual's Big Five personality traits based on mining her email content (Shen et al. 2013), social network content (Chin and Wright 2014), and mobile meta-data like logs of phone calls, SMSs, and location information (Montjoye et al. 2013; Pan et al. 2011). Nevertheless, data used in the predictive models of previous work either only belongs to limited companies like phone manufacturers and telecommunication service providers, or triggers strong privacy concerns by parsing a user's social network content or installing additional surveillance software.

Therefore, a mobile-based, non-intrusive, low privacy-concern, and highly scalable approach of predicting a smartphone user's personality traits is required to enable the personalization of mobile services. With knowledge about each consumer's personality, manufacturers can tailor service offerings to boost service adoption. Addressing this, the last research question becomes:

> ***RQ4:*** *How can personality traits be automatically predicted on an individual level from openly accessible data on mobile?*

Figure 1 demonstrates how the four research questions address business problems along a typical service life cycle. RQ1 aims at helping manufacturers identify and recommend high potential services when consumers are in the phase of purchasing a service. RQ2 tries to compare consumers' adoption of different IoT solutions that leverage mobile devices as a service broker when services are being used on a frequent base. Finally, RQ3 and RQ4 aim to help manufacturers enable service personalization at both service purchase and service use time.

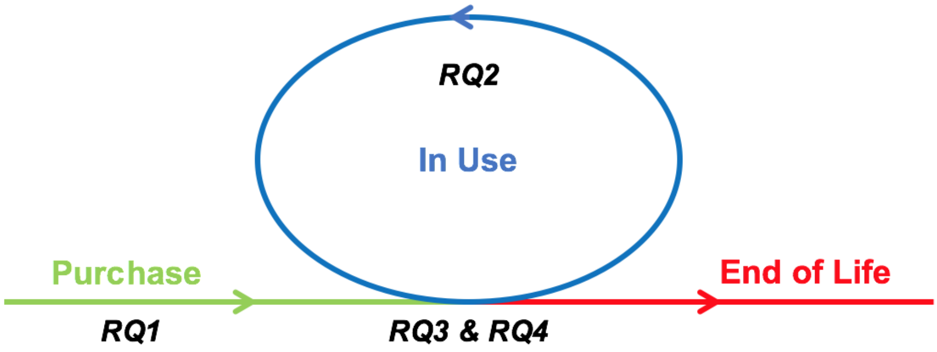


Figure 1: Research Questions in a Typical Service Life Cycle

The goal and contribution of this thesis is to address the research questions with the aim that the presented solutions can be transformed into insights and operationalized into results. In this manner, this thesis aims to be actionable, with an emphasis on providing methods and results that could be easily implemented by manufacturers to enhance their service offerings.

1.2 Research Methodology

To answer the research questions raised in this thesis, four quantitative empirical studies have been conducted.

First, a census-representative online study (Study I) was conducted in Germany to explore the product-related services landscape to identify high potential services that consumers intend to use if mobile devices can serve as a service broker. The study was conducted in cooperation with the ETH Zurich spinoff company qipp AG and its industrial partners. Participants were recruited by a survey company though its online platform. Each participant rated her use of 27 product services in the past 12 months and her intention to use the same services on mobile in the future, given the service search cost would be significantly reduced.

Second, an empirical study (Study II) was carried out to compare consumers' adoption of different IoT solutions (i.e., QR code, Bluetooth beacons, Bluetooth buttons) to enabling products as service end-points. It consists three sub-studies. The first sub-study (Study II-A) was a laboratory experiment conducted in Zurich, Switzerland to quantify the ability of a QR code based mobile IS in reducing service search cost. Participants were students from several universities in Zurich and they were recruited through group emails. The second (Study II-B) and the third sub-study (Study II-C) were carried out for a total of nine weeks to compare consumers' actual adoption of three IoT solutions (i.e., QR codes, Bluetooth beacons, Bluetooth buttons) to enabling products as service end-points. These studies were conducted in cooperation with the Center for Digital Technology & Management in Munich, Germany. They took place in the office of the research partner and all participants were members of the partner. Participants repeatedly used each of the proposed IoT solutions for a length of three weeks and answered a questionnaire to evaluate adoption after each phase. Both actual behavioral data and survey measurements were analyzed to provide guidelines for practitioners to effectively attaching digital services to physical products at a low cost.

The third study (Study III), which investigated the impact of personality traits on mobile service adoption, was carried out in Germany. The study consisted two sub-studies. The first sub-study (Study III-A) was developed and conducted in a collaboration with the ETH Zurich spinoff 42matters AG. A mobile gaming app was developed and then listed on Google Play Store to collect ground-truth about each smartphone user's personality traits and her adopted mobile services. Statistical analysis was conducted to examine the correlation between different personality traits and mobile service adoption behavior. The second sub-study (Study III-B) was conducted through online questionnaire to understand how personality traits impact different cognitive determinants of adopting mobile services. Participants were recruited by a survey company though its online platform. Data was analyzed using Structural Equation Modeling (SEM) to understand direct and indirect effects of personality on adoption.

The last study (Study IV) developed machine-learning models to replace the traditional questionnaire-based approaches of measuring personality traits and demographics. Data used in this study was collected from the same mobile gaming app developed in Study III-A. The Random Forest algorithm was applied to develop predictive models due to its high predictive and explanatory power.

Figure 2 shows the timeline of all the studies conducted in this thesis. However, the literature review and research prepare time, which is mostly done in 2013, is not included. In summary, this dissertation provides methodologies and tools which, taken together, help B2C manufacturers improve consumers' adoption of product-related services. The theoretical methodologies and practical insights and tools have been derived from four quantitative empirical studies.

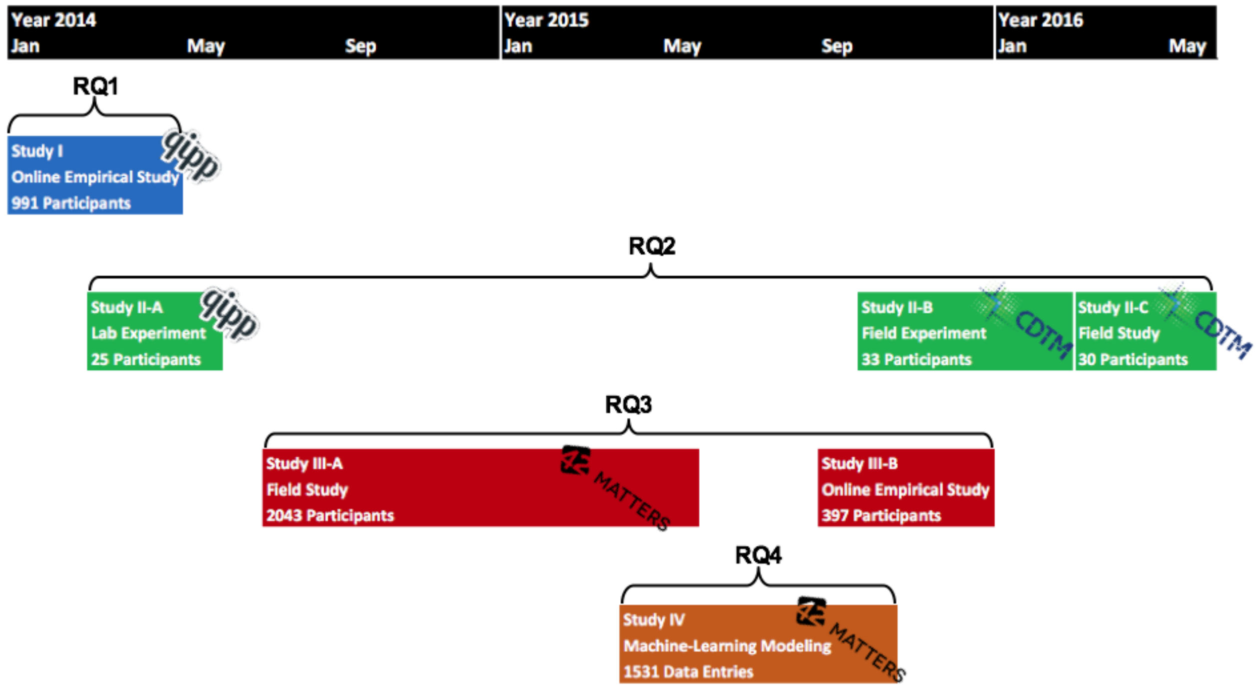


Figure 2: Timeline of the Four Main Studies and Their Relation to the Research Questions

1.3 Structure of the Thesis

The structure of the dissertation is summarized in Figure 3. The introductory Chapter 1 motivates the objectives and research questions addressed in the thesis. It provides an overview of all the empirical studies conducted to address the research questions, and outlines the thesis structure. Chapter 2 presents the research background of the thesis, including an overview of previous research in the field of service science, technology adoption, IoT, and personality research.

The subsequent four chapters (from Chapter 3 to Chapter 6) present four empirical studies corresponding to the four research questions introduced before. In particular, Chapter 3 highlights high potential services that consumers intend to use if mobile devices can serve as a service broker to significantly reduce search cost. Chapter 4 proposes a novel IoT solution to enable physical products as digital service end-points, thus making services easy to access. It also evaluates three alternative implementations of the proposed solution and compares consumers' adoption based on field studies.

Chapter 1: Introduction

The Service Provision Problems & Research Questions

Research Methodology

Structure of the Thesis

Statement of Prior Published Work

Chapter 2: Research Background

Service Science Research

Technology and Service Adoption

Internet of Things Research

Personality and Five-Factor Model

Chapter 3: Understanding Digital Service Offerings on Mobile Devices

- Introduction
- Related Work
- Study Overview
- Analysis and Results
- Discussion and Conclusion

RQ1: Which are the key product-related services that consumers intend to use when mobile devices can serve as service brokers?

Methodology: Census-representative online empirical study

Chapter 4: Enabling Physical Products as Digital Service End-Points

- Introduction
- Related Work
- Study Overview
- Studies II-A, II-B & II-C
- Discussion
- Conclusion

RQ2: What factors are critical for consumers to adopt a mobile solution that enables physical products as digital service end-points?

Methodology: Lab experiment and empirical field studies conducted in a real-world office

Chapter 5: Understanding the Impact of Personality on Mobile Service Adoption

- Introduction
- Related Work
- Study Overview
- Studies III-A & III-B
- Overall Conclusion

RQ3: How can personality traits impact an individual's adoption of different types of mobile services?

Methodology: Online empirical study and field study on real-world mobile app data

Chapter 6: Conducting Automatic User Profiling with Open Smartphone Data

- Introduction
- Related Work
- Study Overview
- Analysis and Results
- Discussion
- Conclusion

RQ4: How can personality traits be automatically predicted on an individual level from openly accessible data on mobile?

Methodology: Machine-learning modeling estimated on real-world mobile app data

Chapter 7: General Discussion and Conclusions

Motivation and Summary of Thesis

Summary of Key Findings

Contributions and Implications

Limitations and Future Work

Conclusion

Figure 3: Structure of the Thesis

Chapter 5 presents the importance of personality traits for impacting consumers' adoption of mobile services. Chapter 6 presents and evaluates a machine-learning approach for automatically predicting a smartphone user's demographics and personality. It shows that the approach can be integrated in any mobile app to replace traditional methods of user profiling in a scalable, low-cost, and low privacy-concern manner.

Chapter 7 recaps the motivation of the thesis, summarizes the key findings, discusses its theoretical contribution and managerial implications, states the limitations, points out future research directions, and then concludes the thesis.

1.4 Statement of Prior Published Work

Parts of this dissertation have been initially published or submitted by myself and colleagues as scientific articles in peer-reviewed conference proceedings or journals. While I am the first author of all of these documents and hereby declare that the majority of the content that has been integrated into this thesis has been written by myself, other co-authors have contributed to these documents with their reviews, suggestions, changes and edits. As a result, some sections of this thesis correspond literally to work previously published by me or bear strong similarities.

In particular, the related work in Chapter 2 is an adaption of the literature review presented in the following published papers: "Product as a Service: Enabling Physical Products as Service End-Points", published in the 2014 International Conference on Information Systems, authored by myself and Alexander Ilic (Xu and Ilic 2014); "Understanding the Impact of Personality Traits on Mobile App Adoption – Insights from a Large-Scale Field Study", published in the Journal of Computers in Human Behavior, authored by myself, Remo M. Frey, Elgar Fleisch, and Alexander Ilic (Xu, Frey, Fleisch, et al. 2016). In addition, a new sub-section that provides an overview of Internet of Things research is added to Chapter 2.

Chapter 3 is an adaptation of the paper "Product as a Service: Enabling Physical Products as Service End-Points", published in the 2014 International Conference on Information Systems, authored by myself and Alexander Ilic. The introduction section has been re-written, the related work section has been modified and extended, and the methodology and discussion sections have been adapted to the thesis.

Chapter 4 is adapted from two papers: "Product as a Service: Enabling Physical Products as Service End-Points", published in the 2014 International Conference on Information Systems, authored by myself and Alexander Ilic; and a work under review "How to Enable Physical Products as Digital Service End-Points? Insights from a Field Experiment", authored by myself, Philip M. Stroisch, and Alexander Ilic. The introduction, methodology, and figures have been adapted to the thesis with minor modifications. The discussion and managerial implication parts has been expanded.

Chapter 5 is adapted from three papers: "Understanding the Impact of Personality Traits on Mobile App Adoption – Insights from a Large-Scale Field Study", published in the Journal of Computers in Human Behavior, authored by myself, Remo M. Frey, Elgar Fleisch, and Alexander Ilic; "Individual Differences and Mobile Service Adoption: An Empirical Analysis", published in the IEEE Big Data Service Conference 2016, authored by myself, Remo M. Frey, and Alexander Ilic (Xu, Frey, and Ilic 2016); and a work under review "Personality and Cognitive Determinants on Mobile Service Adoption", authored by myself and Alexander Ilic. The introduction and methodology sections have been integrated into the thesis with strong modifications. The network analysis part has been conducted with a new method and new results are presented and discussed. The discussion and implication parts have been combined and adapted to the thesis with minor modifications.

Chapter 6 is adapted from the paper "Understanding the Impact of Personality Traits on Mobile App Adoption – Insights from a Large-Scale Field Study", published in the Journal of Computers in Human Behavior, authored by myself, Remo M. Frey, Elgar Fleisch, and Alexander Ilic; and the paper "Individual Differences and Mobile Service Adoption: An Empirical Analysis", published in the IEEE Big Data Service Conference 2016, authored by myself, Remo M. Frey, and Alexander Ilic. The machine-learning models for predicting demographics have been rebuilt with new predictive features and better performance. The discussion section has been expanded.

2 Research Background

This chapter outlines the research background of this thesis. It has four sub-sections that present fundamental knowledge about service science research, adoption research, IoT research, and personality research. The description of more related works and the development of study hypotheses will not be presented here, but in the related work section of subsequent chapters.

2.1 Service Science Research

Service science research was originally an IBM-led discipline that came from practice (Gummesson and Polese 2009; Saarijärvi et al. 2013). IBM has run a project called Service Science, Management and Engineering (SSME) since 2003 to spread service thinking to both academic institutions and practitioners, thus connecting the two worlds to push service science research forward (Gummesson and Polese 2009; IfM and IBM 2008). According to Maglio and Spohrer (2008), the goal of service science "is to apply scientific understanding to advance our ability to design, improve, and scale service systems for business and societal purposes (e.g. efficiency, effectiveness, and sustainability)".

About the same time, the service-dominant (S-D) logic was proposed by Vargo and Lusch (2004, 2007, 2008) to overcome the deficiency of the traditional goods-dominant (G-D) logic in explaining value exchange. Because of the large overlap between service science and S-D logic and the openness of both sides (Saarijärvi et al. 2013), a collaboration occurred at an early stage (Gummesson and Polese 2009). Consequently, S-D logic is now often cited as fundamental to service science research (Alter 2011; Beverungen 2011).

Different from the G-D logic, the S-D logic argues that service, instead of goods, should be the fundamental unit of value exchange. Goods transmit service and act as means for consumers to benefit from the knowledge and skill of companies (Vargo and Lusch 2004, 2007, 2008). The value of goods is not created by companies and embedded in goods during a manufacturing process. Instead, companies only make value proposition. To actualize the value of goods, consumers need to continue the marketing, consumption and value creation process "for these services to be delivered, the consumer still must learn to use, maintain, repair, and adapt the appliance to his or her unique needs, usage situations, and behaviors (Vargo and Lusch 2004)". As a result, value becomes a joint function of the actions of both companies and consumers (Prahalad and Ramaswamy 2000; Prahalad and Ramaswamy 2004a, 2004b), and thus is always co-created (Vargo and Lusch 2007).

Because of the fundamental influence of the S-D logic, many papers in the service science discipline still seem to focus on the traditional set of service marketing topics (Beverungen 2011). However, IS research in service science is getting more important and some IS-related topics like self-service technologies and Customer Relationship Management (CRM) constitute cornerstones in the service science research agenda (Beverungen 2011).

2.2 Technology and Service Adoption

Adoption and diffusion research is regarded as one of the most mature research areas in the IS discipline. It focuses on a better understanding of various factors that lead to the adoption of some innovations or the rejection of others. A number of models have been developed in different context to explain individual-level and organizational-level technology adoption behavior.

The Theory of Reasoned Action (TRA) (Ajzen and Fishbein 1980) suggests that an individual's behavior intention is determined by her attitude towards the behavior and subjective norms that describe the social pressure for her to perform the behavior. The Technology Acceptance Model (TAM) (Davis 1989) is an extension of the TRA model. It does not consider the influence of subjective norms and replaces attitude with two technology measures, namely perceived usefulness and perceived ease of use. The TAM is the most widely applied model in understanding people's use of technologies, but it is also criticized due to its lack of practical value, limited explanatory and predictive power, and triviality (Chuttur 2009). Further development of TAM included TAM2 (Venkatesh and Davis 2000) and Unified Theory for the Acceptance and Use of Technology (UTAUT) (Venkatesh et al. 2003; Venkatesh, Thong, et al. 2012) to increase explanatory power and practical relevance.

Another extension of TRA is the Theory of Planned Behavior (TPB) (Ajzen 1985), which suggests that behavior intention is also influenced by the amount of perceived behavioral control of internal and external resources to perform the behavior. Taylor and Todd (1995) have proposed the Decomposed Theory of Planned Behavior (DTPB) to integrate TPB with constructs of other models thereby increasing model fit and explanatory power.

Although these theories have been developed from different perspectives and researchers failed to find out one to be superior to the others in different context, there are several overlaps and shared cognitive determinants. Venkatesh, Brown, et al. (2012) compared different models and indicated that constructs like perceived usefulness (Fred D Davis 1989; Rogers 1995), perceived ease of use (Davis 1989), compatibility (Rogers 1995), enjoyment

(Choudrie et al. 2014; Venkatesh, Brown, et al. 2012), network influence (Leonard-Barton and Deschamps 1988), perceived cost (Wejnert 2002), and privacy concerns (Rogers 1995; Zhu et al. 2006) usually have direct impacts on an individual's adoption decision.

2.3 Internet of Things Research

The term IoT originated from the Auto-ID Labs at the Massachusetts Institute of Technology in 1999 (Atzori et al. 2010; Mattern and Floerkemeier 2010). It envisioned "a world in which all electronic devices are networked and every object, whether it is physical or electronic, is electronically tagged with information pertinent to that object (Sarma et al. 2000)". With the development of sensor technologies and increased connectivity, a broader definition of IoT is also accepted, where IoT is viewed as "a concept and a paradigm that considers pervasive presence in the environment of a variety of things/objects that through wireless and wired connections and unique addressing schemes are able to interact with each other and cooperate with other things/objects to create new applications/services and reach common goals (Vermesan et al. 2014)". Another well-known definition of IoT was proposed by the International Telecommunication Union, which regarded IoT as "a global infrastructure for the Information Society, enabling advanced services by interconnecting (physical and virtual) things based on, existing and evolving, interoperable information and communication technologies (ITU 2012)". Although IoT was defined differently by stakeholders from their own perspectives, its core concept may be summarized as a notion that "every physical thing in this world can also become a computer that is connected to the Internet (Fleisch 2010)".

Things can be connected to the Internet by different technologies. For instance, microcomputers with sensors, actuators, memories, and communication modules can be integrated into physical products to enable active real-time feedbacks, remote control, and inter-object connection. Representative applications are Fitbit activity tracker, Google Nest thermostat, and Philips Hue light bulb (Notra et al. 2014). Alternatively, passive tags can be attached to products to serve as identifiers and information pertinent to products can be retrieved through the tags by additional readers (McFarlane and Sheffi 2003). Representative applications are enabled by RFID, NFC tags, QR code, and Bluetooth Beacons typically in the areas of logistics (Wyld et al. 2005), supply chain management (Melski et al. 2008), and retailing (Barthel et al. 2013).

As summarized by Fleisch et al. (2014), the value of a typical IoT application can be understood as the combination of a physical product and IT in the form of hardware and software, which provides consumers with not only physical thing-based function that the product used to offer locally, but also with IT-based services that create additional digital values at a global scale.

2.4 Personality and Five-Factor Model

The Five-Factor Model (FFM) (Mccrae and Costa 1987) has been widely used in research studies to define different types of personality traits. FFM of personality has emerged as a broader taxonomy for personality-related issues and has been embedded in a rich conceptual framework for integrating all research findings in personality psychology (Digman 1990). The most widely used FFM is called the Big Five personality traits (John and Srivastava 1999), which consists of extraversion (E), neuroticism (N), agreeableness (A), conscientiousness (C), and openness-to-experience (O).

Extraversion is frequently associated with being sociable, warm-hearted, talkative, and active (Eysenck 1947). Extraverts typically enjoy the company of other people and seek for new excitement; Neuroticism includes traits like being anxious, depressed, worried, nervous, and insecure (Eysenck 1947). Neurotic individuals pay more attention to negative aspects and they have problems in dealing with stress; Common traits associated with the third dimension, namely agreeableness, refer to being friendly, trusting, cooperative, and tolerant (Norman 1963). High agreeable people usually have good inter-personal relationships and are willing to help others; Conscientiousness represents traits such as being careful, self-disciplined, responsible, organized, and achievement-oriented (Norman 1963). People who are high in conscientiousness make thorough plan in advance and carry out the plan strictly; The last dimension, openness-to-experience, is typically associated with being imaginative, curious, broad-minded, and independent (Costa and McCrae, 1985). Open individuals tend to have new ideas and willingly question authority (Costa and McCrae 1992). Personality traits can have significant impact on our decision making (Bettman 1979; Sproles and Kendall 1986). However, most research related to personality focuses on job performance or career development (Penney et al. 2011).

3 Understanding Digital Service Provision on Mobile Devices

This chapter concerns with consumers' current use of different product-related services and how their intention to use the same services will change when mobile devices can serve as a service broker to reduce service search cost. Based on the data collected from a large-scale field study (Study I), a framework was derived to help companies identify high potential services to offer on mobile, thereby addressing RQ1.

3.1 Introduction

Because the traditional G-D logic has its inherent shortcomings in explaining value exchange, Vargo and Lusch (2004, 2007, 2008) has proposed a new S-D logic that is now widely accepted by researchers to understand markets. According to the new paradigm, value is not created by companies and embedded in goods during a manufacturing process. Instead, companies only make value propositions and consumers derive the value by using products (Prahalad and Ramaswamy 2000; Prahalad and Ramaswamy 2004a, 2004b). Consequently, in addition to selling goods, companies should also base their strategies on services as a business logic and provide consumers with additional resources to actualize the value potential of the offerings (Grönroos 2007, 2008a, 2008b).

Meanwhile in the business community, after realizing that in most markets products become similar and the room for product differentiation is limited (Pine and Gilmore 1999), some machinery manufacturers such as IBM, ABB, General Electric, and Toyota (Chesbrough 2007; Gebauer and Friedli 2005; IfM and IBM 2008; Mathieu 2001; Oliva and Kallenberg 2003; Saarijärvi et al. 2014) have changed from G-D business models that aim to maximize the number of products sold to S-D business models that make money by being paid by services offered (Tukker 2013). Aurich et al. (2006) also showed that product-related services accounted for up to 18% of the annual turnover of the German discrete manufacturing industry. Most services in this case were of technical nature, e.g., maintenance, user training or retrofitting. They resulted from a lifecycle-oriented perspective that intended to increase life time of products through additional service offerings and vice versa.

Providing services in a B2B setting is relatively easy because manufacturers know their customers well and services are typically bundled with products based on contracts (Stremersch and Frambach 2001). However, selling services in a B2C context is more difficult due to the lack of knowledge about each individual consumer and the disconnection between products and services for consumer goods (Day 2006; Saarijärvi et al. 2013). Consequently, finding out services is nowadays cumbersome and requires high manual efforts like searching, mapping, and authenticating. This leads to high service search cost, which reduces a consumer's intention to use services (Davis 1989; Venkatesh and Davis 2000).

Novel IoT solutions such as smart products and auto-IDs are able to bring services close to physical products through the help of embedded systems or smartphones, thus reducing the corresponding service search cost. However, services are diverse and consumers' intention of using services might alter significantly based on both the type of a service and the corresponding product. Lacking previous knowledge about consumers' preference of and intention to use product-related services, B2C manufacturers can hardly decide what services to offer on mobile when service search cost can be reduced. This chapter thus aims to understand how the reduction of service search cost impacts consumers' intention to use product-related services.

The chapter is laid out as follows. Previous research on product-related services and how to provide services through mobile IS is first reviewed, which is followed by research questions and study design. After analyzing research data collected from 991 consumers, services are categorized into four groups and practical implications are derived. Finally, the chapter is concluded and opportunities for future research are presented.

3.2 Related Work

3.2.1 Providing Product-Related Services

Oliva and Kallenberg (2003) conducted an inter-disciplinary research with 11 German machinery manufacturers that offered services for their products to understand how manufacturers could successfully sell product-related services. Instead of giving away initial services like installation right after selling a product, the authors suggested manufacturers to generate close relationship with customers and to provide services along a product's life cycle. This could help customers improve the utilization and effectiveness of their purchased products. Services such as preventive maintenance, spare parts management, and condition monitoring are normally bundled with products in maintenance contracts with service level agreement, which enables manufacturers to continuously interact with consumers to provide services (Marceau 2002; Oliva and Kallenberg 2003).

In a B2C setting, however, products and services are loosely bundled and contractual services are not commonly available except for limited cases like phone contracts. There are still several methods for manufacturers to provide product-related services directly to consumers.

One option is to make a product intelligent. An intelligent product is “a product system that contains sensing, memory, data processing, reasoning and communication capabilities at various intelligence level (Kiritsis 2011)”. Such a product is able to get data about its environment, communicate to other smart devices, make decisions and react automatically to different conditions at any phase of its life cycle. For example, if an intelligent product captures an error event, it will report the problem to the manufacturer directly and call repair services automatically. Manufacturers that produce intelligent products can easily know the status of each product at any time, thus interacting directly with products or consumers to provide services. Nevertheless, integrating products with services in the manufacturing process is costly (Marceau 2002). Therefore, intelligent products are usually expensive and their installed base is still limited at the moment.

In addition to making products intelligent, some B2C manufacturers force consumers to provide personal information to enable the functionality of the purchased product. For example, before using new IoT products like Nest thermostat, Fitbit activity tracker, and Hue light-bulb (Notra et al. 2014), each consumer has to provide her personal information (e.g., email address, household size, location) to activate the purchased product. The bundle of registration service to each product is made mandatory. Consequently, those companies are able to know each consumer in detail, which makes it possible for them to proactively reach consumers to sell additional product services in the future.

However, a wider range of products like consumer goods are neither intelligent enough to automatically request services, nor closely bundled with services during the sales process. Instead of providing services proactively, most manufacturers have to wait until being reached by consumers. Nowadays, B2C manufacturers provide product-related services on the Internet to help consumers easily find them (Hassan et al. 2011). For example, Samsung and Lenovo provide Web portals to offer services like product registration and warranty extension. Compared to traditional offline service offerings, digital online services deliver significant benefits to both consumers and service providers (Taherdoost et al. 2012) as consumers do not need to go to companies or physical stores to request or receive services (Taherdoost et al. 2014). Nevertheless, the service search cost is still high in this case. Consumers have to make decisions about defining search key words, judging authenticity of returned Web portals, and checking relevance of listed services during the whole process. To sum up, although product-related services bring solid benefits to both manufacturers and consumers, providing them is still challenging in the B2C context.

3.2.2 Offering Services on Mobile IS

One solution to reduce service search cost is to link product services with consumers' mobile devices like smartphones and tablets. Mobile devices are highly personalized and provide ubiquitous and universal access to information. They thus become an important gateway for manufacturers to directly interact with each individual consumer in a proactive manner. As indicated by Scornavacca and Barnes (2006), companies have opportunities to link products with consumers to provide personalized services through leveraging mobile apps. Before going into the details about how to leverage IoT technologies and mobile IS to facilitate service offerings, which will be presented in the next chapter, this section first provides an overview of the current mobile service landscape.

Mobile services can be defined as "content and transaction services that are accessed and/or delivered via a mobile handheld device (PDA, mobile, cellular or phone, GPS, etc.) based on the interaction/transaction between an organization and a customer (Gummerus and Pihlström 2011)". However, the classification of mobile services has not been well defined and different services were under study in previous research. Pedersen (2009) proposed a research model to understand what factors influence users' adoption of mobile services. The author found that mobile purchasing, searching, alerting, reservation, gaming, entertainment, payment, and location-based services were most widely adopted by end users. Tojib and Tsarenko (2009) generated a conceptual model to explain people's use of advanced mobile services through an online survey with 600 participants. After exploring a wide range of existing mobile services, the authors concluded that services like weather alerting, gaming, email, news, maps, music and video, chatting and messaging, banking, personalization (ringtones and wallpapers), and transportation were the most frequently used ones by smartphone users.

Similarly, Zhao et al. (2012) evaluated a theoretical model to explain the mobile service adoption behavior of more than one thousand students. In the study, the authors defined 15 specific mobile services, including personalization, gaming, messaging, TV and music, newspaper, mobile pocket, location navigation, stock, and email services. Constantiou et al. (2007) conducted a field study in the Danish mobile communication market to determine user categories based on their adoption of mobile services. In addition to the above-mentioned services, photography service was also included in the analysis. Moreover, Martin and Ertzberger (2013) developed a prototype and conducted a user study with 109 undergraduate students to evaluate the use of the mobile learning and education services.

Analyzing the impact of mobile services and understanding the corresponding consumer adoption are becoming a new focus in the community of service science research. However, as presented above, most services under study were not related to physical products, which failed to provide solid knowledge about consumers' perception of using different product-related services on mobile.

To sum up, proliferation of smartphones and advanced technologies makes it possible for B2C manufacturers to facilitate service provision on mobile. Mobile service solutions are thus getting increasingly important to companies (Kleijnen et al. 2007; Lee et al. 2012; Nysveen and Thorbjernsen 2005). However, not all services are perceived equally by consumers and previous research has not yet focused on understanding the acceptance of different product-related services. Among a wide range of product services, what services consumers will use if service search cost can be reduced remains unknown. This work is thus motivated to explore consumers' intention of using different product services thereby helping manufacturers prioritize their service offerings in the future.

3.3 Study Overview

3.3.1 Research Questions

Nowadays consuming product-related services still requires a high search cost. Even for simple services such as getting an online product manual, consumers need to go to the manufacturer's homepage, find out the product Web page and then look for the manual. According to the TAM, high search cost could decrease perceived ease of use and consequently lower consumers' intention of using product services. New technologies such as IoT and mobile IS provide an additional possibility to bridge the physical and digital world thereby reducing service search cost. However, before going deep into technical implementations and proposing new solutions, the benefits of reducing search cost first need to be quantified. Due to the lack of previous research, it is not clear to what extent a consumer's intention to use product-related services will improve if corresponding service search cost is reduced. Consequently, the first research question can be broken down in three parts. The first one is:

> ***RQ1a:*** *How consumers' intention to use product-related services will change if mobile devices can serve as service brokers to reduce search cost?*

According to Edvardsson et al (2005) and Saarijärvi et al (2014), services are different from each other and they are highly dependent on the corresponding products. As a result, research focus should be placed on exploring and comparing consumers' intention to use different services as well as on its dependency on corresponding products to help manufacturers foster a more holistic understanding. Consequently, this study also tries to answer:

> ***RQ1b**: How will consumers' intention to use a service differ according to the type of the service if search cost can be reduced?*
>
> ***RQ1c:** How will consumers' intention to use a service differ according to the type of the related product if search cost can be reduced?*

3.3.2 Study Design

Figure 4 shows the overview of the study design. First, an exploratory pre-study was conducted with manufacturers to determine relevant service types and product categories. The pre-study was conducted by the research partner, qipp AG, which asked 25 managers of consumer goods manufacturers (e.g., sport articles, electronic devices, music instruments, fashion products) to itemize product-related services that the manufacturers were providing or would provide to consumers. After consolidating the results, we categorized the selected services and grouped them into three phases according to the product post-sales lifecycle proposed by Oliva and Kallenberg (2003) and Cao and Folan (2012): Services directly after purchase (SP1), services during the use (SP2), and services at the end of use (SP3). This study focused on post-purchase services because they are more important to retrieve values embedded in products along a product's lifecycle, according to the S-D logic (Vargo and Lusch 2008).

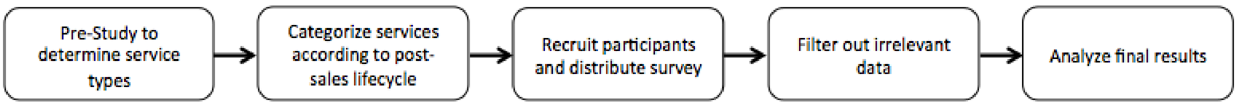


Figure 4: Design of Study I

Based on the selected services, a questionnaire was designed for consumers to rate their use of different services in the past as well as their intention of using the same services if mobile devices can serve as a service broker to reduce search cost. Afterwards, the questionnaire was distributed to consumers by a survey service company through its online platform. As the context of reducing search cost was based on mobile, the questionnaire was thus targeted for mobile Internet affine people instead of the general public. Consequently, only respondents who used advanced features (e.g., mobile email, applications, Internet) of smartphones at least once a week were included in the data analysis. After filtering out irrelevant respondents, a statistical analysis was conducted on the cleaned data set. As each respondent rated each service repeatedly in two scenarios, the paired t-test was used to compare mean ratings if the differences between two paired ratings of the same service were normally distributed. Otherwise, Wilcoxon signed ranks test would be used to compare mean values, according to Field (2009).

Table 1: List of Services Selected in Study I

Product Usage Phase	***Service Name***	***Service Description***
Direct after purchase (SP1)	Manage Invoice	Manage invoice or other proofs of purchase
	Manage Documents	Manage product manuals and other documents
	Register Products	Register products with manufacturers
	Add to Inventory	Add a product to an inventory for management
	Add Personal Info	Attach name, address, phone number to products
	Check Authenticity	Verify whether a product is authentic or not
	Extend Warranty	Extend the length of warranty for a product
	Purchase Insurance	Purchase additional product insurance
During the use (SP2)	Recommend Products	Recommend products on social media
	Remind Update	Remind software update or scheduled services
	Show New Models	Demonstrate follow-up models if available
	Notify Recall	Notify when a product is being recalled
	Show Accessories	List accessories that can improve product usage
	Show Handbooks	Show handbooks digitally to provide information
	Show Parts	Show spare parts or equipment belong to a product
	Ask for Help	Ask for help from others who also own the product
	Show Repair Resources	List service providers for repairing a product
	Protect from Lost	A service that protects products from lost
	Protect from Theft	A service that protects products from theft
	Lend for Free	Lend out products to others for free
	Lend for Remuneration	Lend out products to others for remuneration
	Become a Trial User	Register as a trial user for new products
	Add Notes	Add notes (e.g., tips, configuration info) to products
In the end of use (SP3)	Show Current Value	Show the actual product value for reselling
	Resell Products	Resell products through online platforms
	Hand over for Free	Hand over products to other people for free
	Dispose Properly	Dispose products properly after using them

3.3.3 Questionnaire Design

Based on the feedback collected from the exploratory pre-study, 27 product services (as shown in Table 1) were selected, and a questionnaire that consisted 15 questions was designed.

The first part of the questionnaire asked study participants about demographics such as age, gender, income, and frequency of mobile Internet usage. In the second part, participants were asked to rate each service in SP1, SP2 and SP3 for 1) how frequently they had used the service in the past 12 months, and 2) how frequently they would use the same service in the future if a mobile app were available to reduce service search cost. The mobile app was described in text at an abstract level: Instead of showing mockups or implementation details, the app was described as being able to help consumers easily and quickly access different product-related services. The rating was based on a 7-point Likert scale where 1 stood for the lowest frequency of use and 7 represented the highest frequency. Furthermore, each participant was asked to select a maximum of eight most relevant product categories for all the services in each of the three phases.

Table 2: Characteristics of Participants in Study I

Respondents	***Range***	***N***	***%***
Age	18-25	148	14.9
	26-35	197	19.9
	36-45	272	27.5
	46-55	250	25.2
	56-65	124	12.5
	Total	*991*	*100.0*
Gender	Female	513	51.8
	Male	478	48.2
	Total	*991*	*100.0*
Net Income (EUR per month)	> 4000	83	8.4
	3000-3999	127	12.8
	2000-2999	242	24.4
	1000-1999	271	27.3
	500-999	114	11.5
	< 500	59	6.0
	No Answer	95	9.6
	Total	*991*	*100.0*

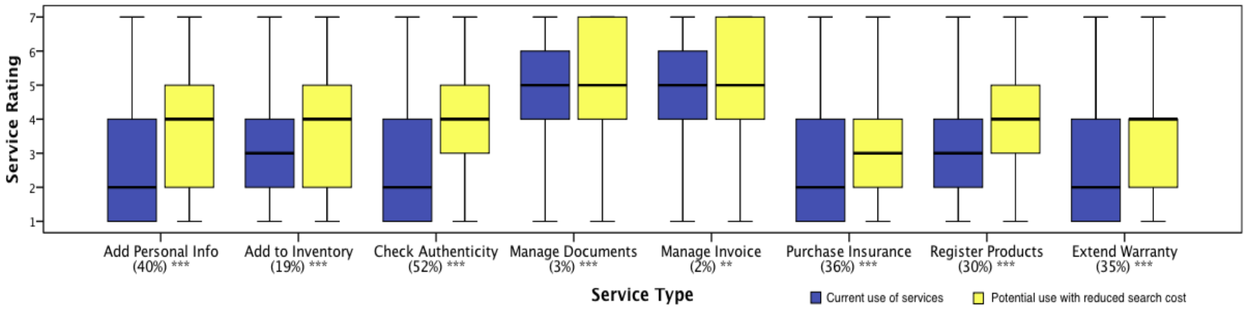
3.4 Analysis and Results

3.4.1 Dataset for Estimation

The study was conducted from January 22nd to January 27th, 2014. An online survey company helped to distribute the questionnaire to participants through its online platform. It sent invitations to 1177 people in Germany and 1012 of them participated in the study. The actual incidence rate was 85.98%. Each participant spent on average eight minutes in finishing the questionnaire. After cleaning the data sample according to Section 3.3.2, the final data set consisted 991 respondents and their characteristics are shown in Table 2.

3.4.2 Differences in Intention to Use

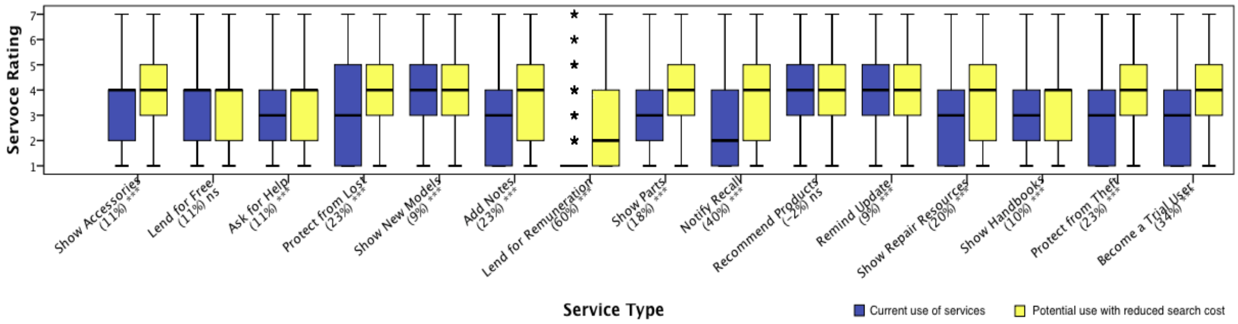
Figure 5 shows the participants' ratings for all the services in SP1. There are two boxplots for each service: The left one represents the study participants' frequency of using a service in the past 12 months, whereas the right one shows the potential frequency of using the same service when service search cost is reduced in the future. The bottom and top of each box are the first and third quartiles, and the horizontal bolt line in the middle represents the median rating. The error bars above and under each box stand for the high and low bound of the 95% confidence interval. A number, which is shown in percentage in the parenthesis at the bottom of each service name, indicates how much the mean value of a service rating will increase when the service search cost can be reduced. Take 'Add Personal Info' for example: With a mobile app to reduce service search cost, consumers' potential frequency of using the service will be on average 40% higher than their current use of the same service. Furthermore, a sign right to each percentage number indicates whether the difference between the two ratings for a service is statistically significant or not.



N=991, Sig. (2-tailed): ns - not significant, p>.05; * significant at p<.05; ** significant at p<.005; *** significant at p<.001

Figure 5: Comparison of Consumers' Service Ratings in SP1

In the past 12 months, the average rating of all the services in SP1 (without any reduction on search cost) was 3.27 (SD=1.89). With a mobile app in place to reduce search cost, the average rating would increase around 25% to 4.09 (SD=1.83). In both scenarios (with and without reduced search cost), 'Manage Invoice' and 'Manage Documents' were the most frequently used services after purchasing a product, while 'Purchase Insurance' and 'Extend Warranty' were the least frequently used services. In SP1, the highest increase on service use due to the reduced search cost occured on two services: ‘Check Authenticity’ with 52% and ‘Add Personal Info’ with 40%.

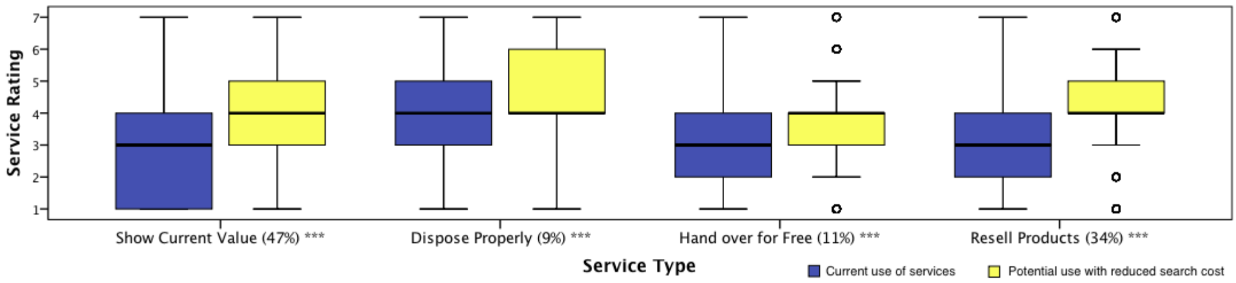


N=991, Sig. (2-tailed): ns - not significant, p>.05; * significant at p<.05; ** significant at p<.005; *** significant at p<.001

Figure 6: Comparison of Consumers’ Service Ratings in SP2

Similarly, Figure 6 presents the results for all the services in SP2. With a reduced service search cost, consumers’ intention of using services would increase on average from 3.18 (SD=1.67) to 3.71 (SD=1.71). The respondents rated ‘Remind Update’ (M=4.22) and ‘Become a Trial User’ (M=4.18) as the most frequently used services in the future. Conversely, ‘Lend for Remuneration’ remained the lowest rated service no matter a mobile app would be in place or not to reduce search cost. However, consumers would use it 60% more frequently if search cost were to reduce, which was the largest improvement among all the 27 selected services in this study. The services ‘Become a Trial User’, ‘Protect from Theft’, and ‘Protect from Lost’ had both high ratings and large increases with a mobile app in place to reduce search cost. Surprisingly, the ratings of ‘Lend for Free’ and ‘Recommend Products’ decreased by 1% and 2%, respectively. Nevertheless, the difference was not statistically significant, which means that reducing search cost would have no impact on these two services.

Figure 7 illustrates the service ratings in SP3. In the past 12 months, the average rating of all the services in this phase was 3.31 (SD=1.62). If search cost could be reduced, the average rating would increase by 24% to 4.10 (SD=1.66). Interestingly, when service search cost was not reduced, consumers chose to hand over a product for free (M=3.25) rather than reselling it (M=3.17) in case a product was no longer needed. Nevertheless, with a mobile app in place to evaluate a product’s value and to resell it, consumers would conversely prefer reselling the product (M=4.25) as opposed to giving it away for free (M=3.62). Therefore, combing ‘Show Current Value’ and ‘Resell Products’ might have a potential to become a useful service in the future.



N=991, Sig. (2-tailed): ns - not significant, p>.05; * significant at p<.05; ** significant at p<.005; *** significant at p<.001

Figure 7: Comparison of Consumers' Service Ratings in SP3

Overall, all the selected services would on average experience a 22% improvement (SD=17%) on potential frequency of use if service search cost could be reduced. Thus, RQ1a is addressed.

3.4.3 Service Categorization

To identify high potential services, all the services under study are loaded in a 2×2 matrix as demonstrated in Figure 8. The horizontal dimension shows how much consumers' intention to use a service will increase if the service can be accessed easily on mobile with reduced search cost. The vertical dimension indicates consumers' intention to use a service, given the service search cost is reduced.

Services at the top-right corner, such as 'Check Authenticity', 'Become a Trial User', and 'Resell Products', are the ones that have high ratings and show large increases. Consumers' willingness to obtain such services (indicated by a high rating) and the current absence of support to facilitate the access to these services (indicated by a large increase) make each service in this quadrant a high potential one for manufacturers to offer in the future.

Services at the top-left corner, like 'Manage Documents', 'Remind Update', and 'Show New Model', are the ones that have high ratings but show low increases. This indicates that although the potential increase is low, it would be good for manufacturers to support the use of services in this quadrant because nowadays consumers already use them on a frequent base.

Services at the bottom-right corner are the ones that have low ratings but show large increases. At the moment, the perceived uptake of services in this quadrant is low; but it is still useful to keep an eye on these services because of their potential large improvements. For instance, as revealed by Byers et al (2013) and Sundararajan (2013), sharing economics is getting more attention in empowering individuals, companies, organizations and governments to distribute, share, and reuse the value of goods and services. Once a large and reliable platform that allows people to share products is in place, the service ‘Lend for Remuneration’ might move from bottom-right corner towards top-right corner and then becomes a useful and widely accepted service.

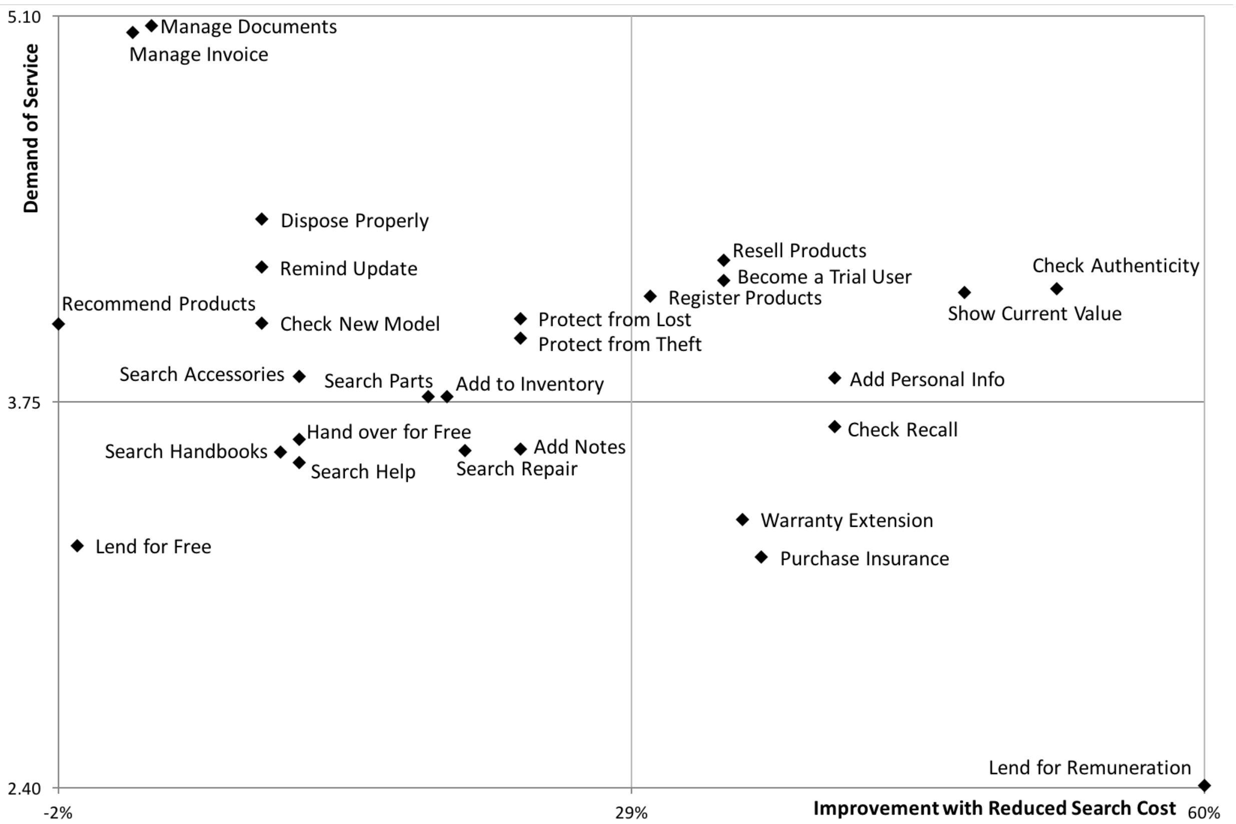


Figure 8: A 2x2 Matrix to Identify High Potential Product Services (N=991)

Finally, services at the bottom-left corner are of less interest because both the intention to use and the potential improvement are lower compared to services in the other three quadrants. If a manufacturer can only provide limited number of services, services in this quadrant should get a low priority. Therefore, RQ1b is answered.

3.4.4 Differences between Products

Edvardsson et al (2005) claimed that services were not only different from each other, but also different from products to products. Therefore, study participants were also asked to select a maximum of eight most relevant product categories for all the services in each phase. Overall, 59.16% of participants chose office equipment as the most relevant category, followed by home appliances (56.98%), mobile gadgets (56.95%), cameras & optics (56.79%), and vehicles & parts (49.57%). Conversely, leisure goods (2.34%), pet supplies (5.14%), baby articles (5.67%) and drugs & medicine (5.76%) were regarded as the least relevant categories.

Figure 9 shows how the ratings of services in each phase (SP1, SP2 and SP3) differ across the eleven selected product categories. The product categories were selected together with our industry partners. The main selection criteria were the participants' rating of product relevancy in the questionnaire as well as the number of selected services that could be used for a product category. There are three boxplots representing the ratings of all services in SP1, SP2 and SP3 for each product category. The horizontal bolt line in the middle represents the average rating of the median service in each phase, and the bottom and top of each box are the first and third quartiles. The error bars above and under each box stand for the upper and lower bound of the 95% confidence interval in each phase.

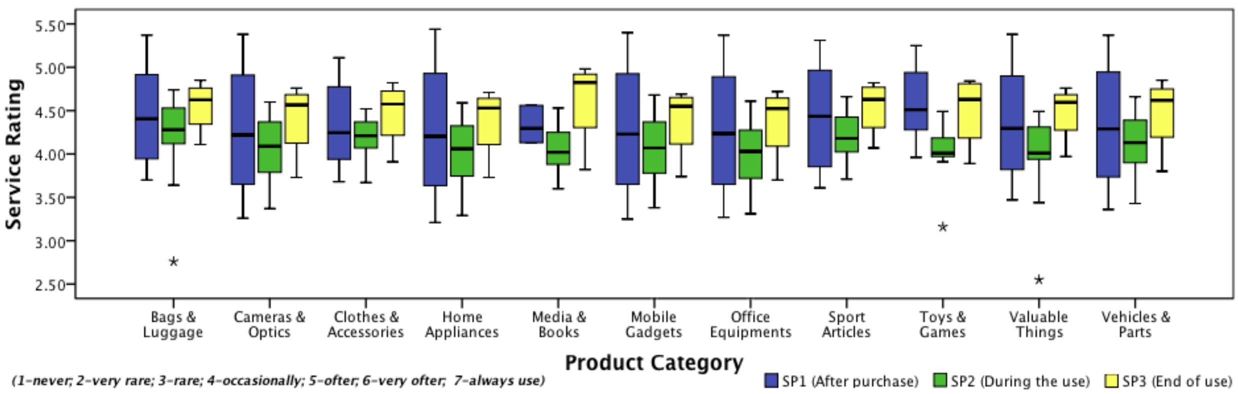


Figure 9: Difference of Service Ratings among Product Categories (N=991)

The figure demonstrates that for the same product category, services in each phase differ strongly. For instance, services in SP2 were rated extremely lower than services in SP1 and SP3 for toys & games and media & books. Overall, services in SP3 were rated higher than those in SP1, and services in SP2 were always the lowest rated ones. On the other hand, services in the same phase also differed from category to category. For instance, services in SP3 were rated much higher for media & books than for bags & luggage, and the ratings of services in SP1 for media & books deviated less than that of the same services for mobile gadgets. The results showed that people's intention of using services could differ significantly among product categories. RQ1c is thus addressed.

3.5 Discussion and Conclusion

Manufacturers of consumer goods are trying to establish a direct link to consumers in order to strengthen their competitive positions by offering additional product services. Nowadays, even for simple services, manufacturers often rely on old-fashioned mail-in coupons and have to encourage consumers to reach out to them over various channels. It is thus suspected that the transaction cost for initiating product services are prohibitively high, which limits the potential service adoption. As a first step into the product-related service research, this study was thus motivated to understand the impact of service search cost on consumers' intention to use different product services.

A census-representative online survey study was conducted on 991 consumers in Germany to test the hypothesis. By exploring 27 different product-related services, the study concluded that consumers would use product services on average 22% more frequently if service search cost could be reduced. For a specific product category, consumers' intention to use services differed significantly from one service to another. Consequently, the study has categorized services into four groups to help manufacturers identify high potential services to offer on mobile. In addition, the study dived into eleven types of products and confirmed that consumers' intention of using similar services could differ strongly among different product categories.

There are several limitations of this study, which provides opportunities for future research. First, the online empirical study was conducted in Germany. It is possible that consumers in different countries have different behavior in using product-related services. Consequently, future studies are called to verify the findings in other countries. Second, because the study consisted many services and product categories, it is cumbersome and time-consuming to ask participants to rate each service for every product category in one questionnaire. Based on the questionnaire design, service ratings were aggregated into three phases and then compared among eleven product categories. The study has shown that consumers' intention of using services is strongly dependent on the corresponding product type. Nevertheless, future research is required to dig more into the one-to-one mapping between individual service and product type.

Third, the main purpose of this study was to confirm the hypothesis that reducing service search cost could lead to significant improvements on consumers' intention to use different product services. Consequently, the mobile IS solution was described on an abstract level in the questionnaire without providing any detail about features and designs. Nevertheless, questions about how to design the mobile app and what IoT technology to use to reduce the product-service mapping barrier are crucial but remain unanswered. Also, an online questionnaire was used as the research method to reach a large number of samples and to explore a wide range of products and services. After confirming the main effect of service search cost, future research is called to move beyond intention to use services.

To address the above-mention limitations, the next chapter will present a follow-up empirical study that digs into different implementations of enabling physical products as digital service end-points, thereby reducing service search cost. In addition, field experiments were conducted to measure consumers' actual use of product services with the proposed mobile solutions as well as to collect constructive user feedbacks.

4 Enabling Physical Products as Digital Service End-Points

In order to answer RQ2 and provide best practices on how to enable physical products as digital service end-points, this chapter proposes and tests different IoT solutions to connecting products with services thereby reducing service search cost. One lab experiment, one field experiment, and one field study were conducted to address the previous research gaps and to provide concrete managerial implications.

4.1 Introduction

As shown in the previous chapter, services generate additional revenue streams and are important for manufacturers to stay competitive. Advanced Internet technology makes it easier and cheaper for manufacturers to provide services online, therefore, consumers do not need to go to companies or physical stores to receive services (Taherdoost et al. 2014). However, even if a product that requires for service is physically in front of consumers, it is still impossible for consumers to interact with it and use its services directly. For consumers, it represents a two-fold search and match problem, which requires a high search cost thereby reducing consumers' intention to use services.

With the paradigm of IoT, the Internet extends to the physical world. As an alternative to fully connected intelligent products that are costly due to the change of manufacturing process, manufacturers can use IoT tags to enhance their existing products with service offerings such as purchase of supplies, spare parts, and repair & support requests. Although not product focused, a first generation of solutions already existed around QR codes and Bluetooth beacons to provide consumers with services such as tour guide (Huang et al. 2010), location-based warning (Namiot and Sneps-Sneppe 2015), room reservation (Ashford 2010), and mobile payment and ticketing (Liu et al. 2007; Scornavacca and Barnes 2006). However, most of the existing solutions have been used for marketing purpose instead of providing product-related services. This work is thus motivated to leverage IoT technologies and mobile IS to enable physical products as digital service end-points, thereby helping consumers easily access services. It aims at comparing user adoption of different implementation alternatives and provides practitioners with best practices.

The work consists of three sub-studies. In the first study (Study II-A), a prototype was developed, which reduced service search cost by identifying each product uniquely with a QR code and matching the product identifier with a list of relevant services. Consequently, consumers could access digital services directly from physical products through scanning the

QR code. A lab experiment was conducted to evaluate the proposed solution. Results have shown that the proposed solution is welcomed by consumers and it has a potential of reducing service search cost by a factor of eleven.

In order to go beyond intention, the prototype was further developed into a fully functioning mobile app. Afterwards, a field experiment (Study II-B) was conducted in an office environment with 33 participants. Study II-B evaluated the actual use of the app and collected user feedbacks on adoption. In addition to QR codes, the app also enabled users to access product services through nearby Bluetooth beacons due to their ease of use and recent popularity. Study II-B aims to compare actual user adoption of different implementations of connecting physical products with digital services.

Results from Study II-B reveal that consumers prefer using beacons to access product services to scanning a QR code. However, existing beacon solutions are not intelligent enough because they are only proximity-based without understanding whether a user is bypassing or requiring a specific service. Consequently, the overloading number of push notifications annoys users and makes the beacon solution only suitable in specific scenarios e.g. checking-in in the airport or receiving coupons at a retailer. To get rid of the spamming problem, a novel Bluetooth button has been developed, which only broadcasts its identifier to start a service request when being pressed. To evaluate the solution, another field study (Study II-C) was conducted in the same office setting for three weeks. Results have shown that the button solution is a good combination of the QR code and the beacon solutions. Consumers ranked it as the best approach of enabling physical products as digital service end-points.

The chapter is laid out as follows. It first summaries previous research on enabling technologies of linking products with services as well as relevant cognitive determinants on service adoption. Afterwards, it raises the research questions and then provides an overview of the study design. The next three sections describe the methodology, implementation, and results of the three empirical studies, respectively. Finally, the chapter is concluded and opportunities for future research are presented.

4.2 Related Work

4.2.1 Using QR Code to Access Services

As indicated by Scornavacca and Barnes (2006), companies have opportunities to link products with consumers to provide personalized services through leveraging mobile apps with product identifiers like QR codes. As product information (e.g., model, serial number, URL) can be encoded in a QR code and consumer information (e.g., contact information, location, preference) can be saved in a mobile app, consumers are able to interact directly with different products through scanning a QR code on mobile.

According to Liu et al. (2007), the QR code technology has many advantages over other technologies, including a large storage capacity, high information density, strong encoding, high reliability, low cost, easy deployment, and fast to scan (Sun et al. 2007). Regarding user acceptance, scanning a QR code to interact with a physical product outperforms other approaches that are available at the moment. Rukzio et al. (2006) surveyed 134 consumers to compare their preference over different mobile interaction approaches, namely touching RFID or NFC tags, scanning QR codes, and communicating over Bluetooth. The authors revealed that scanning QR codes was the best-perceived approach among all the others.

QR codes are used widely in different business scenarios. Lorenzi et al. (2014) proposed to integrate QR code systems and corresponding smartphone apps into existing government services to provide a new level of interactivity for the public. In one of their studies, by scanning a QR code on an existing signage in a national park, people could receive helpful information like geospatial data, recommended itineraries, and park warnings in a mobile app. The study indicated that by deploying the mobile service with QR codes, government systems could provide greater interactivity to the public in an effective and low cost way.

Several museums offered guiding services based on QR codes to allow tourists to browse exhibition contents on their own demand through mobile devices (Huang et al. 2010). In addition to providing supplemental information or audio resources in a simple way, QR codes made it easier to keep information up-to-date compared to installing printed texts. It was more cost efficient for museums because they did not need to invest in additional equipment as visitors get all the information through their own devices. The solution was also perceived as more convenient by visitors (Bard and Markus 2012).

Many libraries used QR codes to present additional book information (e.g., link to the author's Website, book reviews), to provide library guiding service, and to facilitate book searching (Schultz 2013; Wilson 2012). Some libraries placed QR codes on study room doors to provide easy access to room reservation service; others used QR codes to receive user feedbacks through online survey (Ashford 2010). Similar examples existed widely in use cases such as mobile payment, mobile ticketing, mobile couponing, and mobile learning (Liu et al. 2007; Scornavacca and Barnes 2006).

Nevertheless, most QR codes nowadays are still used for marketing purpose or product inventory management instead of enabling manufacturers to proactively support product-service mapping. For some special use cases, manufacturers have started to attach QR codes to their non-intelligent products to help end-consumers directly access product-related services. For instance, HP attached QR codes to products like printers to enable authentication service. SHIPSU attached QR codes to its maritime products to help consumers reorder the same products easily.

On the other hand, however, the limitation of using QR codes is also obvious. First, it cannot enable multiple users to access multiple services at the same time. Second, it only works in a close distance, requires line-of-sight as well as the installation of additional scanning apps on mobile devices. Third, as studied by Quigley and Burke (2013), although QR code has already existed for years, the current scan rate of consumers is still very low.

4.2.2 Using Wireless Communication Technologies to Access Services

Alternatively, short-range wireless communication technologies such as RFID, NFC, and Bluetooth beacons have been named as possible invisible alternatives to QR codes to represent products or other physical objects (Scornavacca and Barnes 2006). RFID has been widely used in the context of manufacturing and supply chain management to enable services like localization, efficient logistics, transparency, and counterfeiting (Melski et al. 2008; Strassner and Schoch 2002; Wyld et al. 2005). Broll et al. (2009) developed a prototype based on RFID and NFC to enable consumers to access additional digital information about a physical object through mobile devices. However, if there are multiple products or services in range, the technology is not able to determine which product has requested a service. In addition, retrieving information encoded in NFC and RFID tags requires specific readers that have not yet been deployed on most of the existing mobile devices.

There existed a variety of work based on Bluetooth technology to interact with a physical object. Most of the related work could be found in the space of indoor positioning, such as the work of Cheung et al. (2006), Chawathe (2008), and Yang et al. (2015). Bluetooth, especially Bluetooth Low Energy (BLE), has been identified as a technology that is supported by consumer devices and easy to deploy and maintain for localization purposes (Hay and Harle 2009). He et al. (2015) introduced a system that provided information to visitors in a museum context. The work focused on the system design aspects but did not deliver a realized prototype nor gathered visitors' feedback. Other applications of the BLE technology could be found in the marketing area. Burzacca et al. (2014) showed the general functionality of the technology with examples for different in-store services, such as location-based digital coupons. Deordica and Alexandru (2014) transferred the concept to an Android-based system and proposed a Bluetooth beacon-based system to improve shopping experience. Namiot and Sneps-Sneppe (2015) suggested a similar approach in a city context to provide better mobility and navigation services. Conte et al. (2014) proposed a solution in a smart home context, where rooms were equipped with beacons to identify occupancy rates in buildings. Based on the results, energy consumption for complex building could be optimized. Bluetooth technologies are easy to use and enabled by most smartphones on the market. However, Jergefelt (2015) argued that challenges of Bluetooth are particularly associated with user experience. Users tend to perceive notifications as spam, which can be considered as a serious obstacle for the successful adoption of the technology. The author called for further research to validate this finding.

In addition to Bluetooth, Bihler et al. (2011) developed an Android-based system to provide context-aware information in a museum. The system leveraged ultrasonic signals sent by emitters to locate smartphones in an indoor space. The study was conducted in a lab setting with 36 visitors and results showed that the app was perceived to be useful by providing a good recognition of exhibits. Nevertheless, user feedbacks also indicated that the app could be regarded as a distraction within an actual exhibition. In addition, this work lacked a holistic evaluation and did not elaborate in detail why ultrasonic sound was preferred over other technologies like Bluetooth. Furthermore, image recognition could also contribute to bringing services closer to physical products. As proposed by Neven (2013), a user could take a photo of a physical object on her mobile device; an image recognition algorithm would determine the object in the taken photo and then provided the user with information and services relevant to the object. However, using image recognition algorithm to identify a physical object is less accurate than directly parsing the name or identifier of the object. Also, unique product information like model and serial number cannot be recognized automatically. Moreover, it is difficult to access multiple products and services at the same time.

Reviewing existing IoT technologies that have a potential of enabling physical products as digital service end-points provides an overview of the pros and cons of different possible implementations. Nevertheless, most of the previous studies focused on a conceptual level or technical aspects but lacked comprehensive and rigorous evaluation by consumers in a real environment. As one of the few studies, Venkatesh et al. (2015) proposed two solutions (barcode scanning and RFID) that assisted consumers with additional product-related services (i.e., product information and product reviews) in the shopping process in a retail context. Through a lab experiment, the authors found that wireless technologies like RFID outperformed the barcode solution in terms of technology adoption and shopping outcomes but not in terms of security beliefs. Nevertheless, the study was also not conducted in a real environment and its evaluation could be biased due to the lack of actual use of the artifacts on a frequent base. As a result, field studies and experiments are required to address the research gaps thereby better understanding consumers' adoption of different technologies and solutions.

4.2.3 Cognitive Determinants Relevant to Service Adoption

This work aims at introducing different approaches of enabling product services and to gather user feedbacks in a real world environment. Following the approach of Venkatesh et al. (2015), a set of constructs has been defined based on related work in technology adoption and IS research to identify which mobile solution would be preferred by consumers. The following section gives an overview of relevant measures that are of interest in this work, and also describes why the other measures have not been selected for evaluation.

Technology adaption measures build on a long tradition and broad discussion in information systems and could be traced back to the work of Davis (1985), and has been further developed by Venkatesh and Davis (2000) and Kim and Garrison (2009) who suggest an extension of the traditional TAM with perceived ubiquity, and perceived reachability to the Mobile Wireless Technology Acceptance Model (MWTAM). Taking technology adoption measures into consideration helps to understand which artifact design will be better adopted. Davis et al. (1989) show that people's intention predicts their actual use of computers. The intention to use computers itself is determined by perceived usefulness as a major origin and by perceived ease of use as an explanation. Similar to most IS adoption research works, perceived usefulness, perceived ease of use, and behavioral intention was measured in this work.

Information overload was traditionally known as "information presented at a rate too fast for a person to process (Sheridan and Ferrell 1974)" so that the individual might respond incorrectly, ignore (i.e. filter) some of the received information or simply quit the receiving of information. Misra and Stokols (2012) suggested an approach to conceptualize and measure perceived information load. According to their work, "information overload occurs when individuals feel overwhelmed by multiple communication and information inputs from cyber-based and place-based sources of stimulation (Misra and Stokols 2012)", which fits in the context of this work. Cyber-based sources of stimulation refer to "information and communication transactions that are mediated by technologies" and can cause information overload such as receiving too many electronic notifications and losing the ability to respond to important notifications by "feeling compelled to do several things simultaneously (Misra and Stokols 2012)". Also, Lee and Lee (2004) found that information overload resulted in customer dissatisfaction and higher consumer confusion.

Furthermore, the tendency to repeat the same course of action was supported by satisfactory experience with a behavior (Aarts et al. 1997). Therefore, satisfaction as a construct was added since the repeated consumption of services on a regular basis via the proposed artifacts was one of the goals of the study. In addition, research has shown that trust is a main aspect in economic transactions and an important factor for consumers to return to an e-vendor or low-touch Internet activity that involves less or no interaction with company representatives. Also, Gefen et al. (2003) has concluded that trust drives consumers' intention to transact with e-vendors and should be considered besides perceived usefulness and perceived ease of use. Pavlou and Fygenson (2006) defined trust as "the belief that the trustee will act cooperatively to fulfill the trustor's expectations without exploiting its vulnerabilities." Since the proposed artifacts were based upon some e-commerce components and purchasing services, trust was thus included in this study.

Recent literature has found that perceived reachability influences the intention to use technology, in particular in context of emerging mobile and wireless technology (Kim and Garrison 2009). In the service context, perceived reachability refers to the perceived degree of an individual of being able to reach a service at any time. This dimension was also measured in the study.

Other cognitive determinants were frequently used in previous literature, but would not be included in this study due to the following reasons. Perceived cost often includes switching cost for consumers between different brands and products, as well as switching efforts from traditional (wired) electronic commerce to mobile commerce (Wu and Wang 2005). Since this work aims at providing a new way that has not existed before to access and consume product services, there is little evidence for looking at perceived (switching) cost from non-existing alternatives. Also, the services that can be accessed and consumed differ depending on the related product. One could argue that there are some services that could be reached in different ways before, but this is highly dependent on the service itself and one consequently would have to differentiate between the service types, which is not in the scope of this work.

Social influence is another popular construct, particularly in the context of virtual communities. “Virtual communities are organized around some distinct interest, which to a lesser or greater extent provides its raison d’etre (Bagozzi and Dholakia 2002)”. These groups aggregate people with common interest or attributes, such as affiliation with a certain brand or similar demographic characteristics, which is of less relevance for the tested services in this study. Although for some cases this construct might make sense, e.g. for reporting technical defects of products that also affect peers, one would have to distinguish between different services which is, as stated above in the case of perceived cost, not within the scope of this study.

According to the IDT, “compatibility is the degree to which an innovation is perceived as being consistent with the existing values, past experiences, and needs of potential adopters”. This and other measures of Roger’s innovation diffusion model such as trialability and observability address the rate of adoption of an innovation (Rogers 1995), which might be of relevance for future studies in this context. The current focus rather lies on whether consumers initially adopt the proposed solutions than on how fast the adoption takes place.

4.3 Study Overview

As digital services are by default separated from most physical products, accessing services related to a specific product is a cumbersome process because it involves effort to identify the desired digital service. To solve the two-fold service search and match problem, a mobile QR code based solution was prototyped and a lab experiment study was conducted to compare the solution with the state-of-the-art solution in terms of service search cost and overall user experience. QR code was used for the proposed solution due to three reasons: First, a QR code is able to encode more information than a 1-D barcode and it is cheap to implement. Second, QR codes have been widely used by people in different contexts, such as marketing and tourist information retrieval. Third, it is a common practice for companies to put QR codes on desktop computers and laptops for inventory management. At the moment these QR codes have not been linked to services, but there is a feasibility to solve a new problem based on existing practices. Consequently, the research question RQ2 can be broken down into three parts. By developing the prototype and conducting a lab experiment, the first part is answered in Study II-A:

> ***RQ2a:*** *How would a mobile QR code based IS solution impact service search cost and user experience compared to the state-of-the-art IS solution?*

In addition to the reduced service search cost, there could be other factors that influence a consumer's decision on whether to adopt the proposed mobile IS to access product services or not. Therefore, Study II-B was conducted to exploit actual user adoption of the proposed solution. To go beyond intention, Study II-B was conducted in a real office environment for six weeks. Due to the fact that QR codes work only in a close distance and require the installation of scanning apps, an additional solution that leveraged Bluetooth beacons was proposed to overcome the drawbacks. Consequently, a new mobile prototype was developed, which enabled accessing product services from both scanning QR codes and interacting with Bluetooth beacons. Participants used both interactive approaches for a total of six weeks and evaluated each of them regarding different cognitive determinants as presented in Section 4.2.3. Study II-B aims at answering the second sub-question of RQ2:

> ***RQ2b:*** *Which interactive approach (QR codes or Bluetooth beacons) is better adopted by consumers in accessing digital services from physical products?*

Although Bluetooth beacons are becoming popular, previous research pointed out that unwanted notifications triggered by beacons without taking consumers' actual demands into account could annoy consumers as spams. To overcome the information overload problem, an improved version of the beacon solution, namely Bluetooth button, was developed. The button is set-off by default and only broadcasts its unique identifier when being pressed. Instead of receiving notifications passively, the button solution gives users the right to initiate a service transaction thereby improving user experience. Consequently, Study II-C was carried out in the same office environment to evaluate the new button solution. It aims at answering the last part of RQ2:

> ***RQ2c:*** *How would the Bluetooth button solution be adopted by consumers in accessing digital services from physical products?*

4.4 Study II-A: Leveraging QR Codes to Enable Products as Service End-Points

Chapter 3 has shown that if service search cost can be reduced, consumers' intention of using product services will significantly increase. As pointed out by previous research (Scornavacca and Barnes 2006), product identifier and relevant information could be encoded in a QR code. By scanning the QR code on mobile, consumers were redirected to a product profile page that presented all product information and related services. This could significantly reduce service search cost. Therefore, a prototype that included a mobile app and QR codes was developed to test the idea of enabling physical products as digital service end-points. Afterwards, the prototype was evaluated and compared with the state-of-the-art IS in a laboratory experiment.

In Study II-A, the state-of-the-art IS was defined as searching for services online on a laptop due to three reasons. First, compared to offline solutions, online information searching has gained more visibility in recent years (Maity et al. 2014). Second, online searching is widely undertaken by users (Pauwels et al. 2011). Third, although mobile devices are ubiquitous and belong to each individual, laptops are more suitable for searching and typing information (Bao et al. 2011). Consequently, this approach served as a baseline for comparing performance.

4.4.1 Prototype Development

4.4.1.1 Design of the System

Figure 10 explains the design and information flow of the prototype IS solution. Four main steps are involved when a user wants to access product services with the system. First, the user scans the QR code on a physical product with the mobile app. If a manufacturer intends to provide product-related services, it can simply attach a QR code on the body of a product. Nowadays, manufacturers already print information like serial number, ingredients, attention notice, and 1-D barcode on products, which makes the proposed solution feasible and relatively easy to implement. The URL of a product's landing Web page is encoded in the QR code. Additional information such as product model and serial number can also be encoded, which makes it possible to identify each individual product and provide highly personalized services.

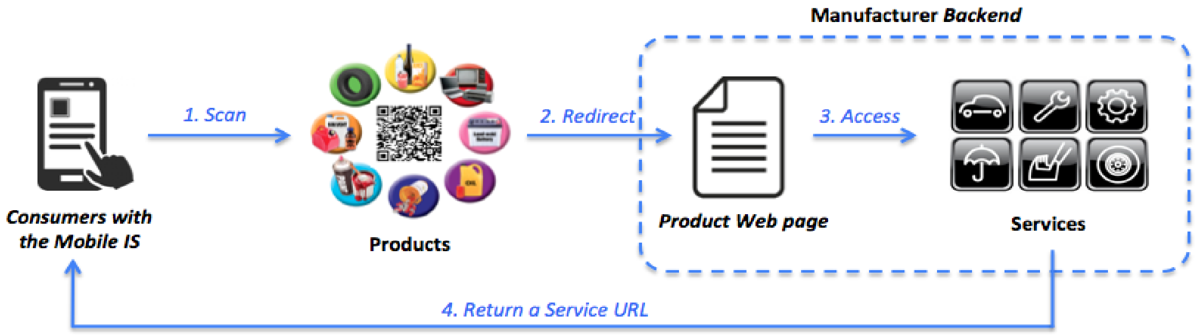


Figure 10: Design and Information Flow of the System

In the second step, the prototype retrieves the URL stored in a QR code and redirects the user to a Web page, on which the user has access to different services offered by the manufacturer (as shown in Step 3 of Figure 10). Each service provided by manufacturers has its own URL that leads to the corresponding Web page. In the last step, the URL of the selected service is returned to and loaded in the mobile app. For services like 'Manage Invoice' and 'Add a Note', the app will retrieve information saved locally on the user's mobile phone and present it directly to her.

Products landing pages and URLs to corresponding service Web pages can be hosted on the manufacturers' backend systems. Manufacturers are able to dynamically update URLs to make sure that the most relevant and up-to-date service information is presented to consumers. Additionally, based on the Internet Protocol (IP) address and Hypertext Transfer Protocol (HTTP) request of a client, manufacturers can modify content or language of the returned product Web page to better serve consumers from different countries.

4.4.1.2 Proof-of-Concept Prototype

Manufacturers can create a landing Web page for each product to present all relevant services. By encoding the URL of the landing page into a QR code and attaching the QR code to a product, manufacturers enable a physical product as a digital service end-point. From consumers' point of view, all product-related services can be accessed by simply scanning the QR code on mobile. Service search cost thus equals to scanning the QR code and clicking the icon that represents the service a consumer intends to use.

Figure 11 demonstrates the mobile app. Figure 11a shows the main screen, which has two buttons: The upper one with a barcode icon triggers the barcode scanning function and the lower rectangle button helps users setup default information (as shown in Figure 11b). A consumer can store personal information such as name, contact details and service preference locally on the app to prevent repeatedly inputting the information in the future. Consequently, if using a service requires the stored personal information, the app will automatically load it to reduce manual efforts. Users can choose what personal data to be saved. For instance, they might prefer storing email address other than home address in the default setting.

Figure 11c presents the landing page of a desktop computer after a user scans the corresponding QR code. When the warranty icon is pressed, Figure 11d will be popped up where the user can select a specific warranty type and input required information to extend warranty digitally. As product information like model and serial number are stored in the QR code and personal information can be retrieved from the app's default setting, the user only needs to type in payment information in case she prefers not to save this piece of information in the app due to privacy concerns.

a) Main Screen | b) Default Setting | c) Product Landing Page | d) Warranty Extension

Figure 11: Demonstration of the Prototype with an Example of Warranty Extension

4.4.2 Study Design

A laboratory experiment was conducted to evaluate the proposed solution to enabling physical products as digital service end-points. Four scenarios were included in Study II-A. In each scenario, a participant was required to look for a specific product service with both the state-of-the-art IS and the proposed prototype. Both qualitative data (e.g., overall impression, general feedback) and quantitative data (e.g., task completion time, number of clicks, Likert-Type questionnaire evaluation) were collected.

The user study was conducted in three steps. First, researchers introduced the goal of the study, demonstrated the prototype and let participants play with the prototype to become acquainted with it. Second, each participant was asked to search for four specific product services online in four different scenarios. The introduction of each scenario was read from a script. Services were selected based on the following criteria to lessen concerns about possible selection bias. First, for easy comparison, selected services should be available online and feasible to be tested in a laboratory environment. Second, the difficulties of conducting the services should be different (some are easy to find while others require for additional effort). Third, services should come from different stages of a product's lifecycle. Last but not least, the services should be perceived differently from consumers' perspective, which means that they are located in different quadrants in Figure 8. In addition, the most relevant product categories as identified in Section 3.4.4 should be combined with the selected services. As a result, the following four scenarios were selected:

- Extending warranty for a desktop computer: It was a two-step action. First, participants need to search for the official Web page of a desktop computer to extend its warranty. Second, they need to type in information (e.g., product serial number, personal information, payment information) required by the manufacturer to purchase the warranty. Dummy data for both personal and payment information was provided in the study. After inputting all the required information, the task was considered as completed.

- Finding out the online manual of a digital camera: Participants were asked to find out the digital version of the manual. When the manual was being loaded, the task was considered as completed to reduce influence of Internet connection quality on the result.

- Checking out new models of a road bike: Participants were asked to find out a list of all new models of an old road bike in this scenario. Information could be found both through search engines and on the manufacturer's official Website.

- Reselling a smartphone on an online platform: It was a two-step action. First, participants need to figure out the correct model and storage capacity of the smartphone. Afterwards, they were asked to resell it on a specific online platform. For participants who were not familiar with the platform, they were guided by the researcher through all the required steps for reselling a product.

After confirming that they understood each scenario and its task, participants began to search for the service with two approaches: a laptop with Internet connection, and the proposed mobile prototype. Each participant had to experience both approaches in a randomized order so as to reduce possible biasing effects of the task order on the dependent measures. Both the task completion time and the number of clicks were recorded to measure service search cost. All participants were told that the goal of the study was to compare different approaches other than evaluating their abilities to avoid biasing them into rushing through the tasks under time pressure.

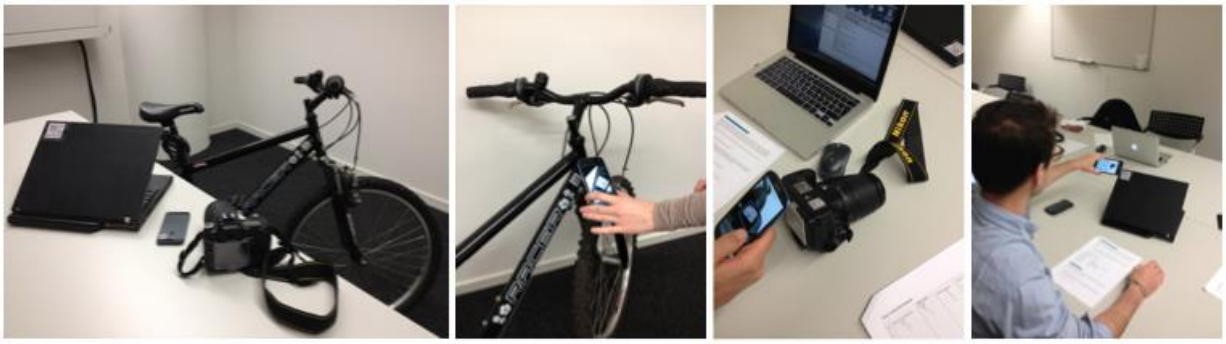


Figure 12: The Set of Products Used in the Tasks together with Users Completing the Tasks

In addition, perceived user experience and usability of each approach was assessed with an AttrakDiff questionnaire (Hassenzahl and Monk 2010) that consisted of 28 bipolar verbal anchors rated on a 7-point scale. AttrakDiff evaluates an interactive system from four aspects: perceived pragmatic quality (PQ) that measures the support of achieving a goal, hedonic quality – stimulation (HQ-S) that measures perceived novelty and potential to attract a user's attention, hedonic quality – identification (HQ-I) that measures potential of identification with a system, as well as perceived overall attractiveness (ATT). In the end of the study, participants were asked to provide qualitative feedbacks for the proposed approach in accessing product services. Figure 12 demonstrates pictures that were taken in the study.

4.4.3 Result Analysis

4.4.3.1 Participants

A total of 15 people participated in the study and five of them were female. Their ages ranged from 18 to 35 years. Fourteen of them used advanced features (e.g., mobile email, apps, Internet) of their smartphones many times a day and the remaining one used such features once a day. All of them were students from different universities in Zurich, Switzerland. Each session took around an hour and each participant got a 20 Swiss Franc voucher as compensation. The study was conducted from April 3rd, 2014 to April 9th, 2014.

4.4.3.2 Quantitative Analysis of Service

Table 3 compares the search time, search effort (indicated by the number of clicks), and information input time required by both approaches in searching for product services. Except for service search time, information input time, and number of clicks in Task 1, the differences between two paired means of the examined items were all normally distributed, therefore the paired t-test was applied. For the three non-normal distributed items, Wilcoxon signed ranks test was used to compare mean values (Field 2009).

Except for the number of clicks in Task 2, test result showed that acquiring services with the mobile prototype IS required significantly less search time, search effort, and information input time than that with a laptop, and all of them represented a large effect *[as r > .5]*. Overall, the total service search time with the mobile IS was 11 times less than that with the state-of-the-art IS. Similarly, the total task complete time and the total search efforts were six times and four times less, respectively.

Table 3: Comparison between Two Approaches on Service Search Cost (N=15)

		With laptop		***With prototype***		***Effect size (r)***	***Sig. (2-tailed)***
		M	***SD***	***M***	***SD***		
Task 1	Service search time (s)	150.2	101.5	7.0	1.8	.62	.001
	Information input time (s)	104.9	25.6	44.3	8.1	.62	.001
	Task complete time (s)	263.9	58.9	63.5	9.7	.97	< .001
	# Clicks	10.5	3.2	2.1	0.3	.62	.001
Task 2	Service search time (s)	22.8	5.6	13.1	2.6	.85	< .001
	# Clicks	2.6	0.7	2.2	0.6	.41	.111
Task 3	Service search time (s)	122.2	61.2	13.2	5.1	.87	< .001
	# Clicks	8.5	3.7	2.0	0.0	.88	< .001
Task 4	Model check time (s)	150.7	104.8	0.0	0.0	.83	< .001
	Service search time (s)	200.7	92.2	11.8	2.7	.91	< .001
	# Clicks	11.4	4.3	2.1	0.3	.92	< .001
All tasks	Total complete time (s)	609.5	145.0	101.6	13.3	.97	< .001
	Total search time (s)	495.9	183.0	45.1	7.1	.93	< .001
	Total # Clicks	33.1	6.8	8.3	0.7	.96	< .001

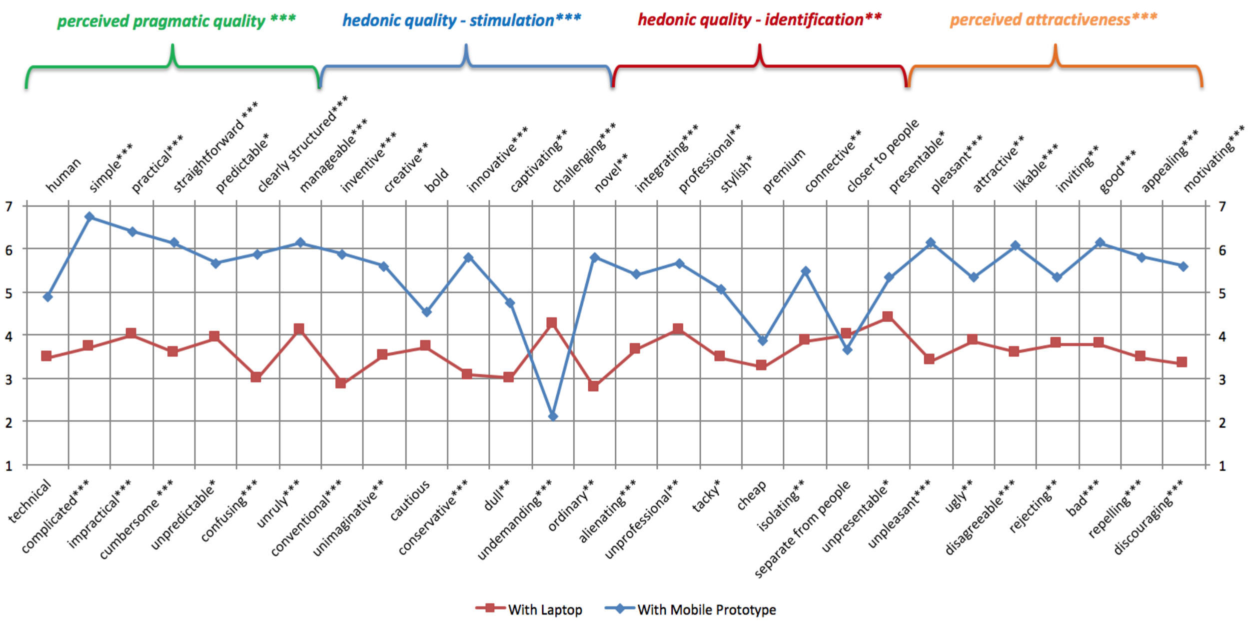
Regarding mistakes and errors made during the search, in the 'with laptop' approach, participants had loaded on average 6.7 Web pages (SD = 1.5) until they found the correct one to extend warranty for the desktop computer in Task 1. Two participants made typos in inputting the product serial number. In Task 3, they clicked on average 1.7 wrong pages (SD = 1.9) before reaching the official Web site. In Task 4, three of the participants received hints from the researcher because they were not familiar with how to check the capacity of a smartphone although they were smartphone users. Two participants resold the smartphone with a wrong model in the end.

In the 'with prototype' approach, two and three participants encountered problems in scanning the QR code in Task 2 and Task 3, respectively. They either scanned the codes too far or too close. Also, one participant clicked 'Help' and 'Specs' service before clicking the

'Handbook' button in Task 2. In Task 4, one participant clicked another service button by mistake. Overall, participants made fewer mistakes with the mobile prototype than with a laptop.

4.4.3.3 Quantitative Analysis of the AttrakDiff Questionnaire

The per-item ratings of the two approaches on the AttrakDiff scales are shown in Figure 13. The 'with mobile prototype' approach was ranked significantly higher than the 'with laptop' approach on most of the scales. It also had significant higher perceived pragmatic quality (PQ) *[t(14) = 7.52, p<.001, r=.90]*, stimulation (HQ-S) *[t(14) = 6.52, p<.001, r=.87]*, identification (HQ-I) *[t(14) = 4.13, p<.005, r=.74]* and attractiveness (ATT) *[t(14) = 7.28, p<.001, r=.89]*.



Sig. (2-tailed): * significant at p<.05; ** significant at p<.005; *** significant at p<.001

Figure 13: User Experience Ratings with AttrakDiff's 28 Bipolar Verbal Anchors (N=15)

4.4.3.4 Qualitative Feedbacks

In the end, the survey asked participants if a mobile IS like the prototype were available on the market, whether they would download and use it to access product services. All the 15 participants answered "yes". Participants also provided qualitative feedbacks for the prototype. Most of them liked it and described it as fast, easy, straightforward, and time-saving. Four of them said it was nice to have all services in one place. One participant said that the prototype also included "some services that the user has not thought about. So it definitely adds value". Another one expressed that it was "a great way to connect two separate things (the object and its information) in the least time and effort consuming way". Regarding the future improvements, two participants claimed their concerns about privacy by linking personal information and personal belongings to the app. One disliked scanning QR codes. Till here, RQ2a is addressed.

4.5 Study II-B: Comparing QR Codes with Bluetooth Beacons

Results of Study II-A indicate that leveraging mobile IS and QR code has a high potential to reduce service search cost and to improve user experience of accessing product-related services. To go beyond intention as well as to examine other factors that could influence consumers' adoption of the proposed solution, Study II-B was thus conducted to extend Study II-A from three aspects.

First, Study II-B was conducted in a real office environment for six weeks to exploit actual user adoption. Second, as reviewed in Section 4.2.2, Bluetooth beacon is an alternative technology that is able to overcome the drawbacks of QR codes. Consequently, a new prototype that integrated Bluetooth connection was developed and evaluated. Third, in addition to the reduced search cost, which is closely associated with the perceived ease of use, other adoption related cognitive determinants were measured to provide a comprehensive understanding.

The goal of Study II-B is to compare consumers' adoption of two IoT solutions (namely QR codes and Bluetooth beacons) of enabling physical products as digital service end-points from a field experiment conducted in a real office environment.

4.5.1 Study Design

As presented in Section 4.2.2, different IoT technologies could contribute to link the physical and digital world. Among all possible alternatives, QR codes and Bluetooth beacons are the most promising technologies. On the one hand, consumers have already fundamental knowledge about how to use a QR code to get additional content in other context like marketing and retailing. Also, there are many QR code scanning apps available on mobile that are free for consumers to download and use. On the other hand, Bluetooth is enabled by almost all mobile devices, therefore, consumers can easily turn on their Bluetooth connection and directly interact with beacons to receive services. Consequently, QR codes and Bluetooth beacons were chosen as the two candidate IoT technologies for evaluation in Study II-B.

An iOS app was developed to help consumers easily access and consume different product-related services. The app has two versions: The QR code version is integrated with an in-app barcode scanning feature and enables users to access different product services through scanning; The beacon version is able to communicate with the beacons directly to enable the same services. To let consumers using the solution in reality, a field experiment was conducted in the office of the Center for Digital Technology Management in Munich, Germany. In order to identify relevant services, a pre-study was first conducted. A survey was designed and distributed to office employees through mailing list and social media. Each participant was asked to rate office-related services that they intended to use. In the end, 44 completed questionnaires were received. Participants indicated that reporting product damages, tracking beverage consumption, giving feedback, receiving upcoming news and events, and ordering office supply were the most relevant services for office employees and visitors. Hence, accessing and consuming these services were supported by the mobile app in this study.

After identifying relevant services and developing a prototype of the proposed solution, a field experiment was conducted in the office environment. Participants of the study were acquired through visits and mailing lists of the institute. Each participant used both versions of the mobile app in a randomized order to exclude effects that could be resulted from a predefined testing sequence. Each version of the app was used by each participant for a period of three consecutive weeks. Afterwards, the participant switched to the other version and used it for another three weeks.

After using each version, participants were asked to fill out a survey that measured the selected constructs as presented in Section 4.2.3. Each construct was measured on a 1 (strongly disagree) to 5 (strongly agree) Likert scale using measurements that were widely used in previous literature. Scales for perceived usefulness, perceived ease of use, and privacy concerns were adapted from Taylor and Todd (1995), Moore and Benbasat (1991), and Venkatesh et al. (2015); scales for behavioral intention were adapted from Cronin et al. (2000) and Zhao et al. (2012); information overload was measured by using items similar to that of Hiltz and Turoff (1985) and Misra and Stokols (2012); trust was measured with items that were almost identical to Gefen et al. (2003); scales for reachability and satisfaction were adapted from Kim and Garrison (2009) and Chiu et al. (2012), respectively. The average of the measurement ratings was taken to compare the different versions, similar to the approach of Venkatesh et al. (2015). In addition to the surveys, app usage logs and qualitative feedbacks about the solution were also collected. Each participant was incentivized with a €15 voucher, and an iPad mini was raffled among all participants in the end.

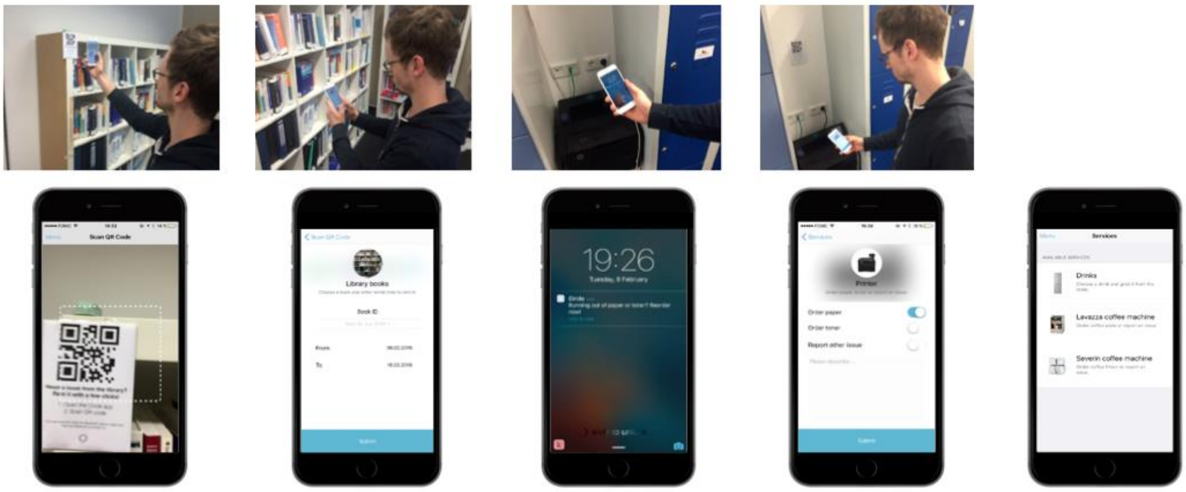
To control the quality of the survey answers, three approaches were taken. First, according to Osborne and Blanchard (2010), a control question was added in the survey, which asked each participant to select a specific answer for this question. Answers of participants who failed to pass the control question would be removed in the analysis. Second, some questions that measured the same construct were reversely coded on purpose. In the re-coded answers, if a participant's answers to these questions were of high deviation, she would be removed in the analysis. Third, the Cronbach's alphas of all the constructs were calculated and constructs that had values lower than 0.7 would be excluded in the analysis.

In the data analysis, the means of the two versions in each construct were compared to identify which version had been better adopted from a user's perspective. Because each participant used and evaluated both versions repeatedly, the paired t-test would be used to compare mean ratings if the differences between two paired ratings of the same construct were normally distributed. Otherwise, Wilcoxon signed ranks test would be used to compare mean values (Field 2009).

4.5.2 Prototype Development

An iOS app was developed because there was a sufficient share of iPhone users in the office environment. According to the result of the pre-study, eight services were selected as being applicable within the study setting. Before the launch of Study II-B, these services were accessed or consumed based on papers, face-to-face request, emails, or phone calls.

Three services were relevant to products in the kitchen. There were two coffee machines in the kitchen and relevant services under study were "ordering coffee" and "report other issues". In addition, there was a refrigerator and "purchasing drinks" service was enabled digitally by the mobile app with the help of QR codes and beacons. Services related to the printer in the office were "order toner", "order paper", and "report other issues". Furthermore, services that were relevant to the paper dispenser in the bathroom were "order paper towels" and "report other issues". In the study room, a "rent books" service could be accessed directly from the bookshelf and used digitally on mobile. Last but not least, a QR code or a beacon at the main entrance of the office provided user with the service "upcoming events".



a) Scanning a QR Code b) Get Services for Book Shelf c) Receive Push Notifications d) Get Services for Printer e) Show All Nearby Products

Figure 14: Settings and Two Means of Accessing Services in Study II-B

In Study II-B, a QR code and a Bluetooth beacon were attached to each physical product to enable services. There are two versions of the mobile app. The first version integrates an in-app QR code scanner. Once a user opens the app, the scanner appears directly for her to scan a code, as shown in Figure 14a. By parsing the content encoded in the scanned QR code, the app will automatically direct the user to a service page, which presents all services relevant to the product, as shown in Figure 14b. The second version has no QR code scanner integrated, but it has instead the ability to interact with nearby Bluetooth beacons. It sends out push notifications to users for them to access and use services, as shown in Figure 14c. After clicking a notification, users can access services of the product similar to that of the QR version, as shown in Figure 14d. To reduce the number of unnecessary push notifications, a push notification will be deleted automatically if it is not clicked by a user after appearing for one minute. Alternatively, users are able to access services of all nearby products actively by opening the app. The app will search for beacons in the proximity and then present all the products and corresponding services to the user, as demonstrated in Figure 14e. No push notifications will be sent out in this case.

Once the app is opened for the first time, a sign-up process will be initiated (as demonstrated in Figure 15). It teaches a user how to use the app to access services as well as creates an anonymous but unique identifier for each user. Every time a user opens the app or performs any action in the app, an event log will be generated and sent to the backend server. In addition, users are not able to change between the two versions of the app themselves.

Switching app versions for each participant can only be conducted from the backend by researchers to control the experiment.

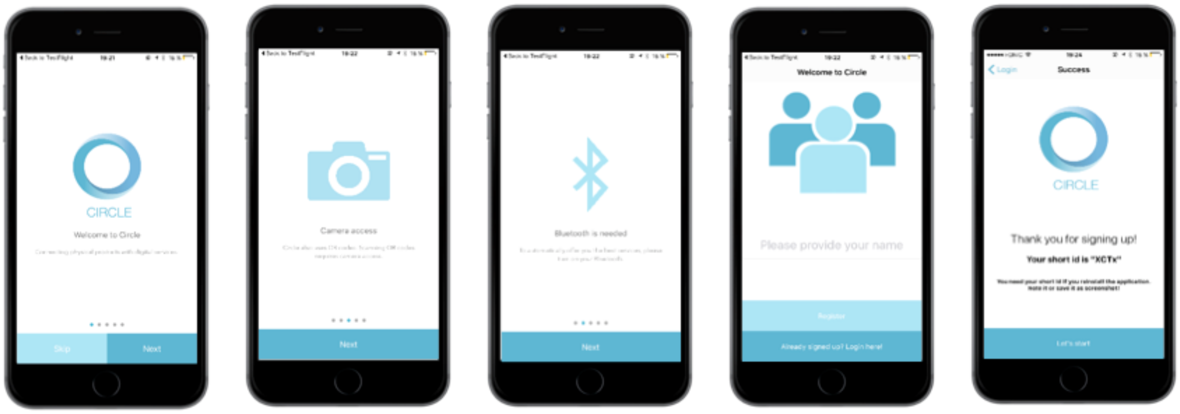


Figure 15: Sign-up Process and App Registration

4.5.3 Result Analysis

4.5.3.1 Demographics and App Usage

Starting from January 1st, 2016, 43 people participated in Study II-B and used each version of the app over the course of six weeks split into two equal halves. In the end, 33 of them finished surveys for both the QR and beacon versions and their responses and feedbacks were taken in the analysis. The demographics of these participants are shown in Table 4.

Table 4: Characteristics of Participants in Study II-B (N=33)

Demographics	***Category***	***N***	***%***
Age	<20	0	0.00
	20-25	17	51.5
	26-30	15	45.5
	>30	1	3.00
	Total	*33*	*100.0*
Gender	Female	8	24.2
	Male	25	75.8
	Total	*33*	*100.0*

In terms of actual use of services, participants started 225 sessions with the QR version and completed 159 of them. Starting a session referred to accessing a service by letting the service screen appear, whereas completing a session referred to the actual transaction and consumption of a service by entering and submitting data. On the other hand, 303 sessions were started with the beacon version and 148 out of them were completed. Overall, the installed beacons sent out 685 notifications and 24 of them led to completed sessions. The session completion rate for the QR version was 71% and that for the beacon version was 49%. A possible explanation could be that in the case of QR code, users actively decided to access and consume a service by scanning a code, whereas in the case of beacon users got notified about an available service, pressed the notification, but then decided not to consume the service in the end.

The average session completion time with the beacon version was 10.4 seconds, whereas that of the QR version was 14.8 seconds or 42.3% longer. This indicates that beacon version has a higher potential of reducing service search cost. The most frequently used services for the QR version were "event information" (37 completed sessions) and "buying drinks" (36 completed sessions), while those for the beacon version were "buying drinks" (40 completed sessions) and "event information" (29 completed sessions).

4.5.3.2 Quantitative Analysis

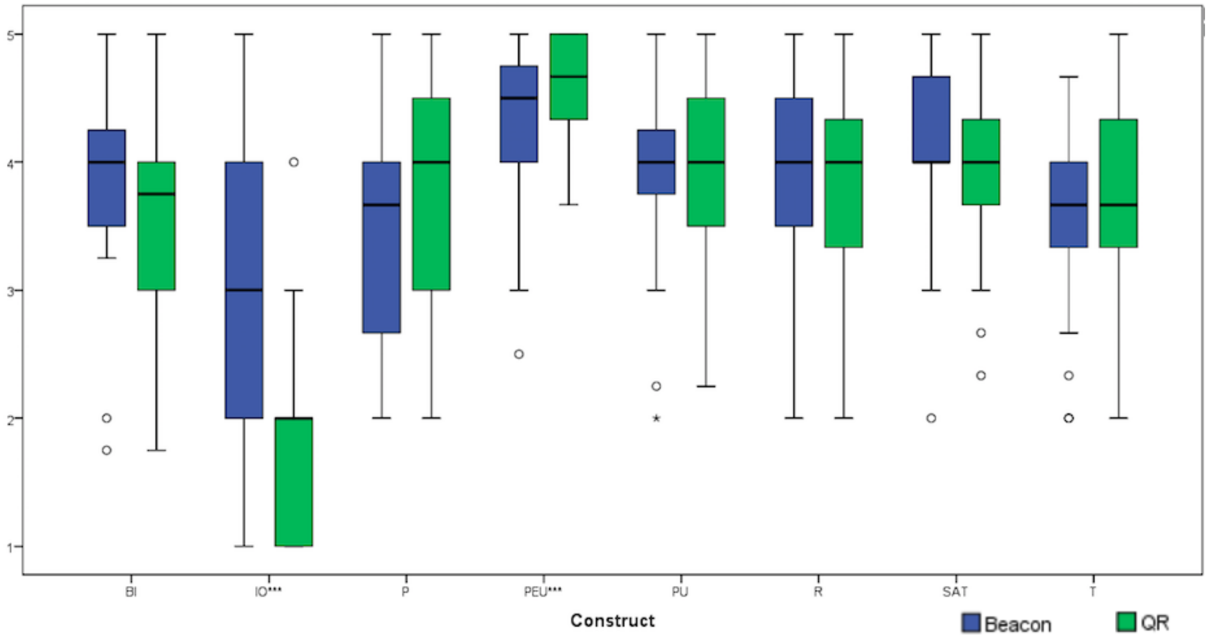
After cleaning the data according to the approaches introduced in Section 4.5.1, a statistical analysis was conducted to compare users' adoption of the two proposed solutions of enabling physical products as digital service end-points.

Table 5: Cronbach's Alphas (α) of the Measured Constructs in Study II-B (N=33)

Constructs	*Beacon*		*QR*	
	Cronbach's Alpha	*# Items*	*Cronbach's Alpha*	*# Items*
Perceived Usefulness	.84	4	.83	4
Perceived Ease of Use	.83	4	.68	3
Behavioral Intention	.84	4	.86	4
Information Overload	.87	3	.77	2
Privacy	.78	3	.64	2
Trust	.78	3	.77	3
Reachability	.54	2	.75	3
Satisfaction	.82	3	.75	3

As reported in Table 5, most of the Cronbach's alphas were above the recommended value of 0.7 with only perceived ease of use of the QR version slightly below the threshold *[α=0.68]*. However, the Cronbach's alpha of reachability of the Beacon version was only 0.54 and that of privacy of the QR version was 0.64. Therefore, these two constructs were only presented for the sake of completeness but not compared statistically and discussed in the follow-up analysis. Due to the fact that the data received from the survey did not follow a normal distribution, a paired t-test could not be applied and the Wilcoxon signed rank test was conducted instead to compare means in each of the constructs.

The box plots in Figure 16 demonstrate how users' perception of the adoption-related constructs differs between the two IoT technologies in using product services. The bottom and top of each box are the first and third quartiles, and the horizontal bolt line in the middle represents the median rating. The error bars above and under each box stand for the high and low bound of the 95% confidence interval.



(Sig. (2-tailed): *: p<.05, **: p<.005, ***: p<.001)

Figure 16: Comparison of Constructs for QR and Beacon Versions (N=33)

Table 6 shows the results of the Wilcoxon signed rank test. Both versions scored high in almost every construct. The QR version significantly outperformed the beacon version in perceived ease of use and information overload. It is important to note that the construct information overload is the only construct where a lower score actually means a better perception. The beacon version ranked higher in the behavioral intention, although the difference was only marginally significant *[p=.084]*. However, it indicated that beacons could have a potential to be preferred by users. Since perceived ease of use of the QR version had a relatively low Cronbach's alpha *[α=.675]*, its reliability should be considered carefully.

Table 6: Results of Comparing Beacons with QR Codes on Adoption (N=33)

Construct	*Beacon*		*QR*		*Sig. (2-tailed)*
	Mean	*S.D.*	*Mean*	*S.D.*	
Perceived Usefulness	3.89	.64	3.98	.71	.301
Perceived Ease of Use	4.27	.61	4.59	.44	.000
Behavioral Intention	3.83	.69	3.53	.81	.084
Information Overload	3.02	1.23	1.73	.75	.000
Trust	3.61	.69	3.73	.71	.304
Satisfaction	4.14	.63	4.01	.67	.299

4.5.3.3 Qualitative Feedback

The information overload effect identified by the quantitative analysis was also supported by the participants' qualitative comments. Some participants stated that "the very frequent push notifications are a little bit annoying". One user asked for improved intelligence, so that push notifications were not send more than once when users were located within the range of a beacon and only move slightly, e.g., when working at a desk. Especially in dense locations with a lot of beacon (i.e., kitchen), users did not like the high number of push notifications they received simultaneously when they entered a beacon's range. Some participants indicated that they always disable push notifications of apps, which would undermine the idea behind the beacons. One participant suggested a feature that users could selectively turn off notifications for services they did not want to receive, while another user suggested to only provide a list of all services available for the specific site in order to replace the push notifications. Particularly for the case of office environments where people were moving on a frequent basis, the removal of push notifications and the provision of a complete list with services was suggested.

Difference in perceived ease of use was also found in the qualitative user feedbacks. Users mentioned in the comments or verbally during the study that scanning QR codes was very fast and reliable. One user reported QR codes to be more intuitive since the process of actively deciding to select a service by scanning seems to be more targeted. However, one user commented that "it can be annoying that you have to start (the) application and camera first to interact", while another user mentioned that "It is not convenient to always scan the QR code first before getting access to a service. It is much more convenient when it happens automatically how it was with the iBeacon version". The fact that "the products/services are not found automatically" seemed to make it "less convenient" than the beacon version. Participants liked the function of being reminded by the notifications on the spot, e.g., replenishment of coffee filters, which they would otherwise have forgotten or only once they would have run out of stock. Users also mentioned that they forgot to take their smartphones out of pockets as soon as they were used to the appearance of QR codes.

Other comments were left for improvements and additional features, which showed a great interest in and relevance of the proposed solutions. One user suggested to have product overviews for purchasing services sorted according to purchase history in order to reduce time for scrolling and selecting a product in the beacon version. Other features such as information and status updates about the processing of requests were suggested. Some participants suggested to have an additional feature that made users aware of new services of a product that they otherwise would have not known about. Participants also showed interest in gamification features such as a ranking of coffee consumption, which they considered to be fun within a group of colleagues in an office setting and could drive engagement. Due to the prototypal character of the mobile app, payment features were not included but it would be a crucial feature in the future, according to the received feedbacks. On the other hand, participants had concerns about energy consumption due to the fact that having Bluetooth constantly turned on consumes too much energy. They also had concerns about privacy issues because the beacons can technically track each user's location and movement in the office. Hence, users asked for automatically turning on Bluetooth once the application is opened. However, this is at the moment not possible due to the restriction imposed by iOS. Overall, the Bluetooth beacon solution was perceived better than the QR code solution in the study. Thus, RQ2b is addressed.

4.6 Study II-C: A Novel Button Solution to Improve User Experience

Result from Study II-B showed that users intended more to use Bluetooth beacons than QR codes to access product services and the difference was marginally significant. From the app logs, it has been identified that the time to complete a session on average took 10.4 seconds with the beacon solution, which was 42.3% less than that of the QR solution. Qualitative feedbacks gathered from Study II-B also indicated that using QR scanning to access product services might be annoying in the long run and participants preferred the beacon solution. However, both quantitative and qualitative feedbacks stated that the beacon solution should be further improved due to the high information overload issue. In addition, users' privacy concerns resulted from the fact that beacons could be used to track each individual's movement required to be addressed. Therefore, a novel button solution was proposed and then evaluated in a field test in Study II-C.

4.6.1 Study Design

Feedbacks gathered from Study II-B indicated that actively triggering the service interaction by scanning a QR code resulted in low information overload and low privacy concerns. Nevertheless, scanning a code to access services required multiple steps and high manual efforts. Thus, the QR and beacon solutions should be combined to keep the advantages of both. Taking IoT approaches from practice such as the Amazon Dash button into account, led to the decision on developing a physical button to enable direct service access based on a user's active action on the spot. Instead of receiving notifications passively, users can take over the control of when to initiate a service request.

Hence, a new prototype for the button version was developed and a follow-up field study was conducted for another three weeks in the same office environment. Participants of Study II-B were asked to participate in Study II-C but without additional incentives. Due to the potentially smaller number of participants, all of them used only the button version instead of having multiple groups. Furthermore, some services in Study II-B were not frequently accessed and consumed, which were removed in Study II-C. Consequently, four products and their relevant services were under study: The event information at the main entrance, the refrigerator and the coffee machine in the kitchen, and the paper dispenser in the bathroom. Similar to Study II-B, participants were required to fill out the same survey to evaluate the button solution after using it for three weeks. In order to compare the overall preference for all the three proposed IoT solutions, an additional question was added in the end of the survey. It asked participants to rank the three solutions to indicate which one they preferred most in accessing product services.

Data was cleaned in the same way as that of Study II-B. When analyzing the data, the means of all three versions in the specific constructs were compared to identify which version performed best in each of the categories from users' perspective. Depending on the distribution of the data from the survey, a one-way analysis of variance (ANOVA) or a Friedman test would be applied, according to Field (2009). These tests are applied to compare the differences in means within a group of participants that are part of three or more treatments, which is the case of Study II-C. If data is normally distributed, the one-way ANOVA will be used, otherwise the Friedman test will be conducted instead.

4.6.2 Prototype Development

A cross-platform Software Development Kit (SDK) and Arduino-based platform was used to develop the Bluetooth buttons (as shown in Figure 17a), which were mounted on the corresponding physical products (as seen in Figure 17b).

a) Developed Bluetooth Button

b) Attach Buttons to Enable Services

Figure 17: The Developed Bluetooth Button Hardware

Figure 18 demonstrates how the physical button, the mobile app, and the backend server interact with each other to provide easy and fast access to product services. When a user is in front of a physical product and needs a service for the product, she can press the button that is already physically attached to the product. The button communicates with the app over Bluetooth to indicate what product is under a service request. When detecting a button press, the app and its backend server will select and present relevant product services to the user based on her preference as well as contextual information (e.g., time, location, movement, etc.) collected from the user's mobile device.

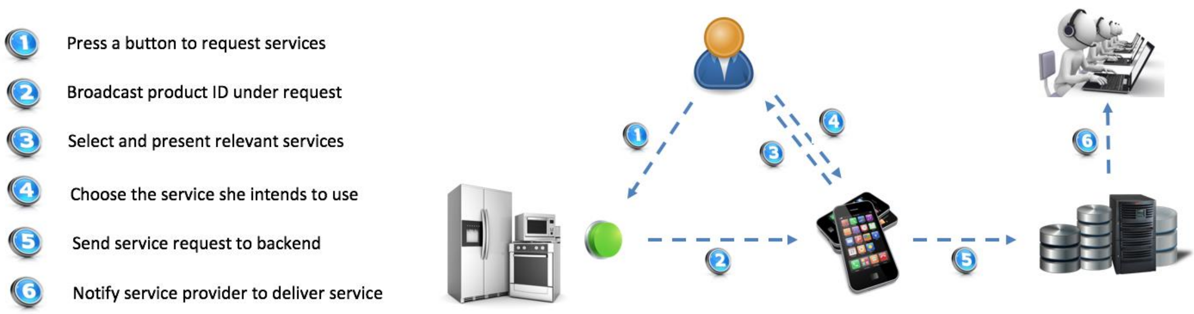
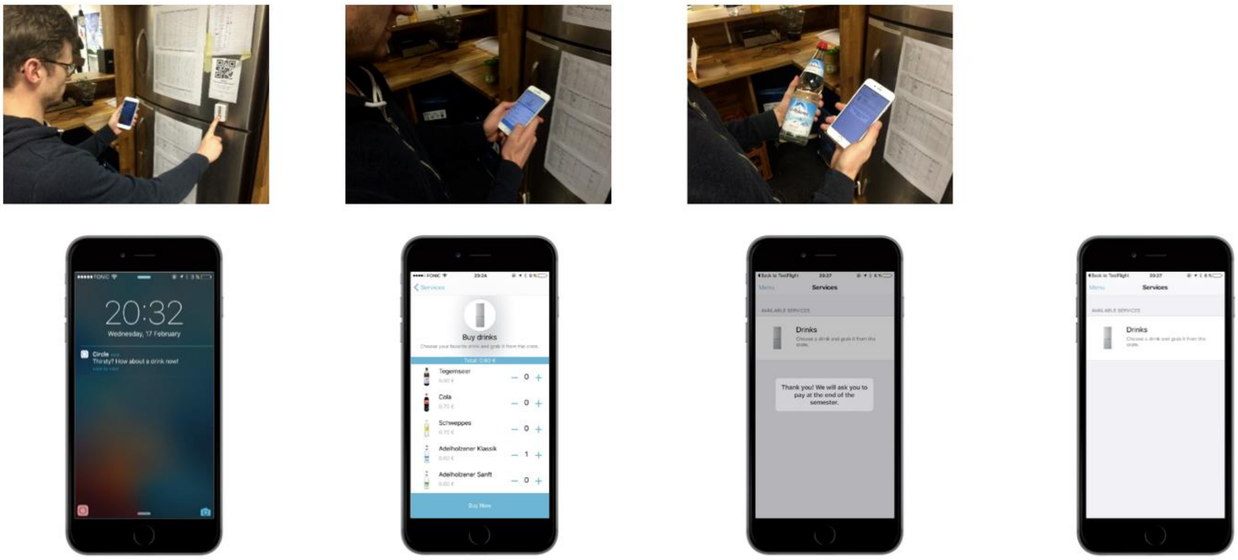


Figure 18: Architecture and Interaction Flow of the Button Solution

If the app is already opened on mobile, the user will see a list of ranked services and can select the one she needs. In case the smartphone is locked, the user will receive an interactive push notification and she can directly react on the locked screen to complete the service request. In case the user does not interact with the notification, the notification will disappear automatically after a certain length of time without annoying the user. In the end, the app sends the service request to the backend and the backend further communicates with service providers to deliver services.



a) Press a Button b) Get Services for Fridge c) Finish Service Request d) Product Nearby

Figure 19: Screen Snaps of the Button Version App

Figure 19 shows some screen snaps of the button version app. After pressing a button attached to a physical product, a notification will be sent to the smartphones in the proximity for 30 seconds, as shown in Figure 19a. By clicking the notification, users can access all services relevant to the product (Figure 19b) and consume the one they intend to use (Figure 19c). If the app is already opened, pressing a button will present the corresponding product directly in the app for 30 seconds instead of sending out notifications, as shown in Figure 19d. Different from the beacon version, the button version app only presents the products whose button have been pressed instead of showing all products nearby. Multiple products will only be presented if multiple buttons are pressed at the same time.

4.6.3 Result Analysis

4.6.3.1 Demographics and App Usage

After having tested the first two solutions in Study II-B, 30 out of 33 participants also used and evaluated the button solution over a length of three weeks from February 15th, 2016 to March 6th, 2016. The demographics of the participating users can be found in Table 7.

Table 7: Characteristics of Participants in Study II-C (N=30)

Demographics	*Category*	*N*	*%*
Age	<20	0	0.00
	20-25	15	50.0
	26-30	14	46.7
	>30	1	3.3
	Total	*30*	*100.0*
Gender	Female	6	20.0
	Male	24	80.0
	Total	*30*	*100.0*

In terms of actual service usage, with the button version, 171 sessions were started and 87 of them were completed in the end. The relatively low number of sessions was due to the fact that the semester ended in the first week of February so that students visited the institute less frequently. In total, 337 notifications were sent out based on users' requests by clicking the buttons, and 37 sessions were completed based on a sent notification. The average session completion time was 9.63 seconds, which was shorter than those of the QR and the beacon versions. But it could be resulted from other facts such as getting used to the app and knowing what information to provide to finish a service request. The most demanded services were "event information" (39 completed sessions) and "buying drinks" (28 completed sessions). The completion rate of the button version was 51%, which was slightly higher than that of the beacon version.

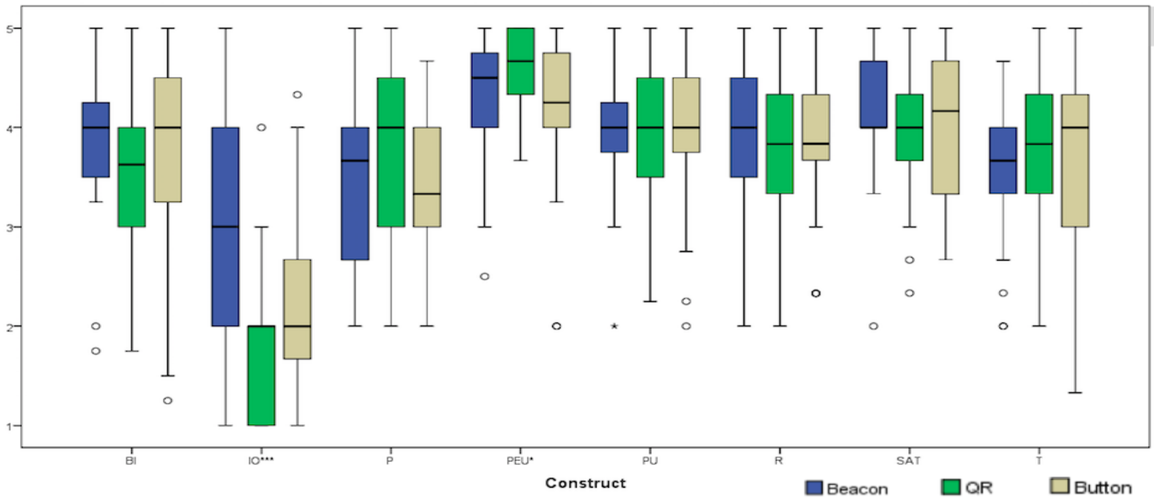
4.6.3.2 Quantitative Analysis

After cleaning the data, a statistical analysis was conducted to compare users' adoption of the button version with the other two (QR and beacon) versions of enabling physical products as digital service end-points. As reported in Table 8, except for privacy, all Cronbach's alphas of the button version were above the recommended value of 0.7 and much higher than those of the other two versions.

Table 8: Cronbach's Alphas (α) of the Measured Constructs in Study II-C (N=30)

Construct	*Button*		*Beacon*		*QR*	
	α	*# Items*	*α*	*# Items*	*α*	*# Items*
Perceived Usefulness (PU)	.93	4	.84	4	.83	4
Perceived Ease of Use (PEU)	.89	4	.83	4	.68	3
Behavioral Intention (BI)	.92	4	.84	4	.86	4
Information Overload (IO)	.88	3	.87	3	.77	2
Privacy (P)	.19	3	.78	3	.64	2
Trust (T)	.77	3	.78	3	.77	3
Reachability (R)	.80	3	.54	2	.75	3
Satisfaction (S)	.85	3	.82	3	.75	3

According to the same criteria of Study II-B, privacy and reachability would not be analyzed statistically, but still presented for the sake of completeness. Due to the fact that the data received from the survey did not follow a normal distribution, the Friedman test was conducted to compare means among the three versions.



(Sig. (2-tailed): *: p<.05, **: p<.005, ***: p<.001)

Figure 20: Comparison of Constructs for QR, Beacon, and Button Versions (N=30)

The box plots in Figure 20 demonstrates how users' adoption differs among the three IoT technologies under this study. Details of the Friedman test are presented in Table 9. There were significant differences in perceived ease of use and information overload among the three versions. The QR version ranked best in the perceived ease of use *[$\chi^2(2)=6.20$, $p=.044$]*. Also in the information overload, the QR version ranked first but with the button version, information overload could be improved from 3.08 (beacon) to 2.23 (button) *[$\chi^2(2)=17.08$,* *p<.001]*. In order to see where the differences in significant constructs actually occurred, a post-hoc analysis was conducted to compare the different combinations of related groups: beacon to QR, beacon to button, and QR to button.

Table 9: Results of Comparing the QR, Beacon and Button Versions on Adoption (N=30)

Construct	***Button***		***Beacon***		***QR***		***Sig. (2-tailed)***
	Mean	***S.D.***	***Mean***	***S.D.***	***Mean***	***S.D.***	
Perceived Usefulness (PU)	3.96	.75	3.95	.60	3.96	.74	.563
Perceived Ease of Use (PEU)	4.22	.78	4.28	.58	4.60	.45	.044
Behavioral Intention (BI)	3.70	1.04	3.82	.69	3.53	.82	.067
Information Overload (IO)	2.23	.91	3.08	1.20	1.78	.76	.000
Privacy (P)	3.47	.60	3.50	.82	3.67	.87	.866
Trust (T)	3.70	.81	3.61	.70	3.74	.72	.691
Reachability (R)	3.78	.77	3.87	.74	3.71	.74	.782
Satisfaction (SAT)	4.03	.74	4.17	.62	3.98	.68	.643

Results of the post-hoc analysis showed that there was no significant difference in perceived ease of use between the beacon and the button versions. However, significant difference existed between the QR and the beacon versions *[difference=.32, p=.001]* as well as between the QR and the button versions *[difference=.38, p=.010]*. In addition, there was no significant difference between the QR and the button versions in terms of information overload. However, the button version had a significantly lower information overload than the beacon *[difference=-.84, p=.009]*. Although only marginally significant, users intended more to use the button version than the QR. This proved that the proposed button version can solve the information overload problem, while still keeping the advantages of the beacon version.

In the end of Study II-C, users were asked which version they liked the most because the three versions were not evaluated equally in groups, thus other facts like increased familiarity and reduced curiosity could lead to potential biases. Also, the length of the study of two months might have led to inconsistency in user ratings over time for the self-reported measurement. Therefore, this additional question was added to explicitly ask users to compare the three versions. As shown in Figure 21, 63.41% of the participants ranked the button version first, followed by the QR version (19.51%) and beacon version (17.07%). This outcome stood in contrast to the measured constructs and indicated that this work might have missed to measure more relevant aspects. This counter-intuitive observation as well as indicators based on user qualitative comments might point towards issues that could arise with the QR version in the long run and solved by introducing a Bluetooth-based (beacon or button) version.

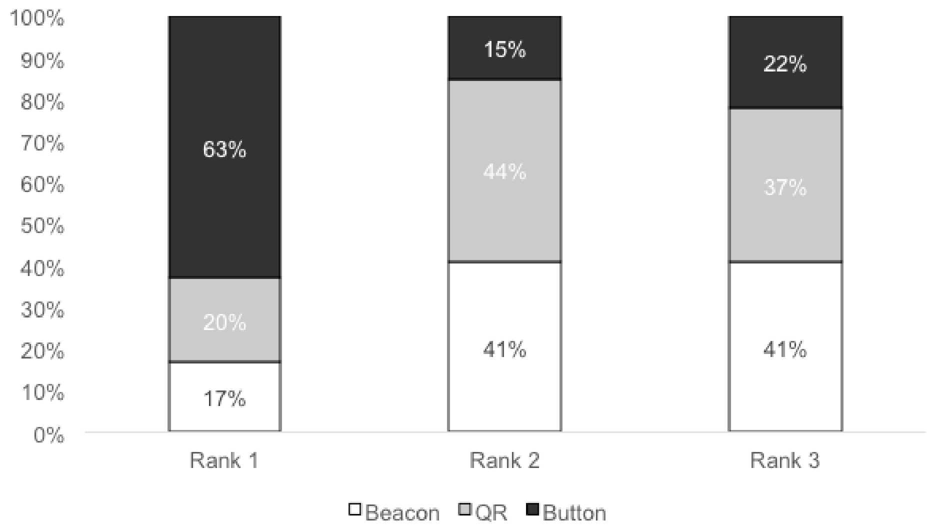


Figure 21: Comparing the Three IoT Solutions to Enabling Product Services (N=30)

4.6.3.3 Qualitative Analysis

Participants described the button version as "a good compromise between (the) other two (QR and beacon) versions", since the interaction with notifications only took place when user actively press the button. "Pressing (a) button is something that people are used to and like. It's an implicit call to action. Furthermore, a button is a visible cue that implicitly reminds me of using the application to consume services." This could help users to be aware of (new) services around them although a button as a visual reminder could lose its attention-grabbing function like a QR code when it is seen on a daily basis. Thus, RQ2c is addressed.

4.7 Discussion

4.7.1 Theoretical Contribution

This chapter contributes to theory from three main aspects. First, service science research has pointed out the importance of providing services and has advised manufacturers in a B2B setting to successfully transform from a P-D logic towards a S-D logic. However, due to the lack of direct customer interaction, service offering in the B2C setting is difficult and has not been well studied in previous research. This work contributes to the service research stream by proposing a novel solution that leverages mobile IS and IoT technologies to help consumers access product services easily and fast, as well as to connect manufactures directly with end-consumers. Although there were some perceived differences between the three versions, namely QR code, Bluetooth beacon, and Bluetooth button, feedbacks from users showed that all the three versions were able to improve the state-of-the-art solution of accessing product services.

Second, prior adoption research was mainly conducted through online surveys, which failed to let participants use the proposed solutions in reality and then provide valuable quantitative and qualitative feedbacks. With regards to IoT adoption research, most previous studies focused on technical issues or design aspects without taking user adoption and feedbacks into account. To the best of our knowledge, the work of Venkatesh et al. (2015) was one of the few studies that compared barcodes with RFIDs in enhancing consumers' shopping experience. However, it was also conducted in a laboratory setting instead of in a real business environment. By comparing the two most prominent IoT technologies (QR and Bluetooth beacon), this work contributes to the IoT adoption research by providing insights into the advantages and disadvantages of both technologies and by giving suggestions about when to use what technology in what context.

Third, this work contributes to the IoT research stream by proposing a new Bluetooth button solution to overcome the information overload problem of the beacon, while still keeping its relative advantages. The information overload problem has already been indicated by previous research but not yet evaluated properly (Jergefelt 2015). In comparison to the beacons, the buttons only broadcast Bluetooth signals when being pressed. It gives consumers the right to initiate service requests based on their demands. Results from the second study have shown that the novel button solution is preferred over both the QR and the beacon versions. This means that it has a high potential to be a better solution in bridging the physical and digital world.

The key findings of this work are stated as follows. Study II-A concluded that a simple prototype based on mobile IS and QR codes could already reduce service search cost by a factor of eleven compared to that of the state-of-the-art IS solution. The perceived usability and user experience could also be improved significantly. Study II-B revealed that both QR and beacon solutions scored high in almost all the measured constructs. Significant differences between the two versions were found in terms of perceived ease of use and information overload. Consumers' behavioral intention to use the beacon solution was almost significantly higher than that of the QR version. Also, qualitative feedbacks indicated that the beacon version was preferred in the long run. There were a variety of comments from users that led to the decision to continue with an improved beacon version, since the QR code paradoxically challenged the long-term attractiveness for some users. First, the fact that the scanning process needs an active decision requires higher efforts than reacting to a push notification. Second, the QR version only supported one way of accessing services through scanning, while accessing services with the beacon version was twofold. On the one hand, users could react to push notifications that were sent out automatically by beacons; On the other hand, they could open the mobile app and scroll through available services if there were beacons around. Such a freedom of accessing services was positively received by users. Further concern arose that the appearance of QR codes might not be acceptable in an office environment due to their visual disturbance as reported by Bihler et al. (2011) in the context of museum applications.

In Study II-C, similarly, the button version scored relatively high in most of the measurements, thus making it difficult to find many significant differences compared to the other two versions. One possible explanation could be the following: Users might have used a baseline for comparison that referred to a situation where no solution existed to consume and access product-related services. This conclusion was also derived from the qualitative feedback of the study participants. For some services such as reporting technical defects and low stocks, users highly valued the proposed solutions and confirmed its usefulness since other ways of accessing these services had not existed. When study participants were asked for their overall rating at the end of Study II-C, the reference point might have changed. At this point in time, participants compared the different versions with each other instead of to a pre-situation before where no solution existed. Results showed that the Bluetooth button is preferred over the other two technologies.

4.7.2 Managerial Implications

Manufacturers can also benefit from adopting the proposed approach. First, providing services creates an additional revenue stream for manufacturers and service in general has a higher and more stable margin (Oliva and Kallenberg 2003). However, products and services are separated for most consumer goods. With the proposed IoT solutions, B2C manufacturers are able to enable physical products as digital service end-points at a low cost, thus helping consumers access product-related services in an easy and fast manner. Furthermore, combining smartphones with services provides manufacturers with an opportunity to know each consumer in detail. Even though a consumer has not registered personal information with a manufacturer, with the help of a mobile app, the manufacturer is able to know what products the consumer has scanned, what services she has looked at, and how frequently she has interacted with a product. Based on analyzing such data, manufacturers can conduct direct and personalized marketing through the app (e.g., in-app marketing, push notification, cross-selling), which is more powerful and efficient than mass marketing (Chen and Hsieh 2012; Dorotic et al. 2012). Consequently, manufacturers in a B2C setting are also able to sell more relevant and personalized services proactively to consumers.

Second, qualitative user feedback on relevant design aspects were gathered in the thesis, which helps managers to further develop the prototype into a market-ready and scalable solution. As emphasized by Prahalad and Ramaswamy (2000), consumers should know what is coming next and how they may profit from new technologies. With regards to the QR code solution, users found that the services added value to their experience but did not know what services were available in the first place. In case of the beacon version, users automatically got notified of the services being available, which led to service interaction that would not have taken place in the other two cases because consumers simply did not know what kind of services to expect. Hence, they would not have been incentivized to trigger the service interaction by scanning the QR code or pressing the button. If the goal of manufacturers is to promote new available services on a frequent base to unleash additional revenue streams, the visibility of service should be taken into account.

When it comes to the deployment of different versions, technical aspects should be taken into consideration. Although the QR version might be less comfortable for users because of the effort for scanning, it is the most robust and reliable solution from a system maintenance point of view. In the cases of the beacon and button version, issues with battery capacity and time lags in sending out notifications have been observed. The efforts for maintaining a system based on beacons or buttons is higher due to more complex hardware components involved. Moreover, the reliability of the Bluetooth variants in this study is highly dependent on a user's device. Especially, models of iPhones earlier than Version 5 had known issues with receiving the Bluetooth signals and pushing notifications that articulated in time lags. In case of the QR version, no major issue that would raise concerns regarding the deployment and reliability of the system on a larger scale has been observed. If availability of and a low maintenance level for the system are prioritized, QR code might be the solution of choice. However, results from this work have shown that a Bluetooth-based solution is preferred from a user's point of view even if some users have experienced issues with system response time on an infrequent base.

Consumers' preference towards using IoT technologies is context based, e.g., depends on the environment and the use case. Independent of the results of this thesis, managers should also think about which technology fits the context in which it is being deployed and what services it incorporates. The log data did not indicate that some services are preferably accessed through a specific version. However, it is recommended to carefully consider the applicability of each version for the respective service. For instance, a physical button might not be the best solution for reordering paper towels in a bathroom since people could have reservations about pressing a button due to hygienic reasons. Instead, they may prefer a solution that does not require physical contact with devices other than their own smartphones. In this study, the button solution was used eight times, QR code eleven times, and beacon sixteen times to reorder paper towels in the bathroom.

There were also comments that went beyond the office context of this study and asked for similar applications in different contexts. For instance, the proposed solutions could also be deployed in a shopping context, enabling customers to retrieve product information or support self-checkout and payment processes. This showed again a strong interest in the proposed solution and many opportunities for different practical applications.

4.7.3 Limitations and Future Work

There are some limitations of this work, both from a methodological and from a technological point of view, which leads to opportunities for future research. In terms of methodology, limitations can be expressed as follows. First, most of the participants of Study II-B and II-C were male and tech-savvy users between the age of 20 and 30 from a technology-oriented study program. This might be one factor for explaining the high outcomes for most of the cognitive determinants. It would be beneficial to re-conduct the study with a larger, more representative user base to explore national, cultural or demographic differences. Second, this work initially aimed at comparing the QR with beacon solutions on accessing product services. However, after finding out the problems of both solutions, Study II-C was conducted to close the gap. Consequently, the order of using the first two versions was randomized with two groups of equal size, whereas the button version was used by all participants at the same time. This is one major limitation and should be addressed by future research.

In addition, no significant difference has been found in many cognitive determinants under study. This work might have missed to measure some constructs that can better predict the actual use of the artifacts. The question remains why no more significant difference exists. There are three possible future approaches to address this issue. First, further relevant constructs that might reveal more significant differences should be identified. This can be done by expanded exploration of related literature. Second, there is a potential for more reliable constructs with higher Cronbach's alphas. This issue could be addressed by using alternative available constructs to measure the involved cognitive determinants. Third, users might have used the state-of-the-art solution as a baseline to evaluate the artifacts or have changed the reference point in the evaluations over time. This implies a need for a more precise definition and communication of the baseline to which the solutions are supposed to be compared to. In addition to comparing mean ratings statistically, Structural Equation Modeling (SEM) with a larger sample size could be applied in future works. This helps to understand the path relationships and how constructs are associated with each other to impact adoption.

Furthermore, future solutions could also take context-aware behavior into account to provide more valuable services to users, such as automatically executing services. This is of particular importance in the case of a possible button version with only one single service attached to it. For instance, if a user presses the button to reorder paper towels, it would make sense to automatically place that order without the need for additional input via a mobile device. It would also make sense to log and consider past interaction of the user to improve service provision. One example could be recommendations for replenishment orders based on past consumption. Further research on the personalization of services could add value to this aspect. The relationship between types of services and different means of accessing them could be a valuable field for future research to exploit.

Also, it would be useful to further explore services that are appropriate for the proposed solutions in the same or different locations. With regard to the substitution to already existing means by IoT enabled services, feedbacks have to be evaluated independently for each service. In case of the "rent a book" service, users found it easier and more convenient to use the app compared to using the existing paper-based solution. Nevertheless, in the case of the "purchase drinks" service, making a simple note on the paper was still perceived to be more comfortable for users.

As already stated, issues with the reliability of the deployed beacons were reported by users and also observed independently. For some mobile devices, it took up to several seconds for the notifications to appear once a beacon had been approached or a button had been pressed. These cases were particularly observed for iPhones older than Version 5. In this case, the functionality was not only dependent on the beacons and buttons but also on users' devices, which could not be fully controlled in the field studies. The delay in receiving notifications was not observed on a frequent basis, but it could not be excluded that these issues affected user experience and their perceived ease of use or satisfaction. In locations with low Wi-Fi connectivity or bad mobile Internet reception, long loading time of services on mobile was observed. The study participants occasionally interpreted this as a failure of the app, according to their comments in the survey, which might have affected the absolute results in the measured constructs. Future research should take such technical impacts into account when developing prototypes and conducting experiments.

4.8 Conclusion

At the moment, even if a product is physically in front of consumers, searching for its services is still cumbersome, complicated, unpleasant, and time-consuming. Consequently, this chapter proposes a new solution to enable physical products as digital service end-points by leveraging IoT technologies and mobile IS. To evaluate different implementations of the proposed solution, mobile prototypes were developed and three empirical sub-studies were conducted.

This chapter contributes to both research and practice from three aspects. First, it went beyond design-centric work and lab experiments and studied actual user adoption through conducting two field studies. Second, it compared the two most popular IoT technologies, namely QR code and Bluetooth beacons, and confirmed that beacons are better adopted by users due to their fast and easy access to services. Third, a novel Bluetooth button solution was developed and evaluated to be better than the beacon solution by solving the information overload problem. An overall user ranking among the three implementation alternatives lastly proved that the button version is the most favorable way of enabling physical products as digital service end-points.

The results of this work have shown that there are alternative ways of bundling products with services in addition to contractual setups. The fact that IoT technologies are welcomed by consumers points out interesting fields for future research to get a more nuanced understanding of auto-ID adoption on the consumer level. Replicating the studies in different contexts and use cases with a larger sample size offers opportunities for the identification of promising applications in practice. Having focused on the user perspective, future research should also address the perspective of manufacturers and service providers in this matter. This could yield a deeper understanding and could further close existing research gaps in this emerging discipline.

5 Understanding the Impact of Personality on Mobile Service Adoption

In the previous chapters, the thesis reveals that consumers' adoption of product-related services is significantly correlated with the type of a service as well as the type of the bundled product. Also, it shows that leveraging IoT technologies has a high potential to enable physical products as digital service end-points, thus further improving service adoption. In addition to tackle the problem from service and product side, from this chapter on, the thesis will look into the consumer side to understand the impact of consumer differences on service adoption, thereby answering RQ3. Recommendations are given on how the generalized knowledge can be deployed with manufacturers to foster adoption.

5.1 Introduction

Previous research indicated that personalizing services according to individual differences and needs could significantly impact a consumer's service adoption and long-term loyalty (Asif and Krogstie 2013; Ball et al. 2006). Furthermore, Datta and Coondoo (2005) have confirmed that innovation adoption could be accelerated along the whole product life cycle through personalization. Therefore, this work refers to the adoption research to understand what personalization factors could have a strong impact on consumers' service adoption behavior.

Adoption research has been widely applied to understand why some people use new technologies or services while others do not. Most individual level adoption studies focused on understanding the impact of cognitive determinants on intention to use new products or services. Although individual differences like demographics and personality could be influential on adoption, it was neglected in previous research (McElroy et al. 2007). However, studies in recent years have found empirical evidence for correlations between individuals' personality and their adoption of the Internet (Landers and Lounsbury 2006; McElroy et al. 2007) and specific apps like 'Facebook' (Ryan and Xenos 2011) and 'Foursquare' (Chorley et al. 2015). Although these studies had a small number of samples and only focused on popular social apps, their promising results have encouraged research community to continue the journey.

Consequently, this chapter aims at understanding how demographics and personality traits impact a consumer's adoption of product services. Due to the fact that the number of product-related services offered on mobile is small at the moment and mobile apps are actually services because 98% of the Fortune 500 companies offer services through their mobile apps (Apple 2015), this work thus chose to study the impact of individual differences on the adoption of mobile apps as a starting point. The derived method and knowledge could be applied to understand the adoption of product-related mobile services in the future once there are more service apps on the market.

To answer the research question, a mobile gaming app was developed to collect ground-truth about each smartphone user's demographics, personality, and app adoption behavior. Afterwards, an empirical field study (Study III-A) involving 2043 Android users was conducted. Results showed that the Big Five personality traits have a significant impact on the adoption of different types of mobile apps. Also, personality traits have been found to be more powerful than demographics in explaining an individual's mobile app and service adoption behavior.

After confirming the correlation between personality traits and mobile service adoption, a follow-up study (Study III-B) was conducted to understand how personality traits influenced adoption in detail. The study was conducted with 397 smartphone users based on an online questionnaire. It concluded that personality traits significantly impact an individual's cognitive determinants (e.g., perceived usefulness, perceived risk, image, etc.) of a service adoption decision, which further leads to her actual adoption behavior.

Adoption research is a well-developed field, but this work still contributes to it by highlighting the importance of personality traits. Instead of using surveys, it collected ground-truth of each smartphone user's adopted apps from an Android Application Program Interface (API), which enables researchers to explore a large range of apps and to examine the impact of personality on adoption on an app category level instead of limiting themselves to one or two popular apps. Compared to previous findings, the results are more generalizable and could provide more insights to both researchers and practitioners. Second, individual differences in demographics like age, gender, and salary were widely used in marketing. Although not well studies previously, this work has shown that personality traits are as important as demographics in understanding an individual's adoption behavior and should be emphasized in the future. In addition, this work went beyond the phenomenon of correlation between personality and installed apps, and went deep into how personality traits impact different cognitive determinants of adoption to understand the root causes. The proposed conceptual model sheds light on what factors to focus on as well as how to remove barriers of mobile service adoption in the future.

The chapter is laid out as follows. After reviewing previous research and presenting study overview, it describes the two empirical field studies in detail. In each study, hypotheses are first developed and then tested with quantitative data. By exploring and understanding personality traits in the different studies, practical implications are derived and limitations of this research are presented. In the end, the chapter is concluded and future research opportunities are discussed.

5.2 Related Work

5.2.1 Personality and Technology Adoption

Adoption research strongly focused on analyzing the impact of different cognitive determinants on behavioral intention, while neglecting the impact of personal differences such as personality. This might come from the argument of Ajzen and Fishbein (1980), who regarded personality as a type of exogenous or external variable and argued that its impact on behavioral intention could be mediated by the cognitive constructs (Agarwal and Prasad 1998). Consequently, as revealed by Wejnert (2002), relatively few research had investigated the impact of personal characteristics on innovation adoption. But it seems that such characteristics could be relevant to an individual's adoption decision (Weimann and Hans-Bernd 1994). As one of the few early studies, Menzel (1960) showed that self-confidence and risk-taking characteristic of individual actors affected their acceptance to novel information and applications.

McElroy et al. (2007) compared the impact of both cognitive determinants and personality traits on users' adoption of three types of Internet use. The authors found that personality traits, other than cognitive styles, significantly added the predictive power of the adoption models. Devaraj et al. (2008) showed that incorporating personality traits with TAM leads to a well-understood and established model to explain the adoption of collaborative software. They suggested future research to examine the role of individual difference and personality on established models in adoption research thereby going beyond these models and enhancing their predictive power. In the mobile service context, Pedersen (2009) called for future research to take individual differences into account when studying mobile service adoption because different people might have different perceptions on the same construct. In addition, the impact of personality traits on adoption should go beyond the constructs of TAM. This could lead to a more comprehensive understanding of adoption and bring more practical implications.

In addition to cognitive determinants, empirical research also found evidence to support the relationship between personality and the use of specific technologies and applications. Several researchers (Agarwal and Prasad 1998; Brancheau and Wetherbe 1990; Constantiou et al. 2006; Leonard-Barton and Deschamps 1988; McElroy et al. 2007) argued that personal innovativeness and openness positively influenced an individual's adoption of new technologies like spreadsheet software. With the wide adoption of the Internet in the beginning of twenty-first century, researchers started to investigate the impact of personality on general Internet adoption. They found that all the Big Five personality traits were significantly correlated with people's use of the Internet as well as some special online apps such as chat rooms, information sharing, and Web browsers (Amiel and Sargent 2004; Constantiou et al. 2006; Landers and Lounsbury 2006; Swickert et al. 2002; Tuten and Bosnjak 2001). In addition to general Internet use, McElroy et al. (2007) called future research to focus on examining the impact of personality on more specific types of IS adoption and use.

With fast development of smartphones and mobile Internet, recent studies started to examine the relationship between personality and mobile app adoption. Most of the studies focused on popular social apps like 'Facebook', 'Twitter', and 'Foursquare' (Chorley et al. 2015; Hughes et al. 2012; Ryan and Xenos 2011) due to their popularity and large user base, however, it could lead to potential biases and failed to provide an overview of the impact of personality on a large scale. Furthermore, the specificity of individual apps of the same type led to contradictory findings even the study settings were similar, which put the generalizability of the findings into question (Butt and Phillips 2008; Correa et al. 2010; McKinney et al. 2012; Ryan and Xenos 2011; Tan and Yang 2014). This work is thus motivated to fill the research gaps by examining the impact of personality on the adoption of a wide range of mobile apps that are categorized into different types.

5.2.2 Network Analysis

Networks are defined as any sets of ties between any sets of nodes, and they are both structured and stochastic. Network analysis therefore helps to understand how and why the ties between nodes form. According to Lusher et al. (2013), there are three main influential factors: The network self-organization (e.g., popularity of activities, closure, brokerage), attributes of each node and tie, and exogenous contextual factors (e.g., impact of other networks, spatial factors). Different from other statistical models that were designed to estimate the effect of covariates on one outcome, network analysis is able to analyze the influence of several outcomes and their interaction. It does not require the assumption of homogeneity or other characteristics of the nodes or ties. Therefore, it can be used to analyze any kind of ties, including market, social, and hierarchical relations (Scott 2000).

In a typical research design, researchers collect data for one instantiation of a network (called observed network). However, there are many possible instantiations of a network with similar characteristics that come from some known or unknown stochastic processes. In other words, the observed network is one particular pattern of ties out of a large number of possible patterns, and it is typically not known what stochastic process formed the patterns of the observed network (Robins et al. 2007). To solve this problem, the Exponential Random Graph Model (ERGM) was designed and applied to understand the formation of network structures. ERGM tries to find a distribution of random graphs that, on average, have similar properties to our observed network in terms of nodes, links, reciprocity, transitivity, etc. Then it tries to find out whether the estimates from the observed network are significantly different from the simulated network or not. If the difference is significant, then it can be concluded that the network formation is resulted from some structural characteristics than by chance (Lusher et al. 2013). An ERGM model typically has two types of variables: Endogenous variables refer to variables that capture features of the network *per se* (e.g., edges, isolated nodes, mutual paths, etc.), while exogenous variables refer to variables that capture attributes of nodes and contextual factors. The presence of both endogenous and exogenous variables allows us to test competing explanations for network formation.

5.3 Study Overview

Research on the impact of personality traits on IS adoption was scarce, but recent findings have indicated that personality could have a significant impact on explaining people's adoption behavior of mobile apps and services. However, due to the limited range of apps under study, previous literature drew contradictory results and failed to generalize the findings. To address the research gaps, this work tried to answer RQ3 by breaking it down into two sub-questions. The first one is:

> ***RQ3a:*** *How well can the adoption of different types of mobile apps be explained by users' personality traits?*

To answer the research question, several hypotheses have been generated from reviewing previous literature. A mobile app was developed to collect ground-truth of each smartphone user's Big Five personality traits and all the apps she had installed on her device. This piece of data was then used to test the hypotheses. In addition, a network analysis was conducted to compare the impact between personality traits and demographics on the adoption of these mobile services.

After confirming the correlation between personality and service adoption behavior, a follow-up study was conducted to understand how personality traits influence each individual's perception on adoption. Previous adoption models focused on understanding the relationship between cognitive determinants and intention to use without integrating personality traits. Therefore, this work is motivated to answer the following research question thereby responding to the call for research of McElroy et al. (2007), Devaraj et al. (2008), and Pedersen (2009).

> ***RQ3b:*** *How personality traits impact cognitive determinants in explaining an individual's adoption of mobile services?*

5.4 Study III-A: The Impact of Personality on Mobile App Adoption

This section aims to answer RQ3a by hypothesis testing. Hypotheses are first developed based on a thorough review of previous literature, which is followed by an overview of study design that introduces the mobile app for data collection and the statistical methods that will be applied to test the hypotheses. Afterwards, empirical results are presented. The section concludes with a discussion on both theoretical and practical implications.

5.4.1 Hypotheses Development

Mobile apps are ubiquitous, mostly free, and designed for individual use (Liu et al. 2014), therefore, what factors influence users' adoption of mobile apps could be different from knowledge about traditional IS adoption. In this part, hypotheses about what personality traits might impact people's adoption of different types of mobile apps are generated based on reviewing previous adoption literature.

The current app categorization on Google Play Store was taken as a reference because it is the largest mobile app store. There were 29 different categories of mobile apps in the Google Play Store when the study was being conducted. Some categories were extremely popular among smartphone users such as social, music, and gaming apps, while others had a small number of users such as comics and medical apps. To prevent information overflow, this work focused on seven categories of mobile apps that were popular among users and could be correlated to the Big Five personality traits, as indicated by previous studies. The seven categories were: mobile social apps (e.g. social media apps, chatting & messaging apps), mobile games, mobile music & video apps, mobile shopping apps, mobile photography apps (e.g. editing and polishing photos, photo filters), mobile finance apps (e.g. mobile banking, budget planning, expense management), and mobile personalization apps (e.g. changing ringtones, wallpapers, fonts).

Extraversion. People who are high in extraversion are social, outgoing, active and talkative. They place a high value on close and warm interpersonal relationship (Watson and Clark 1997). Extraverts do not regard online socialization as a substitute for offline socialization; they tend to make friends offline and keep friends in touch online (Ross et al. 2009). Correa et al. (2010) revealed that extraversion was positively related to the use of social network and instant messaging apps. The finding was also supported by the study of Ryan and Xenos (2011) in examining the use of 'Facebook'. In addition, extraverted people are willing to share information with others (Amiel and Sargent 2004), which is one of the key functions of current social network apps. As a result, it is expected that extraverted people to be more likely to adopt mobile social apps.

> ***H1a.*** *Extraversion is positively associated with the adoption of mobile social apps.*

On the other hand, introverts are more social-isolated and tend to avoid direct social contact. Thus, instead of meeting friends or participating in social activities, introverted people tend to stay alone and take individual activities. Chittaranjan et al. (2013) found out that extraversion had a negative correlation with playing computer games. This negative association was also reported by the work of Meng et al. (2014). Although other researchers found positive correlation between extraversion and game playing (Tan and Yang 2014), it is believed that:

> ***H1b.*** *Extraversion is negatively associated with the adoption of mobile gaming apps.*

Neuroticism. People high in neuroticism are anxious, depressed, worried, nervous and sensitive, while those who are low in neuroticism are emotionally stable and do not react negatively to life situations. The distrust inherent in neurotic people makes them more likely to regard new technologies and services as threatening and stressful thereby reducing their use of the Internet (Devaraj et al. 2008; Tuten and Bosnjak 2001). In addition, neuroticism was also found to be negatively correlated with the perceived usefulness and behavioral control (Uffen et al. 2013), which in return reduced people's intention to adopt new technologies. However, empirical studies have revealed contradictory results. Amiel and Sargent (2004) argued that neurotic people do spend more time online particularly in relation to social uses to gain a sense of belonging. Similarly, they indeed spent more time on social media and instant messenger to avoid loneliness (Butt and Phillips 2008; Correa et al. 2010; Ryan and Xenos 2011). In addition, previous research argued that emotionally unstable people sometimes used shopping to regulate their moods (Tuten and Bosnjak 2001), which leads to the following hypotheses:

> ***H2a.*** *Neuroticism is positively associated with the adoption of mobile social apps.*

> ***H2b.*** *Neuroticism is positively associated with the adoption of mobile shopping apps.*

Empirical studies argued that neuroticism is positively associated with a fussy and picky attitude (MacNicol et al. 2003). Therefore, it is not irrational to assume that people high in neuroticism tend to use apps that improve the quality of existing stuffs. For instance, instead of using default settings, they are more likely to customize wallpapers, fonts, and ring tones to make their smartphones more unique and beautiful. Similarly, they are also expected to use mobile apps to edit and polish photos taken directly from smartphones. On the other hand, neuroticism is positively correlated with an individual's level of creativity (Gelade 1997; Post 1994), which in return makes her more likely to be interested in creative activities such as crafts, photography, design, drawing, writing, etc. Consequently, it is hypothesized that:

> ***H2c.*** *Neuroticism is positively associated with the adoption of mobile photography apps.*

> ***H2d.*** *Neuroticism is positively associated with the adoption of mobile personalization apps.*

Agreeableness. People with high agreeableness are courteous, trusting, tolerant, and are more willing to help others. The tolerant and forgiving nature make them easier to accept new technologies and spend more time online (Devaraj et al. 2008). Agreeable individuals were also found to be more persistent in investigating frustrating Websites that were user-unfriendly and difficult to navigate (Landers and Lounsbury 2006). However, disagreeable people are found to have more online social contacts because the Internet provides a means to build friendships that may be difficult for disagreeable people to build in offline situations (Hughes et al. 2012). On the other hand, other people also prefer to use online social media or telephone to contact disagreeable people in order to avoid direct face-to-fact interaction (Butt and Phillips 2008). This leads to the following hypothesis:

H3a. *Agreeableness is negatively associated with the adoption of mobile social apps.*

Furthermore, disagreeable individuals use smartphones as a means to represent or display themselves. Therefore, they care more about some superficial elements of their smartphones (e.g. changing wallpapers and ring tones) in order to achieve self-stimulatory purpose and/or to attract the attention of other people (Butt and Phillips 2008). Consequently,

H3b. *Agreeableness is negatively associated with the adoption of mobile personalization apps.*

Conscientiousness. Conscientiousness represents traits such as being organized, self-control, careful, persistence, and reliable. As these traits are closely associated with intrinsic motivation, conscientious contributes to an individual's high performance in study and jobs (Barrick and Mount 2000). Conscientious people are self-disciplined and intrinsically motivated to success (Uffen et al. 2013), therefore, they are less likely to use leisure mobile apps because they regard them as distracting and unproductive. The key support of this argument was found in Landers and Lounsbury (2006) and Chittaranjan et al. (2013), who argued that conscientiousness was significantly and negatively correlated with the use of music and video apps. Similarly, it is also expected that less conscientious people are more likely to adopt other leisure apps such as photography apps and personalization apps. Due to the fact that conscientiousness is negatively correlated with creativity (King et al. 1996), it is not surprising that less conscientious people tend to use mobile apps to design, edit and polish photos, wallpapers, and the like. Consequently,

H4a. *Conscientiousness is negatively associated with the adoption of mobile music & video apps.*

H4b. *Conscientiousness is negatively associated with the adoption of mobile photography apps.*

H4c. *Conscientiousness is negatively associated with the adoption of mobile personalization apps.*

In addition, Ryan and Xenos (2011) and Hughes et al. (2012) found that conscientiousness is negatively correlated with the adoption of social network apps like 'Facebook' and 'Twitter' because conscientious individuals are cautious online and may choose to have social contacts offline. Also, people with high conscientiousness are more planful and organized. Therefore, more conscientious people are supposed to be more likely to install finance apps that are typically expense manager, budget planner, and mobile banking. This leads to the following hypotheses:

> ***H4d.*** *Conscientiousness is negatively associated with the adoption of mobile social apps.*

> ***H4e.*** *Conscientiousness is positively associated with the adoption of mobile finance apps.*

Openness to Experience. Openness to experience people are imaginative, broad-minded, independent, and willing to try new things and seek for different experiences. Therefore, they are likely to become early adopters of new technologies and services (Constantiou et al. 2006; Tuten and Bosnjak 2001). Early research showed that openness was correlated with the use of social media and short messaging apps (Butt and Phillips 2008; Correa et al. 2010). However, as social apps like 'Facebook' and 'Whatsapp' are now becoming mainstreams, the impact of openness to experience on the adoption of those apps is much limited than thought. Recent research could hardly find significant correlations (Chorley et al. 2015; Landers and Lounsbury 2006; Ross et al. 2009; Tan and Yang 2014). As the app categories under study in this work are all mainstream apps, it is expected that openness to experience will have no impact on the adoption of any app category.

> ***H5.*** *Openness to experience is not associated with the adoption of any of the seven types of mobile apps.*

The research model is presented in Figure 22. A sign in the parentheses near each hypothesis indicates a positive or negative correlation between personality and the adoption of specific mobile apps.

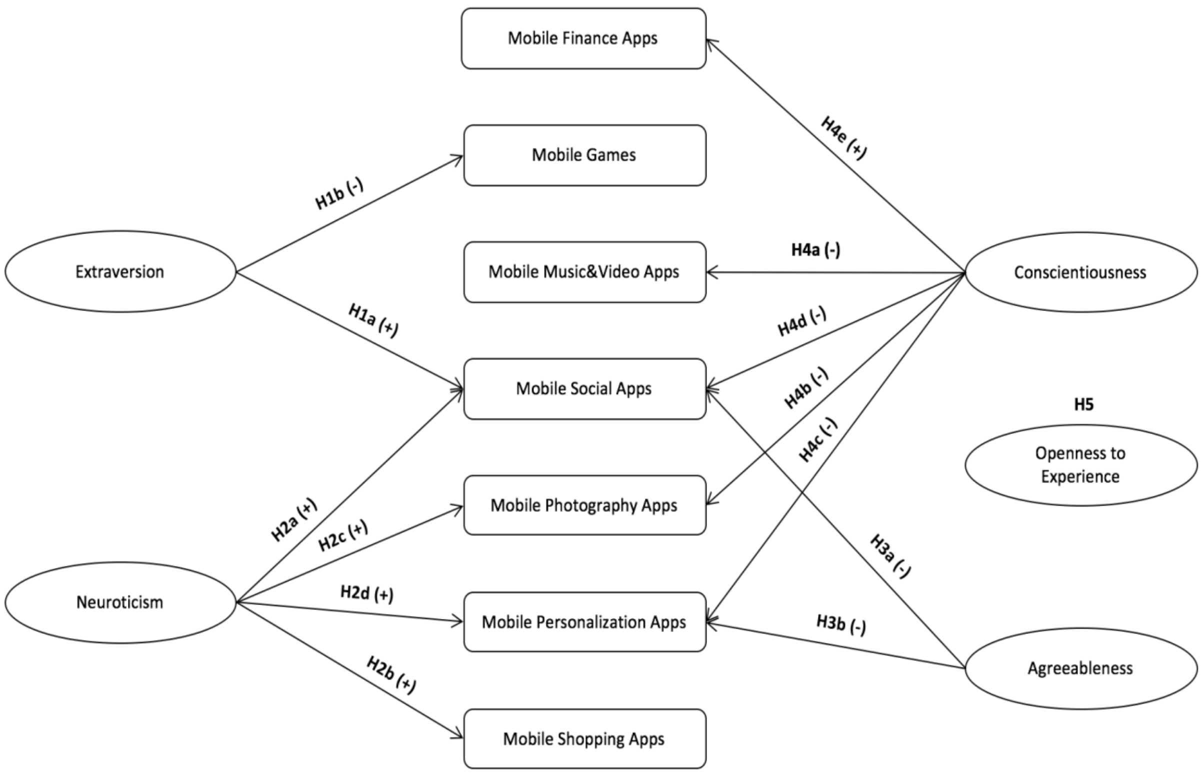


Figure 22: Research Model and Hypotheses of Study III-A

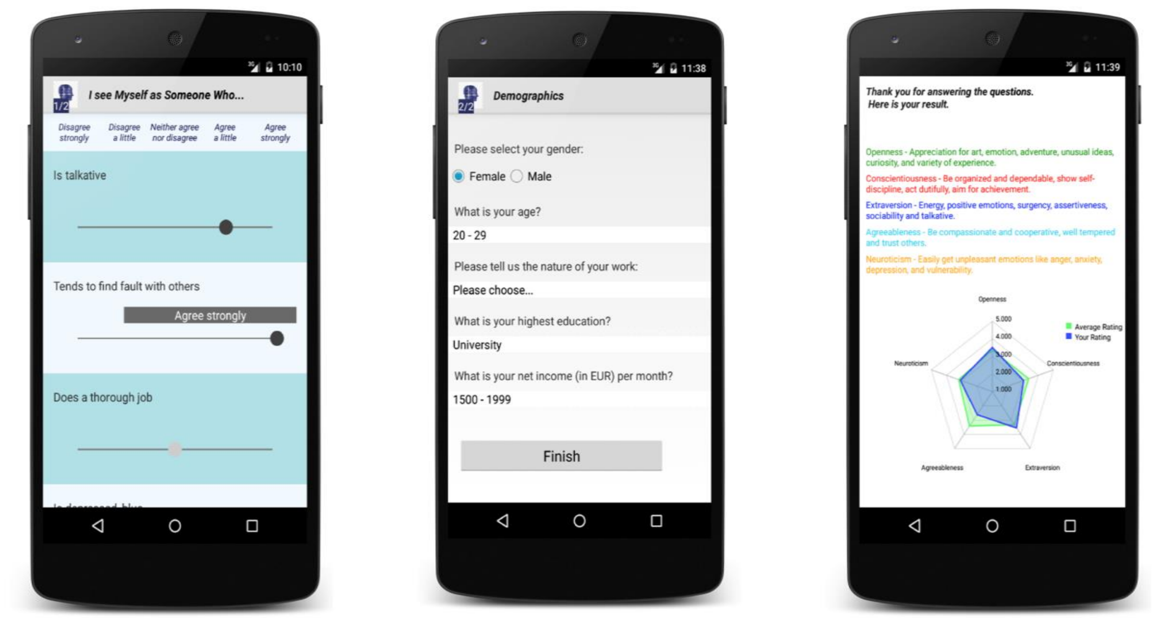
5.4.2 Study Design

5.4.2.1 Data Collection Approach

To test the developed hypotheses, two types of data need to be collected. First, the Big-Five personality traits of each smartphone user need to be measured accurately. The Big Five-44 questionnaire (John and Srivastava 1999) that contains 44 questions to determine each user's Big-Five personality traits was used because it balances well the tradeoff between the length of a questionnaire and the reliability of measured result. As the study was conduct in Germany, the full questionnaire was translated into German according to Lang et al. (2001). Users rated all the measurements on a 1 to 5 scale, where 1 stood for totally disagree while 5 stood for totally agree. The ratings were calculated according to John and Srivastava (1999) and served as ground-truth to represent users' scores on each of the Big Five dimensions.

Second, information about how each smartphone user adopted different types of mobile apps need to be collected. Previous research typically used questionnaire to sample each participant's adoption behavior. In addition to the known disadvantages of the self-reported approach, it is not appropriate in the mobile app adoption context because users typically have installed a large number of apps and it is difficult for them to name all the apps they install and use in daily life. Instead of using questionnaire, Study III-A gathered actual app adoption data directly from the smartphone of each participant. The approach is similar to that of Seneviratne et al. (2014). The Android operation system provides an API for developers to retrieve mobile app data from each Android device (Seneviratne et al. 2014). The data comprises a full set of each user's installed mobile apps with four pieces of information: Each app's package name, the time of the app's first installation, a timestamp that indicates when the app was latest updated, and a string value that represents the category the app belongs to on Google Play Store.

An Android app called 'Personality Test!' was developed to collect the two types of data at once. In addition, demographics like age, gender, salary, and educational level were also collected in the questionnaire to help researchers understand the background of participants. The app was described as a personality test game that presented the user after successful completion with a personality feedback graph. Users gave answers to the Big Five-44 measurement (as shown in Figure 23a) and demographics (as shown in Figure 23b) to compare her personality traits with the average of other people who had already participated in the game (as shown in Figure 23c). The app presented a questionnaire as described above on the one hand and retrieved an Android device's mobile app data through the API on the other hand.



a) Big Five Question Battery b) Demographic Questions c) Results from Star Chart

Figure 23: Screenshots of the Personality Test App

When the app is opened for the first time, the user is requested to accept the privacy policy. It is stated clearly to each user that data will be collected anonymously and will not be shared to any third party. If the user rejects the privacy condition, the app is forced to quit and no data will be collected and analyzed. If the user accepts the privacy terms, a random and unique string will be generated to represent her. Meanwhile, a background process in the app will be initiated, which reads the mobile app data from the device and sends it to our backend Web server. Once all the questions that measure personality or demographics are answered, the answers will be transmitted immediately to the backend server. In addition, after going to the next page, it is not possible to go back to the previous page to change answers. It is also impossible to redo the personality test on the same device more than once. By these restrictions, the study tried to prevent users from providing their own device to others who also want to do the test. The app was listed on Google Play Store and Facebook pages, news feeds and posts were used to encourage users to download the app. In the study setting, participants did not receive any monetary incentives. The only motivation for them to participate into the study was to know her own personality and compare it with the average of other people.

5.4.2.2 Hypotheses Testing

After data collection, participants who failed to answer all the questions that measured the Big Five personality traits were excluded in the analysis to avoid inaccurate ratings. The remaining data points could be used to analyze the impact of personality on mobile app adoption. If a user had installed more than one app in one category, she was regarded as an adopter of that category. Otherwise, she was labeled as a non-adopter. The categorization used in the study was the same as that in the official Google Play Store.

In data analysis, a multivariate analysis of variance (MANOVA) was first performed on the means to help protect against inflating the Type 1 error rate in the follow-up analysis of variance (ANOVAs) and post-hoc comparisons, according to Cramer and Bock (1966). Prior to conducting the MANOVA, a series of Pearson correlation tests were performed between all of the dependent variables to test the MANOVA assumption that the dependent variables were not highly correlated with each other.

In the MANOVA test, whether individuals were adopters of a specific category of apps served as independent variables while their Big Five personality traits served as dependent variables. If the covariance matrices between adopters and non-adopters were tested to be equal, MANOVA would then be applied. A statistically significant MANOVA result suggested that app adopters and non-adopters were different on at least one of the Big Five personality traits. Afterwards, Levene's F tests were conducted to check whether the homogeneity of variance assumption was satisfied. If the test results were non-significant, a series of follow-up ANOVAs and post-hoc comparisons could be applied to test what personality traits led to the difference between adopters and non-adopters.

5.4.2.3 Compare Personality with Demographics

Compared to personality traits, the impact of demographic differences (i.e., age, gender, salary) on innovation adoption were well studied in research and widely used in marketing and customer segmentation. Consequently, this study was further extended by comparing demographics with personality traits on their impacts on the adoption of the selected mobile services.

Two analyses were conducted to evaluate the impacts. First, similar to the hypotheses testing approach, a MANOVA was conducted to compare the differences between mobile service adopters and non-adopters in terms of their gender, age, and salary. Nevertheless, understanding the reasons behind the different adoption patterns was beyond the scope of this thesis. Second, a network analysis was applied to compare what individual differences (demographics or personality traits) were more powerful on explaining the variances of forming an individual's mobile service adoption behavior.

5.4.3 Analysis and Result

5.4.3.1 Study Participants

The personality test app was first published on Google Play Store on March 27, 2015. The corresponding 'Facebook' feeds and posts were distributed between March 27, 2015 and April 1, 2015 to potential participants. During this period, the app promotion page was shown to 107,504 people and 2092 of them installed the app. The conversion rate for installation was around 2%. Among all the 2092 people who had installed the app, 2043 of them finished the full personality survey and 2008 of them completed in addition the demographics questions. The distributions of the participants' demographics are shown in Table 10.

Table 10: Characteristics of Participants in Study III-A (N=2043)

Respondents	***Range***	***In %***		***Respondents***	***Range***	***In %***
Gender	Female	77.1%		Net Monthly Salary (€)	> 5000	0.4%
	Male	22.9%			4000 – 4999	0.4%
Age	10-19	21.7%			3000 – 3999	1.6%
	20-29	50.9%			2000 – 2999	5.2%
	30-39	17.9%			1500 – 1999	13.2%
	40-49	7.8%			1000 – 1499	23.4%
	50-59	1.4%			500 – 999	23.2%
	No Answer	0.3%			< 500	17.9%
Job Type	Permanent Job	42.7%			No Answer	14.7%
	Temporary Job	0.8%		Highest Education	University	5.2%
	Self-employed	2.4%			High School	14.8%
	Student	22.4%			Vocational Education	29.1%
	Seeking for Jobs	6.6%			Secondary School	44.9%
	Housewife/man	10.0%			Elementary School	1.4%
	Retired	0.7%			No Degree	4.6%
	No Job	1.5%				
	No Answer	12.9%				

The 2043 participants had on average 76 (SD=26) apps installed on their smartphones. Figure 24 (left) shows the distribution of the number of apps per participant. After removing all the pre-installed apps, the participants had on average 31 (SD=22) apps installed by themselves. The distribution of apps that were not pre-installed per participant is shown in Figure 24 (right). A total of 155,187 installed apps were observed, out of which 63,688 were not pre-installed and thus eligible for the follow-up analysis.

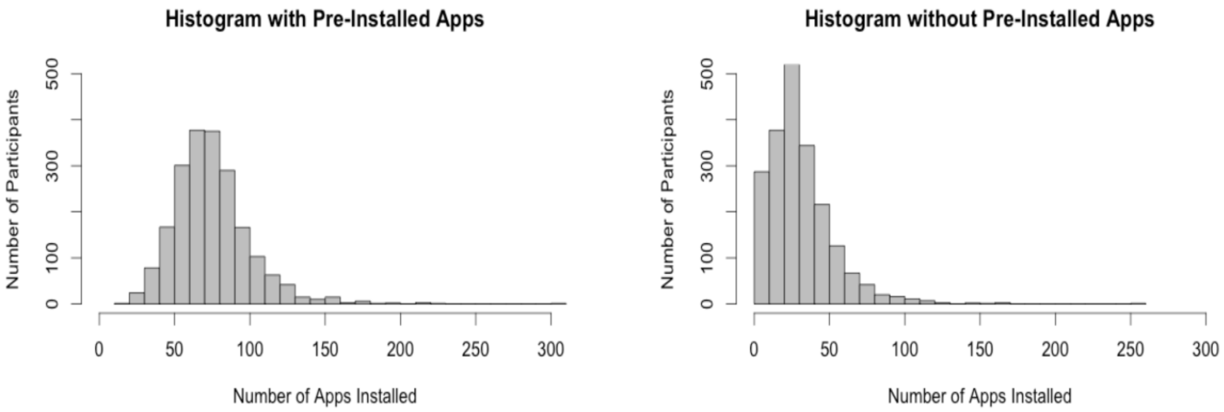


Figure 24: Distribution of Apps Installed per Participant (N=2043)

5.4.3.2 The Impact of Personality Traits on App Adoption

Before analyzing the data, the descriptive statistics and the reliability on each of the Big Five personality traits were examined. A Cronbach's Alpha metric was used to determine the reliability of the question batteries – whereas a Cronbach's Alpha of 0.9 is deemed excellent and a suggested value for a suggested value for a decent reliability is above 0.7. As shown in Table 11, the reliability is very high with only agreeableness being slightly below the threshold. However, Nunnally (1967) claimed that a Cronbach's Alpha above 0.6 is already sufficient for early stages of research. In addition, Pearson correlation test was also performed to test the MANOVA assumption that the dependent variables were not strongly correlated. Results in Table 11 show that correlations between the Big Five dimensions are in the moderate range according to Meyers et al. (2013).

Table 11: Summary Statistics of the Big Five Personality Traits (N=2043)

	Mean	*S.D.*	*Cronbach's Alpha*	*Correlations*				
				1	2	3	4	5
Extraversion (E)	3.335	0.748	0.810	1				
Neuroticism (N)	3.209	0.738	0.752	-.314	1			
Agreeableness (A)	3.423	0.603	0.642	.088	-.237	1		
Conscientiousness (C)	3.382	0.639	0.749	.287	-.281	.291	1	
Openness (O)	3.369	0.629	0.753	.330	-.162	.121	.250	1

The results of hypotheses testing are shown in Table 12. To test H1a, the mean extraversion ratings of adopters and non-adopters of mobile social apps were compared. No statistically significant differences could be confirmed. Therefore, H1a was not supported. On the other hand, less extraverted people were found to be more likely to adopt mobile gaming apps *[F(1,2041)=6.74, p<.01]*, which supported H1b.

Similarly, neuroticism was found to be positively associated with the adoption of mobile photography *[F(1,2041)=11.17, p<.001]* and personalization apps *[F(1,2041)=12.10, p<.001]*, while it was not significantly associated with the adoption of mobile social *[F(1,2041)=.32, ns]* and shopping apps *[F(1,2041)=1.09, ns]*. Therefore, H2c and H2d were supported while H2a and H2b were not supported.

To test H3a, the mean ratings of agreeableness between mobile social app adopters and non-adopters were compared. Although social app adopters were on average less agreeable than non-adopters, the difference was only significant at 90% confidence level *[F(1,2041)=2.69, p=.10]*. Therefore, H3a was not supported. On the other hand, agreeableness was found to be negatively associated with the adoption of mobile personalization apps *[F(1,2041)=4.21, p<.05]* thereby supporting H3b.

To test H4a-H4e, the mean ratings of conscientiousness of adopters and non-adopters were compared among five types of mobile apps. Conscientiousness was negatively associated with the adoption of mobile music & video *[F(1,2041)=6.23, p<.05]*, photography *[F(1,2041)=7.11, p<.01]*, and personalization apps *[F(1,2041)=4.45, p<.05]* thereby supporting H4a, H4b and H4c. In addition, adopters of mobile social apps were found to be less conscientious, however, the difference was only significant at 90% confidence level *[F(1,2041)=2.71, p=.10]*. For H4e, although adopters of mobile finance apps were found to be more conscientious than non-adopters *[F(1,2041)=3.88, p<.05]*, the Pillai's Trace of the previous MANOVA test was not significant *[F(5,2037)=1.065, p=.378]*. Therefore, H4e could not be supported.

Table 12: Results of Hypotheses Testing (N=2043)

Test	*Trait*	*App Type*	*Adopters*		*Non-Adopters*		*F*	*P*	*Outcome*
			N	*M. (S.D.)*	*N*	*M. (S.D.)*			
H1a	E	Social	1705	3.33 (.75)	338	3.36 (.72)	.46	ns	Not supported
H1b	E	Gaming	1630	3.32 (.75)	413	3.42 (.71)	6.74	<.01	Supported
H2a	N	Social	1705	3.21 (.74)	338	3.19 (.74)	.32	ns	Not supported
H2b	N	Shopping	1429	3.22 (.73)	614	3.18 (.76)	1.09	ns	Not supported
H2c	N	Photography	1076	3.26 (.74)	967	3.15 (.73)	11.17	<.001	Supported
H2d	N	Personalization	573	3.30 (.74)	1470	3.17 (.73)	12.10	<.001	Supported
H3a	A	Social	1705	3.42 (.59)	338	3.48 (.64)	2.69	ns	Not supported
H3b	A	Personalization	573	3.38 (.58)	1470	3.44 (.61)	4.21	<.05	Supported
H4a	C	Music & Video	1582	3.36 (.63)	461	3.45 (.65)	6.23	<.05	Supported
H4b	C	Photography	1076	3.35 (.65)	967	3.42 (.62)	7.11	<.01	Supported
H4c	C	Personalization	573	3.33 (.61)	1470	3.40 (.64)	4.45	<.05	Supported
H4d	C	Social	1705	3.37 (.64)	338	3.44 (.61)	2.71	ns	Not supported
H4e	C	Finance	875	3.42 (.59)	1168	3.36 (.63)	3.88	<.05	Not supported

Finally, H5 was tested by comparing the means of adopters' openness to experience with those of non-adopters among all types of mobile apps. No statistically significant difference could be found in any app category so that results were not reported in Table 12. Consequently, H5 was supported.

5.4.3.3 Comparing the Impact of Demographics with Personality on Adoption

Similarly, the impact of demographic differences on mobile service adoption was also tested and statistical result is presented in Table 13. Each cell in the table represents the difference of mean ratings between app adopters and non-adopters. Gender is coded as 0 (female) and 1 (male), therefore, a negative value means that women are more likely to become adopters than men. The uppercase characters in the parentheses next to the value indicate what personality trait has the biggest difference on mean ratings between adopters and non-adopters.

Table 13: Demographic Difference between Service Adopters and Non-Adopters (N=2043)

*(Sig. (2-tailed): * significant at p<.05; ** significant at p<.01)*

App Type	***Gender*** *(0-female;1-male)*	***Age*** *(years old)*	***Salary*** *(€ per month)*	***Personality*** *(rated on a 1-5 scale)*
Finance	.03	2.99***	184.22***	.06 (C)
Photography	-.16***	-1.04*	-61.3	.11** (N); -.08** (C)
Music & Video	.09**	-1.62**	71.06	-.08* (C)
Gaming	-.03	.73	-56.43	-.11** (E)
Shopping	-.06*	1.68**	94.20*	-.07* (A)
Personalization	.00	1.58**	-7.84	.13**(N); -.10**(E); -.07*(C); -.06*(A)
Social	-.04	1.35*	54.51	-.06 (C)

Regarding demographics, gender has a significant impact on the adoption of three app categories. Female users in general were more likely to use photography and shopping apps but less likely to listen to music or watch video on mobile devices. Furthermore, age was significantly associated with all the mobile apps except for mobile games. Elder users were more likely to use finance, shopping, personalization and social apps, whereas younger users tended more to adopt leisure apps like music, video, and photography. In addition, individuals with higher net income were more likely to install mobile finance and shopping apps. In terms of the impact of personality traits, results in Table 13 are consistent with previously tested hypotheses, as reported in Table 12. Although not hypothesized due to the lack of theoretical support, extraversion was found to be negatively associated with the adoption of mobile personalization apps. Understanding the psychological reasons why demographics impact the adoption of the selected seven types of mobile apps is beyond the scope of the thesis and requires future research.

5.4.3.4 Network Analysis

Statistical analysis has shown that both demographics and personality traits have a significant impact on an individual's adoption behavior of different types of mobile services. However, it is not clear what factors explain more variance that exists in forming such behavior. In order to answer this question, an ERGM approach was further applied on a network generated from the collected research data. The network was a two-mode network represented by a table with rows (the first mode) being all the users and columns (the second mode) being the seven selected services (the same as in Study III-A). If a user had adopted a specific type of mobile services, the corresponding cell was set to 1 otherwise 0.

Eight attributes (i.e., gender, age, salary, and the Big Five personality traits) were attached to each user to understand which attribute contributed to explain the network structure, such as who used what services, and who was close to whom in terms of their adoption patterns. After removing all the missing data and "No Answer" choices, a network of 1711 users with eight attributes and seven services was used in the analysis.

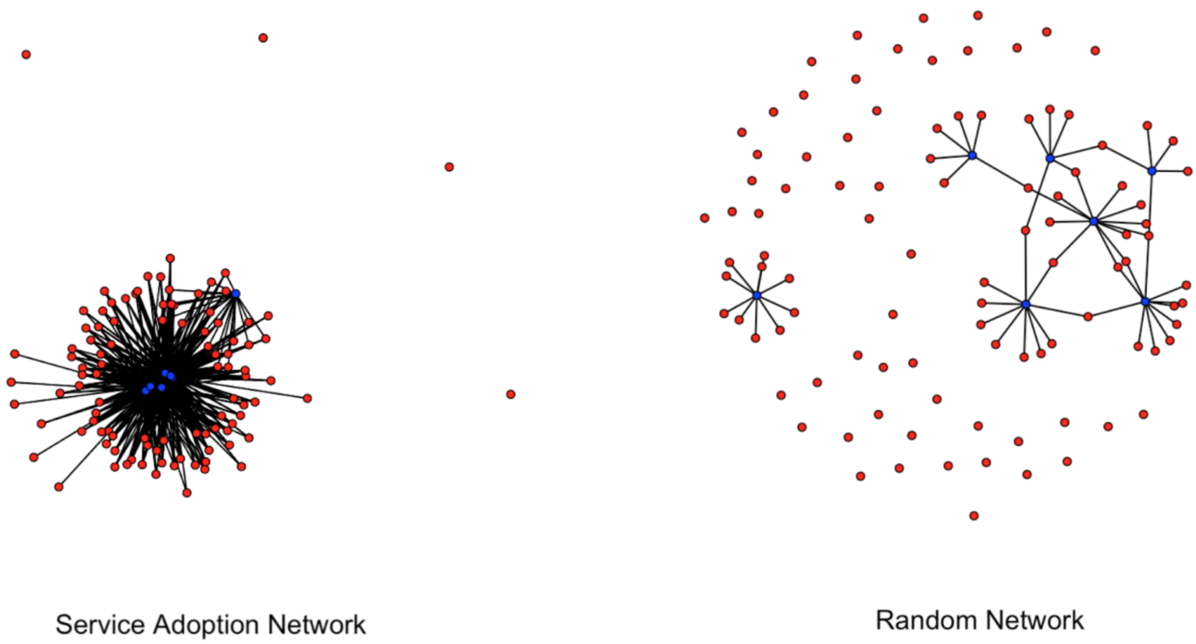


Figure 25: The Formation of a Service Adoption Network Is Significantly Different from a Random Process (Demonstrated with 100 Users)

To get a better understanding of the network structure, 100 users were randomly picked to plot a network graph, as shown in Figure 25 (left). The blue dots represent the seven types of mobile apps while each red dot represents a user. The distance between two dots indicates the closeness between them. In the mobile service adoption context, the closer the two red dots, the more similar their adoption patterns are. As shown in the graph, most of the services are close to each other and they are located in the center of the network. Users who are close to the center of the network typically have adopted more types of mobile apps. Also, users who are close to each other are typically more similar in terms of their demographics, personality traits and adoption patterns.

The right graph in Figure 25 demonstrates a random generated network with the same network characteristics as the one on the left side. In this network, services are separated from each other with a small number of users connected to them. This network is scattered and has more isolated dots. It is clear that the right graph is significantly different from the left one, which proves that there are some structures in users' mobile app adoption network and the formation of such a network is not a random process.

Table 14: Comparison of Five ERGM Models (N=1711)

*(Sig. (2-tailed): * significant at p<.05; ** significant at p<.01; *** significant at p<.001)*

	Model 1	Model 2	Model 3	Model 4	Model 5
Edges	.494***	.701***	.698***	2.634***	2.462***
Isolates		4.103***	3.995***	3.876***	3.879***
Degree		2.430***	2.362***	2.304***	2.298***
Gender			.166***		.049
Age			-.007***		-.001***
Salary			.001***		.001***
Openness				-.036	-.063**
Conscientiousness				.152***	.165***
Extraversion				.010	.037
Agreeableness				-.207***	-.209***
Neuroticism				-.200***	-.134***
BIC	15904	15471	15288	15117	15032
Variance Explain	0.00%	2.84%	4.17%	4.89%	5.43%

In total, four ERGM models were generated to explain the formation of the mobile app adoption network. The result is presented in Table 14. Model 1 had only edges as its predictor and it served as the null model. Model 2 took isolated users and the degree of edge of each node as its predictors and it was able to explain 2.84% of the variance in the service adoption network. In additional to the endogenous variables, Model 3 included the demographics of users as predictors and it was able to explain 4.17% of the total variance. On the other hand, Model 4 removed the demographical attributes but added the Big Five personality traits as predictors. Consequently, it was able to explain 4.89% of the total variance. Model 5 included all the endogenous and exogenous variables, and it could explain 5.43% of the variance existed in the network formation process. Except for gender and extraversion, all variables were statistically significant in the ERGM Model 5.

The network formation process is a structured and stochastic process. Consequently, the ERGM models were not able to explain a large amount of the variance existed in the network. Nevertheless, the percentage of variance explained was still on the same level of similar previous research. Furthermore, the results concluded that users' demographics and personality traits have a significant impact on the formation of a service adoption network. More important, although not being focused in previous research, this study has shown that personality traits are actually 17.3% more powerful than demographics in explaining users' mobile app adoption behavior. RQ3a is thus addressed.

5.4.4 Discussion

5.4.4.1 Findings and Contribution

Recent research has revealed that the Big Five personality traits could have an impact on an individual's adoption behavior of mobile apps. However, the mobile apps under study in previous literature were limited to a small number of mainstream apps like 'Facebook' and 'Twitter', which might prevent researchers from generalizing the findings to other apps of the same type. To demonstrate a more complete, integrated, and coherent view, a new framework was provided to understand such an impact on an app category level. Consequently, hypotheses were first developed from previous literature and then tested with actual behavior data collected from 2043 Android smartphone users.

The large-scale field study revealed that personality traits have a significant impact on people's adoption behavior of mobile apps and such an impact differs from app categories to categories. For example, more conscientious people are less likely to adopt leisure mobile apps such as music, photography, and personalization apps to avoid distraction from their productive activities. Nevertheless, neurotic individuals are likely to adopt such apps due to their fussy and picky nature as well as their interest in creative activities. In addition, introverts prefer to install mobile games, whereas less agreeable people tend to adopt personalization apps so as to customize their smartphones to be a better self-representation.

On the other hand, existing studies that were relevant to mobile app adoption typically took social apps under study due to their recent popularity. These studies showed that the Big Five personality traits were strongly correlated with the adoption of social apps. However, none of the previous findings (as hypothesized in H1a, H2a, H3a, H4d) could be supported by this study. One explanation could be that social apps such as 'Facebook' and 'Whatsapp' are now becoming mainstream apps with most people (83% in the collected samples) have installed them, which narrows the differences on personality between adopters and non-adopters. As indicated by other studies (Ellison et al. 2007; Ross et al. 2009), the impact of personality on adoption becomes weaker or even non-significant with the growing popularity of technologies and apps. Although not significant on app category level, it is suspected that personality traits will have direct impact on sub-categories of social apps. For instance, adopters of apps that focus on photo sharing such as 'Snapchat' and 'Instagram' might be on average lower in neuroticism because sharing and communicating with photos could trigger more privacy concerns compared with text-based communication, which prohibits neurotic people from adopting.

Similarly, openness to experience has no impact on the adoption of any of the seven categories of mobile apps, as hypothesized in H5. Nevertheless, it does not mean that openness has no impact on mobile app adoption. According to early findings that open and innovative people are more likely to become early adopters of new technologies and services, it is suspected that openness will have significant and positive impact on users' adoption of new apps that are not yet widely known. Due to the fact that the seven chosen app categories are popular among smartphone users, such an impact has been weakened on the category level because it is difficult to distinguish early adopters from other users in the data set.

In addition to testing the hypotheses, this work also compared the impact between personality traits and demographics on adoption. Results have shown that both demographics and personality traits have significant impacts on an individual's adoption of different mobile apps. Although neglected in academia and practice, personality traits were found to be more powerful in explaining the variance of people's mobile service adoption behavior than demographic differences.

5.4.4.2 Managerial Implications

This work has implications for managers and practitioners as well. First, it provides an overview of how different personality traits influence the adoption of different types of mobile apps. Based on the type of a new mobile app, managers will know who are more likely to become adopters of the app. For instance, less conscientious and more neurotic people are more likely to install a new personalization app while introverts are more likely to adopt a new mobile game. With the help of advanced machine-learning models, every app publisher is able to predict a smartphone user's personality traits with easily accessible data in real-time. Details will be introduced in the next chapter. Consequently, instead of expensive mass marketing, app publishers can conduct personalized marketing (Dorotic et al. 2012) by selecting targets based on their predicted personality traits thereby improving the effectiveness of their marketing campaigns.

Furthermore, instead of using self-reported questionnaire data, this study collected and analyzed each participant's mobile app data to test the hypotheses. The advantages of this approach are three-fold. First, it goes beyond surveying a user's intention for app usage and leverage actual behavioral data to examine the impact of different personality traits on mobile app adoption. The unique data set provides a new perspective to understand adoption. Second, the quality of data collected by this approach should be better than that of the traditional survey-based research because participants received no monetary incentive for providing the data. Participants were more likely to answer all the questions carefully and correctly because they were intrinsically motivated to know their own personality traits in detail. Third, due to the fact that the data set logged all the mobile apps each participant had installed, this approach is not limited to analyze only a small number of specific apps. Instead, it can be applied to understand the impact of different personality traits on different app categories, as well as on any individual app. The novel and scalable data collection approach provides both researchers and practitioners with a new tool to better understand adoption in the future.

5.4.4.3 Limitation and Future Work

There are several limitations of this work, which provides opportunities for future research. First, although this study has a large sample size compared to previous research, the sample was not representative in terms of age, gender and income. More than 75% of the samples were female and more than 70% of the samples were younger than 30 years old. This is understandable as the app was distributed through 'Facebook' and previous research showed that women are more likely to heavily use 'Facebook' and the like (Raacke and Bonds-Raacke 2008; Thompson and Lougheed 2012). Future research is thus called to confirm the findings with larger and more representative samples. In addition, personality traits are also dependent on cultures and regions. This first study was conducted only in Germany, therefore, findings need to be tested in other countries for triangulation.

Second, the installation of apps was used to determine whether a user is an adopter of a specific app category or not. However, it is possible that some users have installed some apps but seldom use them. Taking a user's daily app usage into account could make it more accurate in deciding whether the user adopts a mobile app on a daily base or not. Google also provides APIs for developers to retrieve app activity logs on Android devices. Future research could leverage such information to gain more insights. On the other hand, new predictors generated from the additional API could also be used in the predictive models to further improve the performance of prediction. However, more granular data might also trigger higher privacy concerns. The trade-off between model precision and privacy concerns is also worth studying to find out the optimal balance.

Along with the discussion about social apps and H5, personality traits that have impact on app adoption in early stages might not be influential when the app becomes popular. Consequently, how the impact of personality traits on app adoption changes over time is also interesting and worth being studied in depth in the future.

5.5 Study III-B: The Impact of Personality on Cognitive Determinants

In Study III-A, the correlation between personality traits and mobile service adoption behavior has been found. However, the reason why some people use a specific mobile app and service while others do not is still unclear. As a result, Study III-B aims to understand the relationship between personality traits and cognitive determinants as well as how they together influence an individual's mobile service adoption behavior. It focuses on mobile commerce service as a starting point because this service has been well understood and relatively widely adopted by consumers on mobile devices.

5.5.1 Adoption Models and Hypotheses Development

Existing adoption models mostly focused on understanding the adoption of technologies such as hardware devices, desktop software and Web applications. Due to the high proliferation of mobile devices, consumers have started to use commerce services on mobile through corresponding apps. However, relatively few research has been conducted to understand mobile commerce service adoption. Also, as indicated by Pedersen (2009), existing technology adoption models need to be extended and modified when applied in the mobile service context. Consequently, based on a thorough review of previous literature, Study III-B developed hypotheses about what cognitive determinants could influence an individual's adoption of mobile commerce services, thus answering RQ3b.

5.5.1.1 Technology Acceptance Model

Several widely used theories formed the foundation of adoption and diffusion research. As one of the oldest theories, the TRA suggests that an individual's behavior intention is determined by her attitude towards the behavior and subjective norms that describe the social pressure for her to perform the behavior. The TAM is an extension of the TRA and it is one of the most well-known models in adoption research. It does not consider the influence of subjective norms and replaces attitude with two technology measures, namely perceived usefulness and perceived ease of use.

First, perceived usefulness has been identified as a significant factor that drives the adoption of innovation in different context (Moore and Benbasat 1996; Rogers 1995; Venkatesh, Brown, et al. 2012; Zhu et al. 2006). In the mobile commerce service scenario, perceived usefulness refers to the expected benefits of using services and to what extent it is perceived to be better than using services or finishing the tasks with alternative approaches.

Second, the TAM reveals that perceived ease of use has a positive effect on behavior intention as well as on perceived usefulness. Perceived ease of use denotes the degree to which using commerce services on mobile devices is perceived as easy to install, understand, use, and maintain thereby leading to favorable outcomes. Also, behavior intention has been found to be directly associated with an individual's actual adoption behavior. This leads to the following hypotheses:

> ***H1a:*** *Perceived usefulness is positively associated with intention of using mobile commerce services.*
>
> ***H1b:*** *Perceived ease of use is positively associated with intention of using mobile commerce services.*
>
> ***H1c:*** *Perceived ease of use is positively associated with perceived usefulness of mobile commerce services.*
>
> ***H1d:*** *Behavior intention of using mobile commerce services is positively associated with actual use.*

5.5.1.2 Theory of Planned Behavior

Another extension of the TRA is the TPB, which suggests that in addition to perceived usefulness and perceived ease of use, behavior intention is also influenced by the amount of subjective norms and perceived behavioral control of performing the behavior. Subjective norms indicate an individual's perception of how other people who are important to her think whether she should perform the behavior in question or not (Ajzen and Fishbein 1980), which strongly predicts her intention to adopt new technologies or services.

On the other hand, perceived behavioral control captures an individual's perception of her ability to perform a specific behavior (Ajzen 1985). Perceived behavioral control is significantly and positively associated with behavior intention. In the mobile commerce service scenario, it refers to an individual's belief on whether both external resources and internal knowledge are in her control to facilitate the use of mobile services. As a result, high level of perceived behavioral control could be associated with an individual's adequate knowledge of using a mobile service, which in return enhances the perceived ease of use. Consequently,

> ***H2a:*** *Subjective norms is positively associated with intention of using mobile commerce services.*
>
> ***H2b:*** *Perceived behavioral control is positively associated with intention of using mobile commerce services.*
>
> ***H2c:*** *Perceived behavioral control is positively associated with the perceived ease of use.*

5.5.1.3 Perceived Risk and Image

Other researchers indicated that the TAM and the TPB models need to be integrated with additional constructs to improve their explanatory and predictive power (Lucas and Spitler 2000; Szajna 1996; Taylor and Todd 1995). The theory of perceived risk has been applied since 1960s to explain an individual's behavior in her decision-making process (Taylor 1974). In a commercial environment, perceived risk used to stand for product quality or fraud, but now it refers more to financial, social, physical, or psychological risks (Forsythe and Shi 2003). In the context of mobile commerce, one of the biggest risk concerns is about device security and data leakage (Xu et al. 2011) because mobile devices like smartphones are one of the most personalized devices and people typically store private or sensitive information on them. The high perceived risk could in return negatively impacts people's adoption of using mobile commerce services.

The IDT proposed by Rogers (1995) is another well-known theory and has been widely used by IS researchers in understanding adoption. One construct outlined by the IDT as well as other researchers like Moore and Benbasat (1991) is the perceived image, which has been found to be positively related to an individual's decision to adopt an innovation. In the mobile commercial service context, it represents the extent to what using such services is perceived to enhance an individual's status or image in her social system (Rogers 1995). In addition to direct impact on intention to use, image could also be positively associated with subjective norms because an individual who cares about her social status tends to have high belief about others' perception of her behavior.

Although other determinants such as perceived cost (Rogers 1995; Wejnert 2002; Zhu et al. 2006) and secondary source influence (Leonard-Barton and Deschamps 1988; Rogers 1995; Valente 1996) were also found to impact adoption of innovations, their impact in the mobile commercial service context is regarded to be limited because using the service *per se* does not directly generate monetary cost. Also, mobile commerce service is not in its early phases where mass media could have strong impact on people's decision on adoption. It thus leads to the following hypotheses:

> ***H3a:*** *Perceived risk is negatively associated with intention towards the use of mobile commerce services.*
>
> ***H3b:*** *Image is positively associated with the subjective norms of using mobile commerce services.*
>
> ***H3c:*** *Image is positively associated with intention towards the use of mobile commerce services.*

5.5.1.4 Impact of Personality on Cognitive Determinants

Adoption research strongly focused on analyzing the impact of the cognitive determinants on behavioral intention, while neglected the impact of personal differences such as personality traits. This might come from the argument of Ajzen and Fishbein (1980), who regarded personality as a type of exogenous or external variable and argued that its impact on behavioral intention could be mediated by the cognitive constructs (Agarwal and Prasad 1998). However, recent studies come to contradicting results, which sheds light on the importance of personality in adoption research. McElroy et al. (2007) compared the impact of both cognitive determinants and personality traits on individuals' adoption of three types of Internet use. The authors found personality traits, other than cognitive styles, significantly added the predictive power of the models. Devaraj et al. (2008) concluded that incorporating personality traits with the TAM led to a well-understood and established model to explain the adoption of collaborative software. They suggested future research to examine the role of individual difference and personality on established models in adoption research thereby going beyond these models and enhancing their predictive power. Empirical research also demonstrated significant relationships between personality and the use of Internet, Web applications, social media, smartphone apps, etc. (Correa et al., 2010; Landers and Lounsbury, 2006; Ryan and Xenos, 2011; Chorley et al., 2015)

In the mobile service context, Pedersen (2009) called for future research to take individual differences into account when studying mobile service adoption because different people might have different perceptions on the same construct. In addition, the impact of personality on adoption should go beyond the constructs of TAM. This could lead to a more comprehensive understanding of adoption and bring more practical implication. Consequently, Study III-B incorporated the Big Five personality traits with cognitive determinants to explain an individual's adoption of mobile commerce service thereby addressing the research gaps.

Extraversion. In addition to social and outgoing, extraverts also tend to be optimistic (Marshall et al. 1992) and have a can-do attitude. Walczuch et al. (2007) found that optimism is positively correlated with perceived usefulness and ease of use. Svendsen et al. (2013) argued that extraversion is positively related to both perceived usefulness and perceived ease of use in the adoption of a software tool. This leads to the following hypotheses:

> ***H4a:*** *Extraversion is positively associated with perceived usefulness of mobile commerce services.*

> ***H4b:*** *Extraversion is positively associated with perceived ease of use of mobile commerce services.*

Neuroticism. Neurotic people are nervous, sensitive, and distrustful. They tend to react more negatively to life situations. This makes them more likely to regard new technologies and services as threatening and stressful thereby reducing their intention to use (Devaraj et al. 2008; Tuten and Bosnjak 2001). In the mobile commerce service context, neurotic individuals might be nervous about potential risks like information leakage and security attacks. It is thus hypothesized that:

> ***H5:*** *Neuroticism is positively associated with perceived risk of using mobile commerce services.*

Agreeableness. Highly agreeable people are sympathetic, warm, tolerant, and more willing to help others. The tolerate nature of agreeable people makes them more likely to focus on the positive dimensions of new technologies and services, which leads to a higher perceived usefulness thereby increasing their intention to use software such as a content management tool (Svendsen et al. 2013). In addition, agreeableness represents an individual's sensitivity to the opinions of others, which will moderate the relationship between subjective norms and intention to use mobile commerce services, as indicated by Devaraj et al. (2008) and Wang and Yang (2006).

> ***H6a:*** *Agreeableness is positively associated with perceived usefulness of mobile commerce services.*

> ***H6b:*** *Agreeableness will moderate the relationship between subjective norms and intention to use mobile commerce services such that the relationship is stronger for higher agreeable individuals.*

On the other hand, although disagreeable individuals have difficulties in building friendships through direct face-to-face interaction (Butt and Phillips 2008), they care about their social status. Evidence was found in the research paper of Butt and Phillips (2008), where the authors claimed that disagreeable people care more about superficial elements of mobile phones (e.g. changing ring tones and wallpapers) for self-stimulatory purpose or to attract the attention of others. Thus,

> ***H6c:*** *Agreeableness is negatively associated with image of using mobile commerce services.*

Conscientiousness. Typical characteristics of conscientious individuals, such as efficient, organized, and dutiful, are closely associated with intrinsic motivation. Therefore, these people usually perform well in study and jobs (Barrick and Mount 2000). Similarly, when facing both external and internal difficulties in using new technologies or services, highly conscientious individuals are more likely to overcome the difficulties thereby improving their knowledge as well as behavioral control (Wang and Yang 2006). In addition, as indicated by Uffen et al. (2013) in analyzing the adoption of security features of smartphones, conscientiousness also interacts with perceived behavioral control in determining intention.

> ***H7a:*** *Conscientiousness is positively associated with perceived behavioral control of using mobile commerce services.*

> ***H7b:*** *Conscientiousness will moderate the relationship between perceived behavioral control and intention to use mobile commerce services such that the relationship is stronger for higher conscientious individuals.*

The self-disciplined and intrinsically motivated nature also makes high conscientious individuals less likely to adopt technologies and services for fun or leisure activities (e.g. watching videos, using social media). They regard such activities as distracting and unproductive (Chittaranjan et al. 2013; Ross et al. 2009). Conversely, if the use of a service is perceived to be useful, conscientiousness will magnify the importance of usefulness on intention to adopt. Consequently,

> ***H7c:*** *Conscientiousness will moderate the relationship between perceived usefulness and intention to use mobile commerce services such that the relationship is stronger for higher conscientious individuals.*

Openness-to-Experience. The curious and broad-minded nature of openness-to-experience individuals makes them more likely to become early adopters of new technologies and services (Constantiou et al. 2006; Tuten and Bosnjak 2001). As open individuals try out different innovations in early stages, they are supposed to be equipped with a higher level of knowledge, which increases their behavioral control over the use of innovations. In addition, trying unproved innovations also requires dealing with uncertainty and risks such as potential monetary loss and privacy issues. Therefore, open individuals are less likely to care about those negative aspects. This leads to the following hypotheses:

> ***H8a:*** *Openness is positively associated with perceived behavioral control of using mobile commerce services.*

> ***H8b:*** *Openness is negatively associated with perceived risks of using mobile commerce services.*

Figure 26 shows the research model with all the hypotheses.

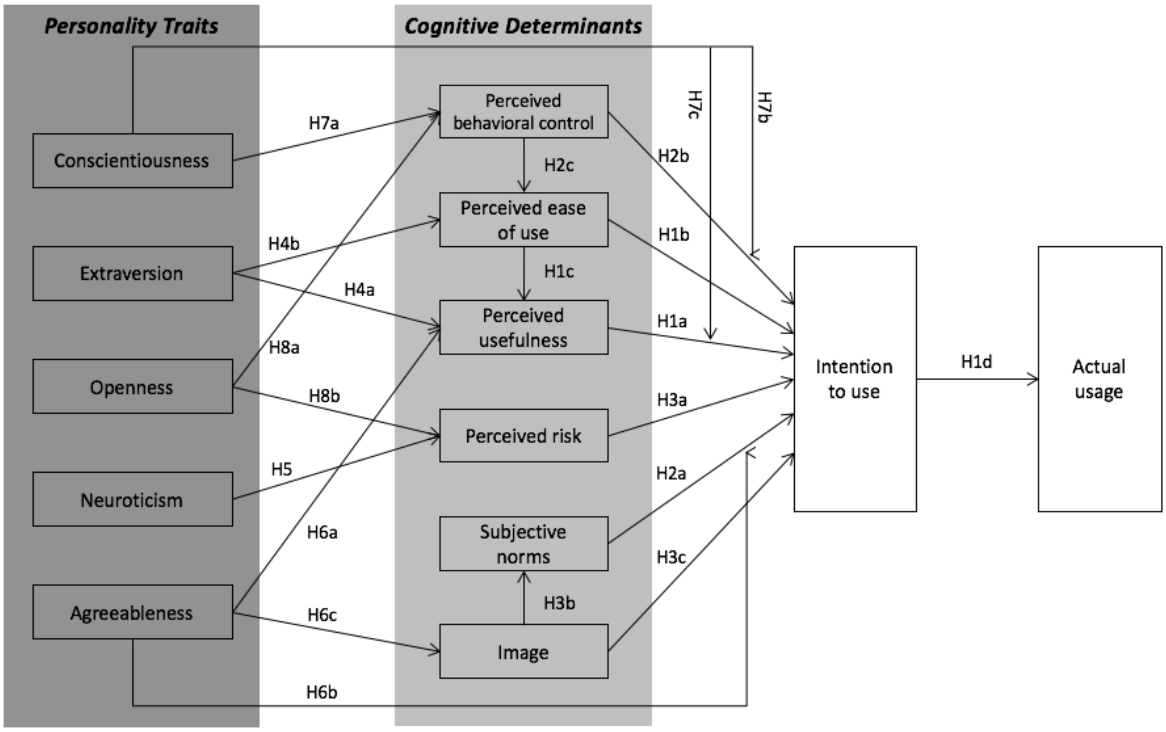


Figure 26: Research Model of Personality's Impact on Cognitive Determinants

5.5.2 Study Design

5.5.2.1 Methodology

This study was confirmatory research as the research model and hypotheses were developed based on existing theory and established models. As suggested by Gefen et al. (2000), covariance-based Structural Equation Modeling (SEM) suits best for this type of research. Consequently, MPlus 6.12 (Muthén 2011), a covariance-based SEM tool, was used to analyze data and test hypotheses.

The sample size of studies using SEM is dependent on model complexity. According to the suggestions of Kline (2015), around 400 samples were required to estimate the hypothesized model. Research data was collected through online questionnaire. According to the two-step methodology suggested by Segars and Grover (1993), a Confirmatory Factor Analysis (CFA) was first conducted to analyze the psychometric properties of the adoption-related scales. Afterwards, a SEM analysis was conducted to test the hypotheses.

5.5.2.2 Used Measures

All measures used in the questionnaire were adapted from previous studies. Items were measured on a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree).

Scales for the perceived usefulness, perceived ease of use, image, and perceived behavioral control were adapted from Taylor and Todd (1995) and Moore and Benbasat (1991); perceived risk was measured with items similar to Tan and Teo (2000); subject norms were measured with items that were almost identical to Venkatesh and Davis (2000), Mathieson (1991) and Bhattacherjee (2000); scales for intention to use were adapted from Brown and Venkatesh (2005); actual use was measured similar to the approach of Pedersen (2009). Nine popular mobile commerce service categories were presented (each with several examples for mobile apps popular in the surveyed country – e.g., Amazon Mobile for purchasing, PayPal for payment, Hotels.com for booking) and each participant was asked to indicate how many services they had used in the past six months and the frequency of their use.

Regarding the Big Five personality traits, the Big Five-44 questionnaire (John and Srivastava 1999) that contains 44 questions to determine each user's Big-Five personality traits was used because it balances well the tradeoff between the length of a questionnaire and the reliability of measured result. The ratings were calculated according to John and Srivastava (1999) and served as independent variables to test the developed hypotheses. In the end of the survey, demographic information of each participant like age, gender, salary, and educational level were also collected to understand the background of the participant.

5.5.2.3 Data Collection Approach

An online panel platform of a survey service provider was used to distribute the questionnaire over the Internet. To control the quality and reliability of the study, additional control questions like solving a simple mathematical problem were added according to the suggestions of Osborne and Blanchard (2010). Furthermore, some questions that measured the same cognitive determinant were reversely coded. In the re-coded answers, if a participant's answers to these questions were of high deviation, she would be removed in the analysis. For instance, a participant who gave "6" to "I have no concern about data and privacy when using mobile commerce service" and "6" to "I have strong concerns about my data and privacy when using mobile commerce service" would be regarded as irrational and therefore removed from the final data set.

5.5.3 Analysis and Result

5.5.3.1 Samples

The study was conducted from September 11th to September 16th, 2015 and it reached 637 participants in Germany. Their demographic distribution was consistent with census in terms of age and gender. People who did not answer all the questions, who failed in the control question, or who gave irrational answers were removed in the analysis. In the end, the study received 397 valid samples. The average survey completion time was nine minutes. Detailed demographics are show in Table 15.

Table 15: Characteristics of Participants in Study III-B (N=397)

Respondents	*Range*	*In %*		*Respondents*	*Range*	*In %*
Gender	Female	50.1%		Net Monthly Income (€)	>4000	9.0%
	Male	49.9%			3000-4000	11.3%
Age	18-25	21.4%			2000-3000	23.7%
	26-35	27.2%			1500-2000	14.4%
	35-45	14.9%			1000-1500	12.6%
	46-55	20.4%			500-1000	11.3%
	56-65	16.1%			<500	6.0%
Job Type	Student	14.6%			No Answer	11.6%
	Professional	31.0%		Highest Education	Doctorate	0.8%
	Academic	5.3%			Master	11.1%
	Self-employed	7.1%			Bachelor	12.6%
	Manager	15.4%			Vocational Education	35.0%
	Technician	4.5%			High School	25.7%
	Retired	6.8%			Secondary School	8.8%
	Housewife/man	5.8%			Primary School	2.5%
	No Answer	9.6%			No Answer	3.5%

In terms of the personality traits of participants, the descriptive statistics, Cronbach's Alpha, and correlations of the Big Five personality traits are demonstrated in Table 16. The reliability is very high with only agreeableness being slightly below the threshold.

Table 16: Statistics and Bivariate Correlations of the Big Five Personality Traits

All bivariate correlations are significant with p < .01 (N=397)

	Mean (SD)	*Cronbach's α*	*E*	*N*	*A*	*C*	*O*
Extraversion (E)	4.57 (.94)	.854	1.00				
Neuroticism (N)	3.70 (.93)	.782	-.488	1.00			
Agreeableness (A)	4.70 (.72)	.677	.288	-.336	1.00		
Conscientiousness (C)	4.93 (.82)	.813	.399	-.395	.451	1.00	
Openness (O)	4.80 (.83)	.838	.359	-.177	.318	.465	1.00

Regarding the use of mobile commerce services, Table 17 presents how many participants have used different types of mobile commerce services in the past six months. Services like mobile purchase (71.5%), mobile product search (62.0%), and mobile payment (54.9%) have been widely adopted, while fewer smartphone users have used services like mobile coupon (20.9%), mobile booking (26.2%), and mobile payback and rewards (28.0%).

Table 17: Adopted Mobile Commerce Services in the Past Six Months (N=397)

Mobile Services Adopted	*Frequency (%)*		*Mobile Services Adopted*	*Frequency (%)*
Purchasing	71.5%		Booking	26.2%
Selling	29.2%		Product Recommendations	47.4%
Payment	54.9%		Couponing	20.9%
Product Search	62.0%		Payback and Rewards	28.0%
Product Comparison	44.6%		No Mobile Commerce Service	7.3%

In terms of when to use mobile commerce services, 57.2% of participants used services in early evening, 47.1% of them used service in late afternoon and 32.5% used services in late evening. On the other hand, only 11.1% participants used mobile services in early morning and around 20% participants used services in late morning and noon.

5.5.3.2 Measurement Model

According to the two-step methodology suggested by Segars and Grover (1993), a CFA was conducted before SEM. Following the guidelines suggested by Gefen et al. (2000), the CFA was carried out with all items simultaneously with factor loadings estimated by the Maximum likelihood algorithm in MPlus 6.12. The overall model fit was good *[$\chi^2/df=1.503$; $RMSEA=.036$; $CFI=.987$; $NFI=.963$; $IFI=.987$]*. Therefore, the analysis continued to test reliability, convergent and discriminant validity of the measurement model.

Cronbach's Alpha was inspected to test the reliability of the deployed scales. As shown in Table 18, all determinants have the value large than or close to the recommended threshold of .70; Therefore, the reliability of the measurement items can be regarded as good. Afterwards, convergent validity was examined by analyzing the factor loadings and corresponding two-tailed t-values for every measurement item, and then calculated the Average Variance Extracted (AVE) for each determinant. As depicted in Table 18, the measurement items load significantly on their corresponding factors, and the AVEs exceed the recommended threshold value of .50 (Fornell and Larcker 1981). Consequently, the convergent validity assumption was supported by the study data.

Table 18: Statistics of Confirmatory Factor Analysis

All t-values are significant with p<.001 (N=397)

	Item	R^2	β Coefficient	t-value	Cronbach's α	AVE
Perceived usefulness (USEF)	1	.632	.795	37.95	.865	.827
	2	.660	.812	40.79		
	3	.762	.873	56.78		
Perceived ease of use (EASE)	1	.784	.885	62.56	.901	.852
	2	.665	.815	41.25		
	3	.733	.856	51.35		
Perceived risk (RISK)	1	.791	.890	9.80	.854	.864
	2	.703	.838	9.72		
Image (IMG)	1	.883	.940	99.32	.933	.824
	2	.728	.853	54.85		
	3	.863	.929	92.34		
Subjective norms (SN)	1	.821	.906	55.24	.941	.825
	2	.822	.907	52.53		
	3	.833	.912	53.81		
Perceived behavioral control (PBC)	1	.746	.864	48.94	.841	.801
	2	.454	.674	49.76		
	3	.750	.866	21.99		
Intention to use (INT)	1	.598	.773	29.90	.835	.730
	2	.861	.928	44.93		
Actual use (ACT)	1	.712	.844	19.98	.692	.588
	2	.463	.680	16.26		

In the next step, discriminant validity was examined by comparing the AVEs to the bivariate correlations between all the latent factors. According to Fornell and Larcker (1981), if the square root of an AVE exceeds the correlation between a construct and other constructs in the model, the assumption of good discriminant validity will be supported. As shown in Table 19, this is the case for all the constructs in our model. Till here, it can be concluded that the measurement model fits the study data well, and its psychometric properties are consistent with prior research. This enables the study to conduct further analysis.

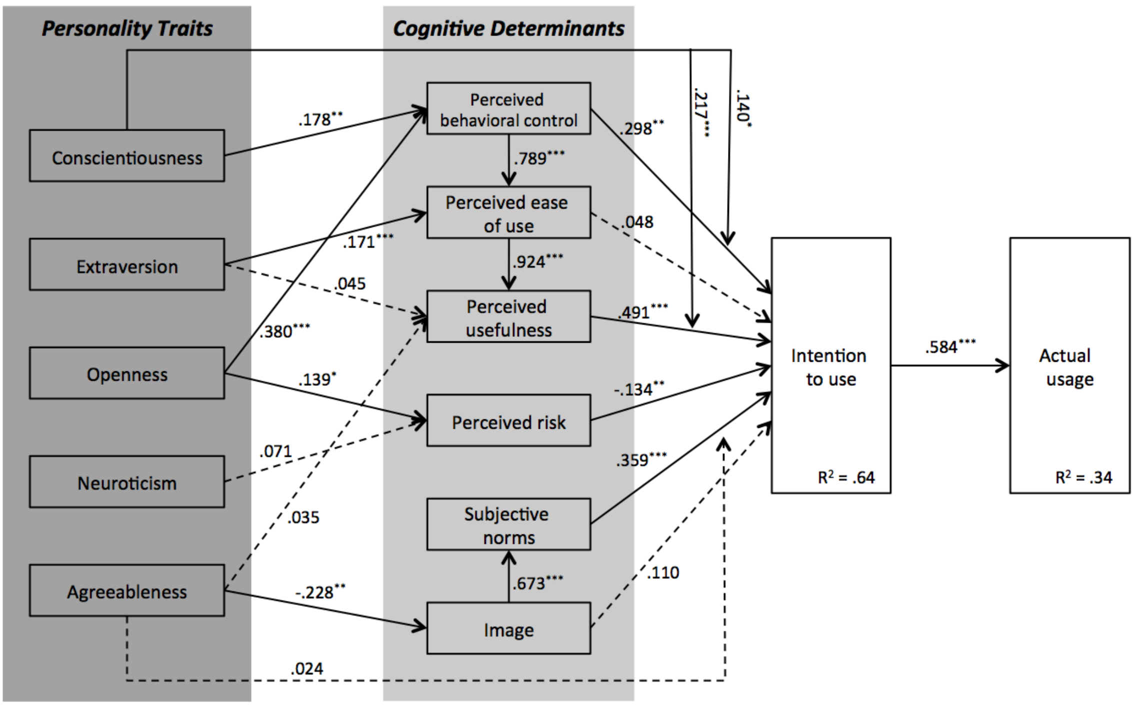
Table 19: Statistics, Bivariate Correlations and Square Roots of AVEs of Latent Constructs

The diagonal terms indicate the square roots of AVEs (N=397)

	Mean (S.D.)	*USEF*	*EASE*	*RISK*	*IMG*	*SN*	*PBC*	*INT*	*ACT*
USEF	5.14 (1.02)	.909							
EASE	5.21 (1.05)	.809	.923						
RISK	4.36 (1.14)	-.081	-.054	.930					
IMG	3.16 (1.39)	.139	-.038	-.001	.908				
SN	3.62 (1.38)	.280	.165	-.061	.628	.908			
PBC	5.22 (0.98)	.633	.740	-.017	.126	.107	.895		
INT	4.59 (1.25)	.607	.526	-.161	.267	.440	.535	.854	
ACT	4.03 (1.66)	.440	.376	-.120	.160	263	.271	.444	.767

5.5.3.3 Structural Equation Modeling

After confirming that the measurement model suffices for further analysis, the hypothesized structure model was fitted to the data. The overall fit of the complete model was good *[χ^2/df=1.726; RMSEA=.043; CFI=.968; NFI=.929; IFI=.969]*. The model explained a large proportion of the total variance of an individual's intention to use mobile commerce service *[R^2=.640]* and her actual use *[R^2=.341]*.



*N=397, Sig.(2-tailed): * significant at p<.05; ** significant at p<.01; *** significant at p<.001*

Figure 27: Structural Equation Model with Standardized Path Coefficients

The results of the structural equation modeling are demonstrated in Figure 27. In consistent with the developed hypotheses, empirical evidence was found for supporting a positive association between the perceived usefulness and intention to use (H1a), between the perceived ease of use and the perceived usefulness (H1c), and between intention to use and the actual use of mobile commerce services (H1d). Although most of the adoption research models claimed a positive association between perceived ease of use and intention to use, such an association could not be confirmed by this study. Therefore, H1b was not supported. Furthermore, perceived behavioral control was found to be positively and significantly related with perceived ease of use and intention to use, which supported H2b and H2c. Also, H2a was supported as a positive relationship between subjective norms and intention to use was tested to be significant. The study also found a positive association between perceived risk and intention to use (H3a) and between image and subjective norms (H3b). Although image was positively associated with intention to use mobile commerce services as hypothesized, the relationship was marginally significant *[β=.110, p=.060]*. H3c was thus not supported.

Regarding the impact of personality traits on cognitive determinants, a positive and significant relationship between extraversion and the perceived ease of use *[β=.171, p<.001]* was found, which supported H4b. Although revealed by previous research in other field (Uffen et al. 2013), this study did not find a significant impact of extraversion on perceived usefulness of adopting mobile commerce services. Thus, H4a could not be supported.

With regard to H5, neuroticism was found to be positively associated with perceived risk, but the relationship was not significant. In addition, agreeableness was found to be negatively associated with image but not significantly associated with the perceived usefulness. This supported H6c but rejected H6a. A positive and significant relationship between conscientiousness and perceived behavioral control (H7a) could be confirmed by this study. Consistent with previous research, the study also revealed that openness was positively and significantly associated with an individual's perceived behavioral control thereby supporting H8a. Another significant relationship was confirmed between openness and perceived risk, however, the direction was opposite to the hypothesis H8b. More open individuals actually had higher level of perceived risk.

In terms of the moderating effects, the study confirmed that conscientiousness positively and significantly moderates the effect of perceived behavioral control and usefulness on the intention to use mobile commerce services. This supported H7b and H7c. Nevertheless, the moderating effect of agreeableness on the relationship between subjective norms and intention to use (H6b) could not be supported.

5.5.4 Discussion

5.5.4.1 Findings and Contribution

Personality researchers emphasized the importance of integrating personality variables into established models, and on the other hand, IS researchers have suggested future research to move beyond the basic adoption models to make them more explanatory and useful in practice (Devaraj et al. 2008). Moreover, scholars in studying service adoption also proposed to take personal differences into account when understanding service adoption behavior in future research (Pedersen 2009). They argued that different cognitive determinants (e.g. the perceived usefulness and ease of use) might be of different importance according to different types of users. Consequently, this work responded to these calls for future research by integrating personality traits into an extended adoption model to understand people's adoption of mobile commerce services.

This study has three theoretical contributions. First, adoption models in the context of technology confirmed that perceived ease of use has both direct impact on intention to use and indirect impact through perceived usefulness. However, perceived ease of use was not found to be significantly associated with intention but strongly associated with perceived usefulness. Ling (2002) suggested that perceived ease of use might not be an issue in the context of mobile services due to the fact that most of the services on mobile are self-explanatory and easy to use. Also, Venkatesh and Davis (2000) found that perceived ease of use become less powerful in the TAM over time. In the study of Pedersen (2009), the author also failed to find a significant impact of perceived ease of use on intention to adopt mobile services. Due to the fact that smartphones are getting more ubiquitous and most users are familiar with using apps on smartphones, it is believed that perceived ease of use has no direct impact on people's intention to use mobile services.

Second, as using mobile commerce services typically requires transactions and financial information, this work suggests to involve perceived risk in future adoption models. Empirical evidence has shown that perceived risk is significantly and negatively associated with intention to use. Because smartphones are highly personalized devices and users store private and sensitive data on them, researchers should always take perceived risk into account in understanding the adoption of other types of mobile services.

Third, the role of personality traits on mobile service adoption is highlighted. On the one hand, personality traits are strongly related to cognitive determinants that further impact an individual's adoption decision. Some relationships are counter-intuitive. For instance, it is hypothesized that openness is negatively associated with perceived risk, but a positive relationship has been confirmed in the analysis. One explanation could be that open people typically experience new services at an early stage where they have to deal with unproved ideas and large amount of uncertainty, which makes the perceived risk to become more visible. On the other hand, personality also moderates the effect of perceived usefulness and behavioral control on intention to use. Although several research papers hypothesized that agreeableness could positively moderate the effect of subjective norms on intention to use (Devaraj et al. 2008; Uffen et al. 2013), none of them found empirical support for such a relationship. The moderate effect was also examined in this study, but no significant effect could be confirmed. Instead, a negative correlation between agreeableness and image and a positive association between image and subjective norms were confirmed.

5.5.4.2 Managerial Implications

Recent development in machine-learning and artificial intelligence sheds light on using accessible data on a smartphone to predict each user's personality traits automatically (Chittaranjan et al. 2013; Montjoye et al. 2013). Combining tools in this research stream with findings of this work enables new opportunities for practitioners to further enhance mobile service adoption. In marketing, when promoting a digital service on mobile, service providers can adapt their advertisement based on different smartphone users' personality traits to increase conversion rate as well as to reduce cost. For example, if a person is highly disagreeable, advertisement that emphasizes the improvement of image and social status by using a mobile service is more likely to make the person become an adopter than delivering the same message to an introvert. Similarly, service providers should emphasize the functionality and productivity of using a service when showing their marketing campaigns to highly conscientious people, while applying persuasive technologies to open-to-experience individuals to reduce their perceived risk if a service is relatively less well known. In addition to marketing, the design of service could also be customized depends on each user's personality traits. This could help to reduce certain barriers as well as to enhance certain cognitive determinants thereby improving intention to use and ultimately actual use of mobile services.

5.5.4.3 Limitation and Future Work

There are several limitations of this work, which leads to further research opportunities. First, instead of collecting behavioral data, this study measured the actual use of mobile commerce services by sampling the frequency of use and the total number of different mobile commerce services used in the past six months. Although this approach was well-accepted in similar research studies, the reliability of such a measurement was relatively low compared to other constructs. A more accurate and reliable measurement is required in future research. For example, a mobile app could be developed to collect data about the number of transactions, the frequency and session length of using mobile commerce apps from smartphone logs.

Second, compared to previous studies that always used student samples, participants in this study were more representative in terms of gender, age, educational level, and net income. However, all participants came from one country. As personality and its impact on adoption could be highly culture dependent, it is likely that personality might have different impact on cognitive determinants of users from another country (Rhodes et al. 2002). Therefore, future research is encouraged to integrate cultural differences and take samples from multiple countries.

Third, this study focused on mobile commerce services due to the fact that they were well-known and widely adopted by people from different age groups. As the trend of digitalization is moving fast in recent years, new services become available on mobile and provide additional benefits to companies and consumers. Future research could focus on emerging mobile services thereby providing more insights to both researchers and practitioners.

5.6 Overall Conclusion

New information systems like smartphone apps generate opportunities for companies to provide services in a scalable and cost-efficient manner in a B2C environment. In addition to making services easy to access, personalization is also important in enhancing and accelerating service adoption. Although not well addressed in previous literature, this chapter analyzes the impact of personality traits on mobile service adoption from two empirical field studies.

Study III-A explored 2043 smartphone users' mobile app adoption behavior based on openly accessible data collected from smartphones. It confirmed a strong correlation between the Big Five personality traits and the adoption of seven types of mobile apps. In addition, the study concluded that personality traits are more powerful than demographics in explaining an individual's mobile app adoption behavior. Further research opportunities include aspects such as studying a more balanced gender sample, the stability of our approach over time, the impact of app novelty for different adoption stages and the impact of regional and cultural differences.

Based on the findings of Study III-A, an online survey study was further conducted to understand what cognitive determinants impact a smartphone user's decision to adopt mobile services and how personality traits influence these determinants. It extended the knowledge of IS adoption research by proposing a theoretical model that included personality traits and cognitive determinants to better understand mobile service adoption. Future research opportunities include aspects like measuring the actual use of services in the wild, examining the impact of culture differences, as well as studying other emerging mobile services.

Aside from the above contributions, the data collection approach used in Study III-A is also novel. With this approach, researchers are able to go beyond intention and use actual behavioral data to understand each individual's mobile app and service adoption pattern. Additionally, as information becomes available about all the apps installed by each user, researchers are not limited to analyze only a small number of specific apps. One drawback of the approach is that it does not reflect how frequently a user accesses each app. Nevertheless, this can be overcome by calling other Google APIs in an Android app.

6 Conducting Automatic User Profiling with Open Smartphone Data

In order to answer RQ4 - predicting a smartphone user's personality traits and demographics automatically – this chapter presents, develops, and evaluates a set of machine-learning models to perform automatic user profiling with openly accessible data collected from smartphones. The proposed models can be integrated into any mobile app to provide knowledge about each user in the digital world, thus making findings of the previous chapter useful in practice.

6.1 Introduction

In the previous chapter, the significant importance of personality traits on mobile service adoption has been presented. With a better understanding about how personality traits impact cognitive determinants as well as the corresponding adoption behavior of different mobile apps and services, practitioners like app publishers and service providers could conduct more precise customer segmentation, better customer relationship management and recommender systems, and more effective personalized marketing campaigns.

However, in contrast to user profiling in the physical world where individual differences in age and gender can be guessed from look and feel, such knowledge remains unknown in the digital world until being measured. Furthermore, an individual's personality traits can only be assessed reliably through lengthy survey, which makes them more difficult to be acquired in both physical and digital world (Montjoye et al. 2013). This might also explain why the impact of personality on consumer behavior has not been well understood, as presented in the previous chapter.

To overcome the effectiveness and scalability problem of current questionnaire-based approaches, this chapter will present a scalable machine-learning approach to predict personality traits with information like app installation and update events (henceforth referred to as mobile app data) since they might be suited as robust features (Pan et al. 2011). Unlike other studies in the field of automatic user profiling, data used in the proposed approach is openly accessible to any app developer, which makes it possible to integrate the approach into any mobile app. The findings suggest that existing questionnaire-based approach can be replaced by this highly scalable and efficient method.

6.2 Related Work

6.2.1 Questionnaire-based Approaches

An individual's personality traits like the Big Five are usually measured based on questionnaires (Barrick and Mount 1991; Gosling et al. 2003; John and Srivastava 1999; Judge et al. 2002). Instruments such as the Trait Descriptive Adjectives (Goldberg 1992), 60-item NEO Five-Factor Inventory (Costa and McCrae 1985), NEO Personality Inventory, Revised (Costa and McCrae 1992; McCrae and Costa 2004), and the Big Five-44 Inventory (John and Srivastava 1999) were developed for accurate measurement. However, in spite of the ubiquity of the questionnaire-based approach in research and practice, its problem is obvious: Answering a questionnaire is time-consuming. To finish a questionnaire with one of the above-mentioned inventories typically requires five to fifteen minutes (Gosling et al. 2003). A vast amount of research therefore dealt with addressing non-participation through survey length reduction (Bergkvist and Rossiter 2007; Childers and Ferrell 1979; Gosling et al. 2003) or interpreting unanswered questions (Porter 2004; Bosnjak et al. 2005). Even though the Internet has facilitated addressing vast amounts of people simultaneously, participation rates for online surveys are roughly 30% (Nulty 2008). Taking the time and cost occurred in distributing and collecting questionnaires into account, such an approach is only limitedly scalable (Montjoye et al. 2013).

6.2.2 Automatic User Profiling

Advances in information technology and machine-learning techniques have drawn the attention to data-driven and automatic approaches to overcome the limitations of the questionnaire-based approach. For instance, Kucukyilmaz et al. (2006) predicted a person's gender by mining her chatting records. Ying et al. (2007) predicted a user's gender from analyzing her online Web browsing behavior. In addition to gender, a person's age could also be predicted automatically. Nguyen et al. (2011) concluded that a person's age was predictable through analyzing her blog texts, telephone conversations, and online forum posts. Guo et al. (2008) and Han et al. (2014) detected a person's age and gender by leveraging face recognition technologies. Kosinski et al. (2013) were able to predict a Facebook user's gender, race and marriage status from investigating her Facebook Likes.

Recently, researchers tried to predict not only demographics but also other user characteristics like personality traits. Pianesi et al. (2008) extracted audio and video features from meetings and used them to predict each meeting participant's two personality traits, extraversion and locus of control. Wright and Chin (2014) predicted an author's Big Five personality traits based on the texts she had written. Similarly, researchers revealed a possibility to automatically predict a person's personality through analyzing her email content (Shen et al. 2013) and social network content like Facebook and Twitter (Bachrach et al. 2012; Chin and Wright 2014; Minamikawa et al. 2012). With the proliferation of smartphones, other researchers (Chittaranjan et al. 2013; Montjoye et al. 2013; Pan et al. 2011; Trestian and Nucci 2009) started to use mobile meta-data such as logs of phone calls, SMSs, and location information to predict a mobile phone user's personality traits.

The data-driven approaches are cost-effective and scalable (Montjoye et al. 2013), and contribute to overcome the intention-behavior gap (Conner and Armitage 1998; Godin and Kok 1996; Sheeran 2002). However, while the results of these approaches are promising, they have a few drawbacks. First, part of the data used in the studies (like phone call and message records) is only available to phone manufacturers or telecommunication service providers. Second, some approaches require the installation of additional data logging software on a mobile phone, while others have to parse the content of personal emails and social network activities like Facebook Likes and number of friends. Those actions could trigger strong privacy concerns thereby limiting the feasibility of use in reality. Third, some approaches require a long history of events (typically half a year) to provide reasonable results. Last but not least, most of the above-mentioned studies, especially the ones that make predictions based on mobile phone data, leveraged modern machine-learning algorithms to conduct user profiling. However, with small samples in those studies, the result was not reliable and could overestimate the prediction performance due to over-fitting (Hastie et al. 2009; James et al. 2014). Consequently, a large-scale study that leverages a non-intrusive and highly scalable approach to predict a user's personality traits is required to fill those research gaps.

6.3 Study Overview

6.3.1 Research Data

To generate machine-learning models to accurately predict each smartphone user's personality traits, two types of data need to be collected. First, ground-truth about each user's personality traits is required to serve as labels for the classification models. Second, input features need to be generated to capture personality differences. As both mobile app data and personality ground-truth have already been collected for each participant in Study III-A. The same data set was used in this study (Study IV) to develop predictive models.

To generate reliable predictive models, three steps need to be further conducted on the original data set. As shown in Figure 24, around 60% of all the apps were pre-installed on Android devices by smartphone manufacturers. As such apps were not related to a user's behavior, they should be removed in the analysis. Second, users who installed few apps or used their smartphones only recently should also be excluded because the corresponding mobile app data might not fully capture their adoption behavior. Third, each user should be labeled as high, medium, or low on each of the Big Five personality traits to generate prediction models for classification. As indicated by Codish and Ravid (2014), there is no widely accepted guidance about what values account for a high or low personality trait. Previous research divided samples into two sets (high and low) based on the median value. However, Maccallum et al. (2002) argued that dichotomizing quantitative variables could lead to loss of information about individual differences, loss of effect size and power, overlooking nonlinear effects, etc., and there have been no findings of positive consequence of dichotomization. Consequently, each participant was classified into one of the high, medium, or low groups on each of the Big Five personality dimensions according to Maccallum et al. (2002) and Shen et al. (2013).

6.3.2 Predictive Indicators

As introduced in Section 5.4.2, four types of mobile app data were collected in the study: Each app's package name, the time of the app's first installation, a timestamp that indicates when the app was latest updated, and a string value that represents the category the app belongs to on Google Play Store. Based on the literature of current data-driven approaches of predicting personality traits, novel indicators that could be easily and directly computed from the mobile app data. The indicators that would meaningfully represent potential differences in personality traits are described below. The focus of this study is not to understand the causality between these indicators and individuals' personality traits. Instead, it aims to use readily accessible mobile app data to predict personality traits automatically and accurately.

Five genres of indicators were calculated from the four pieces of mobile app data. The first genre was related to the number of app installations. Indicators were the total number of app installs, the average number of app installs per month, the maximum, third-quartile (Q3), median, first-quartile (Q1), and minimum number of app installs per month, and the entropy of app installs per month. Entropy is a quantitative measure that reflects how evenly numbers in a group are distributed and it can be calculated according to Shannon and Weaver (1963).

The second genre was related to the number of app updates. Indicators of this genre were similar to those of the first genre.

The third genre was related to the app install intervals. An install interval was defined as the number of days between two sequential app installation days. Indicators of this genre were the average install intervals, the standard deviation of install intervals, as well as the maximum, third-quartile, median, first-quartile, and minimum number of app install intervals. In addition, the number of distinct app install days and the number of days since the first app was installed also belong to this genre. Similarly, its counterpart for app update formed the fourth genre of indicators.

The last genre was calculated based on the number of app installs in each app category. The current app categorization on Google Play Store was taken as a standard because it is the largest app store on the market. Google Play Store distinguished between 44 categories (27 general and 17 game categories) which were taken as indicators in this study. A Web crawler was developed to retrieve information about in which category an app belongs to from the Google Play Store Web site. In total, 78 indicators that could be easily calculated based on mobile app data were generated and used for predicting a user's personality traits.

6.3.3 Feature Engineering and Model Selection

Based on the 78 basic indicators, an additional feature engineering was conducted to improve the accuracy of the machine-learning models. According to Guyon and Elisseeff (2003), interaction terms could be easily calculated and they were able to explain variance that cannot be explained by a single predictor. Therefore, interaction terms of influential app categories were used together with the basic indicators as independent variables to train the machine-learning models.

Because the relationship between behavioral factors and personality traits are often non-linear (Benson and John 2007; Cucina and Vasilopoulos 2005), the Random Forest algorithm (Ho 1995) was used in the modeling due to its ability to capture both linear and non-linear relationships and it usually performed better than other models in terms of predictive accuracy. In addition, Random Forest provides insights on what factors are more important in model generation and it almost cannot overfit (Hastie et al. 2009), which makes models less sensitive to variance.

All data samples were divided randomly into two sets: 70% samples in a training set and 30% samples in a test set. Parameters of the predictive models like number of predictors to consider at each branch split in Random Forest was tuned through 10-fold cross-validation (James et al. 2014) on the training samples. The best-performed model was then applied on the separate test data set to check the prediction precision and recall.

6.4 Analysis and Results

6.4.1 Dataset for Estimation

Before modeling the Big Five personality traits with mobile app data, the data set was cleaned according to the approach described in Section 6.3.1. This resulted to 1531 useable data points with one representing a participant. 70% or 1072 data points were randomly assigned into a training data set and the remaining 30% or 459 data points were assigned into a test set.

As shown in the previous chapter, personality traits have positive or negative impacts on the adoption of different types of mobile apps. Because more than half of the participants belonged to the 'Medium' group in each of the Big Five traits, a model that focused on the overall accuracy would predict most of the participants to be in the dominant class. However, people who belong to each 'High' and 'Low' group are more useful in decision-making applications because they behave differently from the majority (Wright and Chin 2014). Take participants of this study for example, the proportion of adopters of 'Personalization' apps among people who were high in neuroticism was 35% higher than that who were medium or low in neuroticism. Consequently, instead of treating 'High', 'Medium', and 'Low' groups equally, the predictive models focused on accurately classifying people in the 'High' and 'Low' groups of each Big Five trait.

6.4.2 Evaluation of Predictive Models for Personality Traits

RStudio with version 0.99.486 was used to generate predictive models. The package 'randomForest' with version 4.6 was used to build all the Random Forest models and to tune the parameters. Table 20 compares the performance of the Random Forest models with a random guess. There are in total ten prediction models with one predicting each target group. Precision is defined as the fraction of the retrieved instances that are relevant. It is a measure of the accuracy provided that a specific class has been predicted. On the other hand, recall is defined as the fraction of relevant instances that are retrieved and it is a measure of the ability of a model to select instances of a certain class from the whole data set.

The baseline for performance comparison was a random model, which was defined as randomly allocating each user in the test set into one of the three groups ('High', 'Medium', or 'Low') of each personality trait. The approach is similar to that of previous studies (Wright and

Chin 2014). Take the first model Extraversion (High) for example, 27.10% of instances that had been predicted as high in extraversion by a random model were actually high, while the remaining 72.90% of instances were either low or medium in extraversion. On the other hand, the final predictive model generated by our algorithms was able to increase the prediction accuracy by 44.54% from 27.10% to 39.17%. Overall, the predictive precision of a random guess was 25.81% on average while that of the random forest models were 42.72%, which was 65.50% better. Given the large number of smartphone users, the recall rate could cover a significant part of the population (26.94%). Also, it was comparable to similar studies (Wright and Chin 2014).

Table 20: Performance of Predicting Personality Traits (N_{train}=1072, N_{test}=459)

Prediction Group	*Precision Random*	*Precision Our Model*	*Improvement*	*Recall Random*	*Recall Our Model*	*Improvement*
Extraversion (High)	27.10%	39.17%	44.54%	32.56%	36.43%	11.89%
Extraversion (Low)	23.57%	51.61%	118.96%	31.36%	13.56%	-56.76%
Neuroticism (High)	22.30%	41.94%	88.07%	28.70%	22.61%	-21.22%
Neuroticism (Low)	22.00%	38.61%	75.50%	27.73%	30.71%	10.75%
Agreeableness (High)	22.30%	48.48%	117.40%	31.73%	22.70%	-28.46%
Agreeableness (Low)	25.33%	39.76%	56.97%	29.69%	25.78%	-13.17%
Conscientiousness (High)	30.77%	44.76%	45.47%	34.78%	34.06%	-2.07%
Conscientiousness (Low)	28.99%	36.36%	25.42%	28.57%	48.57%	70.00%
Openness (High)	29.14%	44.83%	53.84%	32.59%	19.26%	-40.90%
Openness (Low)	26.62%	41.67%	56.54%	32.28%	15.75%	-51.21%
On Average	25.81%	42.72%	65.50%	30.99%	26.94%	-13.08%

In addition, the top-three most powerful indicators in each of the ten Random Forest models are presented in Table 21. As shown in the table, the feature engineering approach that combined two indicators together brought in several powerful indicators in predicting extraversion, agreeableness, and conscientiousness. Also, the number of apps and games installed in some specific categories, as well as app installation intervals were very frequently used by the Random Forest models in classification.

Table 21: Powerful Predictors Used in the Predictive Models for Personality

Prediction Group	***First Most Important***	***Second Most Important***	***Third Most Important***
Extraversion (High)	# Apps in Board & Word Game	# Apps in Family & Puzzle Game	# Apps in Family & Word Game
Extraversion (Low)	# Apps in Board & Word Game	# Apps in Family & Puzzle Game	# Apps in Education
Neuroticism (High)	First Quartile Install Interval	# App Install Days	Entropy of App Categories
Neuroticism (Low)	# Apps in Shopping	Maximum Monthly Install	# Apps in Puzzle Game
Agreeableness (High)	Median Install Interval	# Apps in Trivia Game & News	# Apps in Casual Game
Agreeableness (Low)	S.D. Install Interval	# Apps in Life Style & News	# Apps in Life Style & Casino Game
Conscientiousness (High)	# Apps in Video	Third Quartile Install Interval	# Apps in Social & Trivia Game
Conscientiousness (Low)	# Apps in Lifestyle & Photography	# Apps in Action Game & Music	# Months with Updates
Openness (High)	Mean Monthly Updates	Age of the Phone	# Apps in Role Playing Game
Openness (Low)	Mean Install Interval	Median Install Interval	Number of App Categories

6.4.3 Evaluation of Predictive Models for Demographics

Similarly, Random Forest model was used to predict each smartphone user's demographics like age, gender, and net income. Gender was classified into two groups, male and female, while age and salary were classified into three groups similar to that of classifying personality traits. Also, the models focused on the 'High' and 'Low' groups.

Table 22: Performance of Predicting Demographics (N_{train}=896, N_{test}=384)

Prediction Group	***Precision Random***	***Precision Our Model***	***Improvement***	***Recall Random***	***Recall Our Model***	***Improvement***
Female	76.56%	88.47%	15.56%	49.66%	88.18%	77.57%
Male	22.39%	60.67%	170.97%	51.14%	61.36%	19.98%
Age (High)	28.70%	42.74%	48.92%	30.89%	40.65%	31.60%
Age (Low)	19.84%	36.23%	82.61%	45.45%	45.45%	0.00%
Net income (High)	8.33%	37.50%	350.18%	32.35%	35.29%	9.09%
Net income (Low)	51.59%	55.38%	7.35%	35.71%	56.59%	58.47%
On Average	34.57%	53.50%	54.76%	40.87%	54.59%	33.57%

Table 22 compares the performance of the predictive models with random guess. The machine-learning models performed extremely well to predict males, age groups, and high income individuals. Overall, the predictive precision of random guess was 34.57% on average while that of the random forest models was 53.50%, which was 54.76% better. Also, the recall of the predictive models was 33.57% better than that of a random guess.

Table 23: Powerful Predictors Used in the Predictive Models for Demographics

Prediction Group	***First Most Important***	***Second Most Important***	***Third Most Important***
Female	# Apps in Casual Game	# Apps in Puzzle Game	# Apps in Sports
Male	# Apps in Casual Game	# Apps in Puzzle Game	# Apps in Sports
Age (High)	Entropy of App Categories	Entropy of Updates	S.D. Install Interval
Age (Low)	Entropy of App Categories	Entropy of Installs	Maximum Install Interval
Net income (High)	Entropy of Installs	Entropy of Updates	Entropy of App Categories
Net income (Low)	Entropy of Updates	Entropy of Installs	S.D. Install Interval

Furthermore, the top-three most powerful indicators in each of the six Random Forest models are presented in Table 23. As shown in the table, entropy of installed app categories as well as entropy of install and update intervals were heavily used by the models to split the Random Forest trees, which was totally different from the key indicators of predictive models for personality traits.

6.4.4 A Demo App that Leverages the Predictive Models

To illustrate how the machine-learning approach can be used in practice, another mobile prototype app was further developed. It leveraged the machine-learning models based on a user's mobile app data and predicted the user's personality traits and demographics. The predicted profiles of two users in the data set are shown in Figure 28.

The predictive confidence of each user's characteristic is shown in the right-most column. As the Random Forest algorithm uses majority voting for classification problems, the value thus indicates how much percentage of all the decision trees votes the corresponding characteristic to be the value that is presented in the app. The confidence value lies between 0 and 1; the higher the value, the more confident the model is of the predicted characteristic. Due to the fact that there were three groups for each personality trait, a value that was much higher than 0.33 gave the model more confidence in its prediction. In the demo app, if a predictive model failed to allocate a case into the high or low group with a confidence level that was 20% higher than the baseline (0.33), it would then show the corresponding characteristic to be unknown.

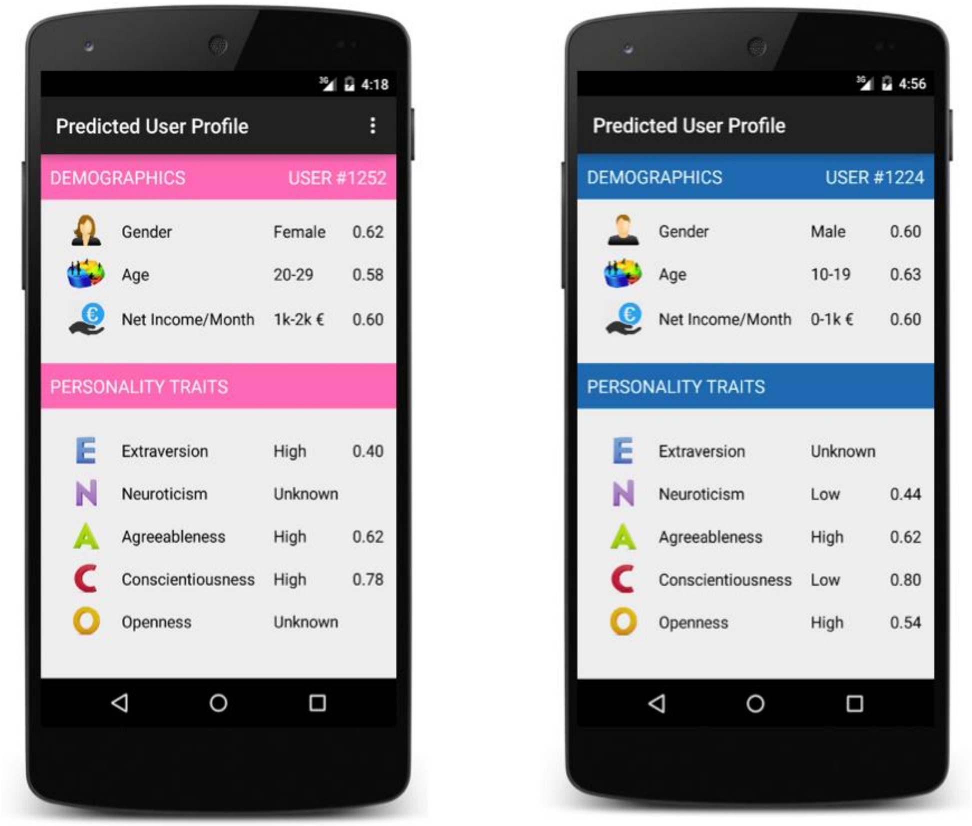


Figure 28: A Demo App That Presents Each User's Predicted Profile

The user on the left side of Figure 28 was predicted to be a female in her twenties with a net monthly income between one and two thousand Euros. The model was confident that she was highly conscientious and agreeable, however, although predicted to be an extravert, it was comparatively less confident because the corresponding confidence value was slightly above the threshold. Similarly, the right side of Figure 28 presents an example of a male smartphone user under twenty with low income. This user was very likely to be low in conscientiousness and high in agreeableness and openness, while whether he was an extravert remains unknown.

6.5 Discussion

6.5.1 Findings and Contribution

Although personality traits have impacts on adoption, using the findings in reality to improve marketing effectiveness or customer relationship is still limited. In contrast to user demographics like age and gender, which can be guessed from look and feel or be sampled with a single question, an individual's personality traits remain unknown until being measured by lengthy survey. The completion rate of survey studies is typically only around 30% (Nulty 2008) because it is tedious and time-consuming to answering all the questions of measuring personality traits (Gosling et al. 2003). This might be one reason why compared to age and gender, the impact of personality on adoption has been neglected in previous research (McElroy et al. 2007).

To overcome the deficiency, a feasible, scalable and automatic machine-learning approach has been developed to predict an individual's personality traits based on a snapshot of her app installation and update events. By leveraging this approach, personality becomes predictable for everyone who uses a smartphone without the pains of answering any kind of survey. The predictive models perform around 65% better than a random guess in classifying users based on their Big Five personality traits. Compared to the performance of similar studies (Chittaranjan et al. 2013; Montjoye et al. 2013), the proposed approach is able to achieve a similar or higher level of precision.

Instead of being available only to phone manufacturers or telecommunication companies, data used in the proposed approach is openly accessible. Therefore, everyone can leverage the approach and integrate the predictive models as part of her frontend mobile apps and/or backend customer relationship management or decision support systems. Also, the approach complies with privacy laws and regulations in Europe. Compared to other studies of user profiling, this study has a relatively large data set, which makes the predictive performance more stable and reliable.

6.5.2 Managerial Implications

With the proposed real-time predictive models, findings about how personality traits impact the adoption of mobile apps and services as described in Chapter 5 can be operationalized in practice. In addition to use cases in adoption areas, managers can use the predictive models in other business context. Existing marketing literature showed that personality traits influence people's decision on product choice, purchasing behavior, store selection, brand loyalty, reaction to marketing campaigns, etc. (Kassarjian 1971; Matzler et al. 2006; Odekerken-Schröder et al. 2003). By combining such findings with the predictive models, manufacturers are able to conduct better market segmentation and targeting, to improve customer relationship management, to enhance customer brand loyalty, as well as to cross-sell other products and services to potential adopters in their mobile apps.

Similarly, researchers revealed that different personalities influence the effectiveness of different mobile persuasive technologies. For instance, badges work better on introverts while progress bar is significantly preferred by people with high levels of agreeableness (Codish and

Ravid 2014); Conscientious people are less likely to be motivated by socially-based technologies like leaderboard, whereas individuals with high openness are more likely to favor goal setting and leaderboard, as well as new persuasive technologies that they have not yet experienced (Brinkman and Fine 2005; Halko and Kientz 2010). Based on the predicted personality traits of each individual user, a mobile app could adapt its user interface and gamification features to the user's personality traits thereby further improving adoption. In addition to smartphones, the proposed approach can also be applied to other smart products (e.g., smart watches, smart glasses, TV boxes, virtual reality headsets) to understand users' corresponding adoption behavior.

Although powerful, both retrieving mobile app data and conducting personalized marketing might trigger users' concern about privacy (Chen and Hsieh 2012; Lam et al. 2006). Therefore, firms that leverage the approach should state explicitly to the corresponding app users regarding information like when and what data will be collected and for what purpose. Each well-designed app should be transparent on data collection. App publishers should also give users the right to opt-in for providing the mobile app data and for receiving personalized in-app recommendations and promotions, according to the suggestions from Pentland (2014). Nevertheless, compared to existing approaches that traced the installation of specific apps and phone call logs, the developed predictive models should lessen privacy concerns because only aggregated information like the total number of apps installed in each category and the frequency of installation was used by our approach.

6.5.3 Limitations and Future Work

There are several limitations of this paper, which provides opportunities for future research. First, new predictors generated from the additional Google APIs could also be used in the predictive models to further improve the performance of prediction. For example, there are APIs available for developers to retrieve information about what apps are used at what time. However, more granular data might trigger higher privacy concerns. Also, more data gathered on smartphones requires more network bandwidth to transfer the data to backend, which will generate addition costs. The trade-off between model precision and privacy concerns and cost is worth studying to find out the optimal balance.

Second, the Random Forest algorithm was used to predict personality traits due to its good performance as well as high model explanatory power. Nevertheless, other machine-learning models such as Support Vector Machines (SVM) and Artificial Neural Network (ANN) might outperform Random Forest in terms of precision and recall. Future study is called to apply other modern algorithms on the data set and compare the corresponding predictive performance.

Furthermore, the personality test app is still active on Google Play Store and it is being installed by new users every day. With more data samples collected, a further research can build the predictive models again and examine whether performance will be improved. As the number of data samples used in previous user profiling research varies significantly, it will be helpful to test and recommend a rule of thumb sample size for similar studies in the future.

Last but not least, studies in predicting demographics and personality traits typically used various types of features collected from mobile devices. Comparing the predictive powers of those features and giving recommendations on the most important features for prediction will help researcher and practitioners better understand what data to collect and what features to compute in the future.

6.6 Conclusion

Personality traits are typically measured by a lengthy survey, which comes with difficulties regarding costs and scalability. Therefore, a set of machine-learning models were developed to automatically predict each smartphone user's Big Five personality traits and demographics based on her mobile app data. The models showed a 65% higher precision than a random guess for predicting personality and a 56% higher precision for demographics.

Compared with other data-driven approaches, the proposed approach uses openly accessible data through standard APIs. Thus, it can be integrated into any mobile app in a non-intrusive, low privacy-concern, and highly scalable manner. Furthermore, a mobile prototype was developed to demonstrate how practitioners could use the predictive model to enable other services such as improving user experience and conducting personalized marketing.

Future research opportunities include studying the trade-off between predictive performance and privacy concern, conducting user profiling using other machine-learning algorithms, recommending a suitable sample size for similar studies, and giving recommendations on the most important features by comparing similar studies.

7 General Discussion and Conclusions

The previous four chapters present empirical results that address the four key research questions posed and practical issues raised. The results contribute to enabling product-related services for manufacturers and service providers in a B2C setting. This chapter summarizes the key findings, discusses the limitations, and outlines the implications for managers and researchers. The chapter closes with a conclusion and directions for future research.

7.1 Motivation and Summary of this Thesis

As product differentiation is getting more difficult and services can typically provide higher and more stable revenues, manufacturers are moving from a G-D business towards a S-D business (Vargo and Lusch 2004, 2007, 2008). While in a B2B setting manufacturers are able to build their strategy on contractual product-service bundles, this concept is difficult to be applied to most B2C products (Day 2006; Saarijärvi et al. 2013). In a B2C setting, products and services are loosely coupled. In many cases, manufacturers do not interact directly with end-consumers, which prevents them from providing additional services proactively to consumers along a product's life cycle. On the other hand, due to the separate nature of products and services, consumers find it difficult and cumbersome to access relevant services of a product even if the product is in front of them. This leads to the current low adoption of product services in a B2C environment.

The core obstacles for manufacturers to improve product service adoption are as follows. First, lacking direct connection to consumers, most manufacturers do not know what services to provide to consumers to meet their demands. Second, except for producing smart products which are costly and require the change of manufacturing processes, manufacturers have no concrete solution to providing services directly to end-consumers at a low cost. Third, customer segmentation and personalized recommendation have been proved to be effective in various use cases. Nevertheless, lacking knowledge about individual consumer, it is not yet possible for most manufacturers to tailor service offerings according to each consumer's characteristics and preferences.

Accordingly, this thesis aimed to help manufacturers overcome the aforementioned core obstacles to improve product service adoption in a B2C context. As smartphone is a ubiquitous and highly personalized mobile device, the proposed solution to improving service adoption is smartphone based. Thus, Chapter 3 explored what services consumers expect on mobile if smartphones can serve as a broker to significantly reduce service search cost. It provided manufacturer with recommendations on high potential services for different types of products. Chapter 4 addressed how to leverage different IoT technologies to enable physical products as digital service end-points at a low cost. In addition to making services easy to access, previous adoption research pointed out the importance of individual differences on adoption. Consequently, Chapter 5 presented the impact of personality traits and demographics on consumers' adoption of different types of mobile services. However, an individual's age, gender, salary, and personality traits remain unknown until being measured by lengthy questionnaire. To operationalize the findings of Chapter 5 in practice, Chapter 6 thus proposed a machine-learning approach to conduct automatic user profiling based on a snapshot of each smartphone user's app installation and update events.

In a nutshell, offering services along a product's life cycle has already been identified as important for manufacturers to stay competitive and to create a long-term customer relationship. Mobile devices provide an opportunity for manufacturers to proactively offer services in a B2C environment, but it is still crucial for manufacturers to understand 1) what services to offer on mobile, 2) how to bring services close to products, and 3) whom to target for a specific service.

7.2 Summary of Key Findings

In order to better address the issues raised in the previous sub-section, four distinct empirical studies were conducted in the context of this thesis. All the studies sought to fill the previous research gaps as well as to solve the corresponding business problems. Research questions raised in Chapter 1 were fully answered, which are presented as follows.

7.2.1 The Need for Prioritizing Service Offerings on Mobile Devices

RQ1: Which are the key product-related services that consumers intend to use when mobile devices can serve as service brokers?

Consumers' intention to use product-related services increased by 22% if mobile devices could serve as brokers to significantly reduce service search cost. One key aim of this thesis was to identify factors that could significantly boost service adoption. Previous adoption literature (Heijden 2004; Venkatesh and Davis 2000; Wu and Wang 2005) has shown that perceived ease of use has both a direct impact on intention to use and an indirect impact through perceived usefulness. Nevertheless, accessing product services at the moment is not perceived to be an easy and comfortable process. On the one hand, digital services are typically separated from most physical products. Even if a product is in front of a consumer, it is not possible for her to directly interact with the product to consume services. On the other hand, the state-of-the-art approach of looking for product-related services is based on online search engines. Although high coverage of search engines makes it possible to find out most required services on the Internet, the whole process is cumbersome as it involves high manual efforts including typing search key words, checking authentication of returned pages, finding out product model and serial numbers, etc. Consequently, it was hypothesized that making services easy to access by reducing service search cost would significantly improve consumers' intention to use product services. A large-scale online survey study with around thousand consumers was conducted to test the hypothesis. Results showed that consumers' intention to use 27 product-related services would increase on average by 22% if service search cost were to reduce significantly thanks to the help of a mobile IS.

Product services are not perceived equally by consumers and high potential services have been identified. Results of Study I also showed that consumers' intention to use product services differs significantly across service types. Services such as checking authenticity, showing current value, and reselling have high potential to impact existing business models because consumers are willing to use them but lacking support of easy access at the moment. Services like showing accessories, managing invoice, and reminding update have been identified as a good starting point for manufacturers to engage consumers due to the fact that consumers have already adopted them on a frequent base even without any digital support. Services such as showing handbooks and lending for free were found to be less attractive to both manufacturers and consumers therefore should not be focused.

The results showed, from a service category point of view, which products would be attractive for consumers to use. Edvardsson et al (2005) claimed that services are not only different from each other, but also different from products to products. Consequently, how consumers' intention to use product services changes according to a specific product type was also analyzed in the thesis. Eleven product categories were selected based on several rounds of review and discussion with our research partner and its interviewed manufacturers. Overall, consumers are most likely to use services for products like home appliances, mobile gadgets, cameras and vehicles, but least likely to use services for products like leisure goods, pet supplies, baby articles, and drugs & medicine. Results have shown that intention to use the same service differs among product types. For instance, consumers prefer more to resell media and books than other products including home appliances and clothes, also they tend more to register and check authenticity for products such as luggage, toys, and sport articles than others.

7.2.2 How Manufacturers and Service Providers Could Leverage IoT Technologies to Connect Products with Services

RQ2: What factors are critical for consumers to adopt a mobile solution that enables physical products as digital service end-points?

IoT technologies can significantly reduce service search cost by a factor of eleven times compared to the state-of-the-art IS solution. IoT extends the digital to the physical world to enable powerful and context-aware applications. With IoT, it becomes possible to link physical products with digital product-related services, thereby enabling manufacturers not only as goods providers but also as service providers. The state-of-the-art IS solution of accessing digital services of a physical product is based on online search engines, which has been well accepted but still cumbersome due to high manual efforts. Combining IoT with mobile IS has a high potential of reducing service search cost because products can be uniquely identified by IoT tags and mobile IS is highly representative to a smartphone user's personal behavior. Therefore, a laboratory experiment was conducted to quantify the reduction of service search cost of a QR code enabled mobile IS solution. Results have shown that the proposed IoT solution is able to reduce service search cost by a factor of eleven, compared to the search engine based solution. Also, user experience could be significantly improved in terms of perceived pragmatic quality, hedonic quality, and attractiveness.

Bluetooth beacon is well adopted in accessing product services, however, it has a severe problem of information overload. After identifying the potential of QR codes in reducing service search cost thereby making services easier for consumers to access, the thesis continued to compare QR code with another popular IoT technology, namely Bluetooth beacon, in terms of consumers' actual adoption. A mobile prototype was developed to enable consumers access services through both technologies. Afterwards, a field experiment was conducted with 33 participants in a real office environment. Each participant used the two technologies (QR codes and Bluetooth beacons) to access eight different product-related services at a random order for a total length of six weeks, and then compared them in terms of different adoption related cognitive determinants. Results showed that both IoT solutions have been well adopted and participants regarded them as a better approach of accessing product-related services. In particular, QR code has been perceived as easy to use in a short term but might be perceived as annoying and inconvenient in the long run. Comparatively, participants intended more to adopt the Bluetooth beacon solution because services could be found automatically without additional efforts. As a result, actual service usage data showed that the average session length of using a service through beacons was 42.3% less than that of the QR codes. However, consumers pointed out one main disadvantage of the beacon solution: The proximity-based push notifications triggered by beacons could be annoying and might lead to information overload. App usage log collected in this thesis showed that 96.5% of the service notifications were not responded by consumers.

A novel Bluetooth service interaction solution was developed to overcome the deficiencies of the QR code and the beacon solutions, which has been proved to be better adopted by consumers. To solve the information overload problem of the beacon solution, a Bluetooth-based button was developed which only broadcasts its identifiers to nearby devices when being pressed. To evaluate consumers' adoption of the new solution, a follow-up field study was conducted in the same office setting for three weeks. Results have shown that the button solution is able to reduce information overload significantly while still keeps other advantages of the beacon solution. Also, participants commented that pressing a button is a nature action, which they had already been adopted in other use cases. Overall, around 63% participants rated the button solution to be the best approach of accessing product services among all the three IoT technologies.

7.2.3 How Manufacturers and Service Providers Could Leverage Personalization to Enhance Mobile Service Adoption

RQ3: How can personality traits impact an individual's adoption of different types of mobile services?

Personality traits have a significant impact on people's adoption behavior of mobile services and such an impact differs from service categories to categories. A mobile gamification app was developed and a large-scale field study with 2043 smartphone users was conducted to collect ground-truth about each individual's Big Five personality traits and her mobile service adoption patterns. Results have shown that an individual's adoption of a specific type of mobile services is significantly influenced by different personality traits. Less extraverted individuals have been found to be more likely to adopt mobile gaming services, whereas less agreeable people are identified to be more likely to adopt mobile personalization services. In terms of neuroticism, positive correlations between neuroticism and the adoption of both mobile photography and mobile personalization services have been identified. In addition, results confirmed that highly conscientious individuals are less likely to adopt mobile music & video, personalization, and photography services.

Personality traits were 17.3% more powerful in explaining the variance of people's mobile service adoption behavior than demographic differences. In terms of individual differences, previous adoption research focused on understanding the impact of demographics (i.e., age, gender, salary) on innovation adoption while neglecting the impact of personality traits. In this thesis, a statistical analysis and a network analysis were conducted to compare the impact between personality traits and demographics on mobile service adoption. Results from MANOVA tests indicated that both personality and demographics are significantly associated with the adoption of mobile services. Furthermore, a network analysis based on four ERGM models was conducted. Compared to demographics, personality traits were found to be 17.3% more powerful in explaining the variance of forming consumers' mobile service adoption behavior.

Personality traits have significant impacts on people's cognitive determinants of adopting mobile services. After confirming the fact that personality traits are significantly correlated with people's adoption of different types of mobile services, a follow-up study was conducted to understand how personality traits impact an individual's decision on adopting or rejecting a mobile service. Based on reviewing previous technology and service adoption literature, a theoretical service adoption model was developed by integrating the Big Five personality traits. The model was evaluated through an empirical online survey study. Results showed that both conscientiousness and openness have a significant and positive impact on perceived behavioral control of adopting mobile services. Extraversion was identified to be positively associated with perceived ease of use, while agreeableness was found to be negatively related to image. Also, openness was found to be positively associated with perceived risk. In addition to direct impacts, the thesis has identified that conscientiousness positively moderates the relationship between perceived behavioral control and intention to use, as well as between perceived usefulness and intention to use.

7.2.4 The Need for a Data-Driven Approach to Conduct User-Profiling

RQ4: How can personality traits be automatically predicted on an individual level from openly accessible data on mobile?

It is feasible to leverage modern machine-learning techniques to identify an individual's personality traits and demographics based on mobile app installation and update

events. Empirical studies conducted in this thesis revealed that personality traits are significantly associated with consumers' adoption of mobile services through direct and indirect impacts on cognitive determinants. However, identifying an individual's personality is not straightforward. The state-of-the-art approach uses questionnaires to measure personality, which is costly, time-consuming, and not scalable (Gosling et al. 2003; Nulty 2008). This makes the knowledge of personality traits on adoption difficult to be operationalized, which might explain why the impact of personality traits has not been well studied in previous adoption research. Emerging machine-learning techniques provide new opportunities to predict an individual's personality traits in a lightweight and automatic way. This thesis thus tested the possibility to predict a smartphone user's Big Five personality traits based on her mobile app data. Results showed that personality traits are predictable based on a snapshot of mobile app installation and update events. The developed machine-learning models were able to predict personality 65% better than a random guess in terms of precision while still kept the recall at an acceptable level. Models to predict demographics were also developed with the same approach. Results indicated that these models performed 55% better than a random guess in terms of precision and 34% better in terms of recall.

7.3 Contributions and Implications

7.3.1 Implications for Researchers

7.3.1.1 Service Science Research

Previous service science literature typically focused on the B2B manufacturing industry or marketing-related activities. B2C manufacturers are empowered by the diffusion of smartphones to serve consumers in a new way but lacking support from the research community on what services to offer. Existing research studies in the field of mobile services were mostly related to phone connectivity, navigation, email, and messaging services, which were obsolete and not product focused. Thus, the findings of Study I contributed to the service science literature by exploring the differences of consumers' adoption of 27 product-related services that B2C manufacturers intend to offer on mobile. Furthermore, previous works usually took one specific service and a corresponding product under study, which failed to generalize the findings because consumers' perception is highly dependent on both product and service types. Study I showed how such a perception differs and provided insights into what services and products are similar in terms of consumers' intention to adopt. Consequently, it enabled researchers and practitioners to apply previous product/service specific knowledge to similar products and services thereby generalizing existing findings in the field. Also, it pointed out high valuable product services for researchers to study in the future.

7.3.1.2 Internet of Things Research

Study II compared consumers' adoption of three IoT technologies to enable physical products as digital service end-points. The implications for researchers are three-fold. First, it quantified the improvement of a QR code based mobile IS compared to the state-of-the-art IS solution. The proposed solution was able to reduce service search cost by a factor of eleven times, meanwhile significantly improving usability and user experience. Second, previous research in this field was mainly conducted through online surveys to sample consumers' intention to use instead of measuring actual service use. In addition, most of the existing studies focused on technical and design aspects but not consumers' adoption issues. Thus, a field study was conducted in this thesis to compare consumers' actual adoption of different IoT solutions (i.e., QR codes, Bluetooth beacons) to connect consumer goods with relevant services. It presented the pros and cons of different technologies, thus providing researchers with a good starting point to come up with improved solutions. Third, the thesis proposed and evaluated a novel Bluetooth button solution to improve both the QR code and beacon solutions. The button solution has been well adopted and perceived to be the best approach to enable physical products as digital service end-points. However, Study II-C also identified some potential problems of the button solution e.g. invisibility of services behind each button. Researchers are thus encouraged to confirm and solve the problems thereby further improving the solution.

7.3.1.3 Adoption Research

This thesis contributes to adoption research from three aspects. First, previous adoption research typically focused on understanding the impact of different cognitive determinants on adoption but neglected the importance of personality traits. Based on two empirical field studies, this thesis concluded that personality traits have significant impacts not only on consumers' adoption of different types of mobile services, but also on the related cognitive determinants. Thus, it encourages researchers in the future to focus on examining the impact of individual differences in adoption research as well as in other research fields.

Second, previous works typically had a small number of participants and only studied the impact of personality traits on popular apps like 'Facebook' and 'Twitter', which limited the generalizability of the findings and always led to contradictory results. Consequently, this thesis classified a large number of apps into corresponding mobile service categories and analyzed the impact of personality traits on a category level. It thus provided a new framework to demonstrate a more complete, integrated, and coherent view on the impact of personality traits on mobile service adoption.

Third, previous works in both research and practice used self-reported questionnaires to collect data, which is costly, limitedly scalable, and might lead to biased results (Montjoye et al. 2013; Nulty 2008). This thesis proposed a novel approach to collect research data directly from each participant's smartphone. On the one hand, it goes beyond intention and leverages actual behavioral data to test the developed hypotheses. On the other hand, it enables researchers to go beyond a limited number of popular apps and to study the impact of personality traits on any type of mobile services, as well as on any individual app. The proposed data collection approach can be integrated into any mobile app, which opens the door for future research to study adoption in a more scalable, less costly, and more generalizable way.

7.3.1.4 Applied Machine-Learning Research

The contributions and implications of this thesis to the applied machine-learning research are stated as follows. First, existing literature has tried to predict demographics and personality through text-mining, face recognition, mobility patterns, mobile phone usage, etc. Nevertheless, the number of samples used in these studies were typically between fifty and hundred, which is extremely small for training stable machine-learning models and could overestimate the predictive performance due to over-fitting. With a relative large sample size, the machine-learning models developed in this thesis are more reliable.

Second, the thesis presented a new possibility to predict personality traits and demographics based on only mobile apps installed on each smartphone. Previous research has also tried to conduct user profiling based on smartphones. However, data used by these predictive models was only accessible to phone manufacturers or telecommunication companies. On the contrary, the data used by our predictive models is openly accessible from Google APIs. Therefore, the developed models can be integrated into any mobile app without difficulties. Furthermore, unlike existing approaches that require to track a user for a certain period of time before developing a reliable predictive model, the proposed approach only requires a snapshot of app installation and update events. This enables the approach to easily overcome the cold-start problem as well as to conduct user profiling in real-time.

Third, findings of this thesis suggested that existing questionnaire-based approaches could be replaced by this highly scalable and efficient approach. Thus, personality becomes predictable for everyone who uses a smartphone without the pains of answering any kind of survey. On the one hand, the thesis contributes to make previous knowledge about the association between personality and adoption, marketing, gamification, etc. more useful in practice. On the other hand, presenting both the importance of personality and the possibility to predict personality in an automatic way, the thesis encourages researchers to focus on studying the impact of personality traits in different research fields in the future.

Forth, the proposed approach should lead to lower privacy concerns from consumers' perspective. Existing approaches usually require the installation of specific surveillance apps, need to track phone call logs and location information, or have to access personal emails and social media content to parse texts. This could trigger strong privacy concerns. On the contrary, the proposed approach needs none of above requirements. It uses only aggregated information such as the total number of apps installed in each category and the frequency of app updates to conduct user profiling.

7.3.2 Implications for Managers

In this thesis, a novel solution that leverages IoT technologies and mobile IS to connect non-intelligent products with relevant digital services has been proposed and evaluated. Manufacturers can attach QR codes or Bluetooth tags to products to help consumers easily and quickly find product-related services. With the reduced service search cost, consumers will be more likely to use those services, which creates additional revenue streams for manufacturers. Compared to producing new intelligent products, the proposed solution is much cheaper for manufacturers to adopt. Also, it can be applied to bring intelligence to already manufactured products. Manufacturers have already attached barcode or metal tags to products to provide information such as model, serial number, etc. Technically, the proposed solution is so similar that does not require additional large investments.

The thesis also compared alternative technical implementations and design aspects of the proposed solution. Overall, the Bluetooth button solution is strongly recommended to manufacturers. Pressing a button is a nature action and consumers have adopted it in other use cases in daily life. Moreover, the thesis pointed out the importance of giving the control of initializing a service request back to consumers. In addition to the button solution, manufacturers could also improve the mobile side to make it more context-aware, thus reducing the number of unnecessary notifications.

In addition to helping consumers easily access product-related services, the proposed IoT solution also creates a new channel to connect manufacturers directly with consumers. In contrast to B2B settings where manufacturers know each individual customer in detail, consumers are usually shown as aggregated sales numbers to B2C manufacturers. This prevents manufacturers from proactively providing services to each consumer. With the proposed solution, however, manufacturers are able to gain knowledge about each consumer's behavior such as purchased products and requested services, thus tailoring service offerings to individual demands and preferences. Such benefits could not be achieved previously for manufacturers in a B2C context. By exploring the product services landscape, the thesis also provides manufacturers with concrete suggestions on what services to offer on mobile for what type of products.

In practice, consumer information like age, gender, and salary has been widely collected for analytics. Manufacturers leverage such information to boost the performance of CRM or recommender systems. The thesis argued that personality traits are more powerful than demographics in understanding consumers' service adoption behavior. Consequently, manufacturers are strongly recommended to collect information about each consumer's personality traits in the future.

Furthermore, findings of this thesis have provided actionable knowledge about how to further enhance mobile service adoption through personalization. For instance, when promoting a mobile service to an open-to-experience individual, persuasive technologies could be applied to reduce the perceived risks because openness is positively associated with perceived risk, which negatively impacts service adoption. Similarly, perceived image and social aspects of using a mobile service should be emphasized when recommending a mobile service to a less agreeable consumer due to the fact that agreeableness is negatively correlated with image, which indirectly impacts the intention to use a mobile service in a positive manner.

Also, previous literature concluded that personality traits could strongly impact the effectiveness of various user interaction approaches, such as user interface designs, gamification features, and so on (Brinkman and Fine 2005; Codish and Ravid 2014; Halko and Kientz 2010). Customizing service offerings and mobile app designs according to the personality traits of each targeted consumer could help to reduce certain barriers as well as to enhance certain cognitive determinants, thus improving the intention to use and ultimately the actual use of mobile services.

The thesis provides managers with a powerful tool to conduct automatic user profiling, which is non-intrusive, low privacy-concern, highly scalable, and can be integrated into any mobile app. In contrast to user demographics like age and gender, which can be guessed from look and feel or be sampled with simple questions in physical world, an individual's personality traits remain unknown until being measured by lengthy survey. In digital world, however, the situation becomes even worse because both demographics and personality traits of consumers are unknown to manufacturers. The developed machine-learning models enable practitioners to obtain such unknown information accurately in real-time. For the first time, manufactures in a B2C setting are also able to know individual consumers in detail, similar to that in the B2B setting. According to Apple (2015), 98% of the Fortune 500 companies have their own mobile apps to interact with end-consumers. Integrating existing brand apps with our predictive models opens the door for new business opportunities. For instance, modern machine-learning research has shown a huge potential of improving the performance of recommender systems by taking user characteristics into account (Li et al. 2010). This thesis provided the enabling technologies for applying these machine-learning algorithms.

In addition to better personalized marketing and service recommendation, having highly granular knowledge about individual consumer also helps manufacturers gain more insights into consumer behavior. For instance, combining previous data about in-app consumer behavior with the new obtained knowledge about detailed characteristics of each consumer makes it possible for manufacturers to understand which customer group uses what type of services, how service usage differs between customer groups, who are high-value customers, who react to a specific marketing campaign, etc. Having such actionable knowledge in hand, manufacturers can in return improve their marketing effectiveness by addressing more relevant consumers.

Although the predictive models bring additional benefits for manufacturers and enables new business opportunities that did not exist in the B2C context before, managers should pay special attention to the potential privacy issues. Each well-designed mobile app should be transparent on data collection approach and all collected data should be anonymized to protect privacy. Consequently, manufactures are suggested to state explicitly to consumers regarding when and what data will be collected and for what purpose. They are not allowed to collect any data from a user's device without user consent. Also, users should be given the right to opt-out for providing the mobile app data and for receiving promotions and recommendations at any time.

7.3.3 Implications for Society

The knowledge and tools created in this thesis contribute to foster product-related service adoption, thus helping consumers retrieve more values of their purchased products. On the one hand, it reduces service search cost and contributes to recommend more relevant services to address consumers' unmet service needs. On the other hand, it helps to improve the efficiency of our society. For instance, increasing the adoption of services like 'Dispose Properly' educates consumers to apply the right method to dispose a product in the end of its life-cycle, which means less environmental impacts, less resources and energy used, and less money. Also, product sharing services can increase the utility of existing products and connect people closely. The IoT solutions proposed in the thesis are not limited to consumer goods. For instance, the Bluetooth beacons and buttons can be equipped in public transportation stations to reduce check-in time or to enable smart ticketing.

The developed machine-learning tools help manufacturers enable more personalized service offerings, which eventually optimizes the adoption S-Curve. Consequently, the speed of innovation diffusion can be accelerated and more consumers are able to enjoy new products and services earlier. The steeper slope of the S-Curve also reduces the total length of innovation diffusion time, which encourages manufacturers and service providers to come up with improved products and services to meet new consumer needs. As a result, the development of technologies and society will be accelerated.

7.4 Limitations and Future Work

To summarize, the research in this thesis contributes to enable manufacturers to provide product-related services in a low cost and high effective way in a B2C context. The thesis also lays the groundwork for future projects in both research and in practice, summarized as follows.

Understanding manufacturers' perspective of deploying low cost strategies to enable physical products as digital service end-points. The results in the thesis presented consumers' perspective of the proposed solution that leverages IoT technologies to enable physical products as digital service end-points. After comparing different technical implementations and collecting consumers' feedbacks, future research is encouraged to study manufacturers' perspective of adopting the proposed IoT solution. Study setting should be extended from a closed office environment to an open and wild business setting to enlarge the sample size as well as to remove potential selection biases. Also, researchers are encouraged to work together with manufacturers to provide digital services for a specific physical product and quantify the resulting benefits and costs. Other than having monetary incentives, participants should be motivated to adopt the solution due to the intrinsic values of the solution and the related services.

Integrating service offerings with emerging technologies and standards. Three enabling IoT technologies, namely QR code, Bluetooth beacon, and Bluetooth button, were compared to identify which one consumers preferred the most to access product-related services. Results showed that the Bluetooth button has been better adopted, but all the three technologies were perceived to overwhelm the state-of-the-art solution that used online search engines to access services for products. The three enabling technologies were chosen in the field experiment due to their popularity and easy-to-implement nature. However, other emerging technologies such as augmented reality and wearable devices might bring better usability and additional benefits. Furthermore, new standards like the Google Physical Web might help consumers access and use product services without installing a mobile app. Staying compatible with emerging technologies and standards enables manufacturers to provide services in a more ubiquitous and user-friendly way. Future research is thus called to compare solutions based on emerging technologies with the solutions that have been evaluated in this thesis.

Validating the impact of personality traits on mobile service adoption in other cultures and regions. Previous research argued that personality and its impact on human behavior are highly dependent on cultural environment. As all empirical studies of this thesis were conducted in German-speaking countries, it is thus hypothesized that the impact of personality traits on mobile service adoption will be different for consumers from different cultures like American and Asian. Similarly, the machine-learning models that were developed to predict demographics and personality traits might also be different for consumers from another region. As a result, future research needs to validate the findings and the developed models in other countries for triangulation.

Having a better definition of service adopters in the mobile context. In this thesis, whether a smartphone user had adopted a mobile service was determined by whether she had installed at least one app in the corresponding service category. However, it could happen that a user had installed a specific app but seldom used it. A recent statistical study indicated that around 20% of the mobile apps were installed but only used by consumers once (Localytics 2014). Consequently, the simple approach used by this thesis to label service adopters should be improved to better mirror the reality. Future research could take a user's daily app usage into account to decide whether the user really adopts a mobile service or not. Google provides APIs for developers to retrieve app activity logs on each Android device, which should present sufficient data for researchers to make reliable judgements.

Leveraging other machine-learning algorithms to further improve the predictive performance. Predictive models developed by this thesis showed a significant improvement compared with a random guess. Also, they have reached the same level of precision and recall as that of previous studies. However, there are several limitations which could be overcome by future research to further improve the predictive performance. On the one hand, more personality-related features should be used as predictors. This thesis did not focus on identifying the most relevant and representative features for prediction, instead, it used all features that could be easily retrieved and calculated from mobile app logs as predictors. But it could happen that more powerful predictors were neglected in the current models, or irrelevant features were added to the models which did not contribute to the reduction of biases but significantly increased variances. Future research should try to identify a set of potential powerful predictors for user profiling. On the other hand, the Random Forest algorithm was used by the presented models due to its good predictive power, low tendency towards overfitting, and high model interpretation. However, other machine-learning algorithms such as kernel SVM, artificial neural network, and deep learning might better capture linear and non-linear relationships thereby further improving the predictive performance. Future research could try to apply different machine-learning algorithms and compare their performance.

Integrating the user-profiling models into business applications and quantifying the benefits. Previous research indicated the importance of demographics and personality traits in business applications such as recommender systems and CRMs. Research in the future is suggested to work closely with manufacturers to integrate the user profiling models into existing business applications. Afterwards, the effects of the models on personalized marketing, tailored service recommendation, or adaptive user interface design can be quantified. This would provide manufacturers with a better overview on the cost-benefit relationship of implementing digital user profiling strategies.

New solutions that keep the benefits of big data analytics while at the same time reduce consumers' privacy concerns should be developed. Smartphones now serve as a gateway to connect consumers with different physical devices and digital services. The highly personalized nature of smartphones makes it possible for manufacturers to better understand individual consumers thereby offering more relevant products and services. However, on the other hand, privacy concerns might arise due to the increasing amount of private data being collected on smartphones. Although the proposed data-collection approaches comply with the current European privacy regulations, this situation might change in the future when new privacy laws and regulations are in place. Further research is needed to better understand how new approaches of collecting, anonymizing, and sharing personal data can make automated personalization even more standard while preserving privacy. Such approaches are recommended to be compatible with existing data analytics systems to significantly reduce consumers' potential privacy concerns.

7.5 Conclusion

This thesis investigated the possibility of leveraging IoT and mobile technologies to help manufacturers enhance product-related service offerings in a B2C setting. It explored the product service landscape to help manufacturers identify high potential mobile services to address unmet consumer needs. Afterwards, it proposed a mobile IoT solution to enable physical products as digital service end-points at a low cost. Consequently, consumers can easily interact with non-intelligent products to access and consume services on the spot.

The proposed mobile solution created new opportunities for B2C manufacturers to interact with consumers in a new way that did not exist before. On the one hand, it generates a new channel for manufacturers to connect consumers directly through mobile apps. On the other hand, the developed machine-learning models enable manufacturers to gain granular knowledge about each individual consumer in the digital world. As a result, personalized service recommendations and tailored consumer interaction approaches can be applied to improve product service adoption.

Furthermore, the thesis pointed out the importance of personality traits on mobile service adoption, thereby encouraging future studies to analyze the impact of individual differences in adoption research. It also presented a novel data collection approach that leverages mobile app installation logs to study adoption. This goes beyond the traditional questionnaire-based approach and enables researchers to understand adoption in a low-cost and high-scalable manner. Other research opportunities include understanding manufacturers' perspectives of adopting the proposed solutions, quantifying the business impact of the solutions in the wild, validating the findings in other cultures, and deploying solutions based on the recommendations of this thesis to address potential privacy concerns.

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