Individual Differences and Mobile Service Adoption: An Empirical Analysis

Runhua Xu, Remo Manuel Frey
Dept. of Management, Technology and Economics
ETH Zurich
8092, Zurich, Switzerland
Email: rxu@ethz.ch, rfrey@ethz.ch

Alexander Ilic
Institute of Technology Management
University of St.Gallen
9000, St.Gallen, Switzerland
Email: alexander.ilic@unisg.ch

***Abstract*—Smartphones make it easier for brands and manufacturers to provide services in a digital and ubiquitous way. Consumers' adoption of different mobile services could be influenced by their individual differences in demographics and personality traits. Therefore, we developed a mobile app and conducted an empirical study with 2043 Android users to understand the impact of individual differences on their mobile service adoption behavior. Our contributions are two-fold. First, we find that age, gender, salary, and personality traits have significant impact on the adoption of 16 different mobile services. Second, we propose a data-mining approach to automatically determine a user's personal profile based on her installed apps. The prediction precision and recall of our models are 70% and 35% higher than random, respectively. Our approach can be deployed in a non-intrusive and highly scalable manner as part of any mobile app thereby enabling better business intelligence and decision-making.**

Keywords—Mobile service adoption, user profiling, data mining, prediction, individual differences

I. INTRODUCTION

As product differentiation is getting more difficult and services can typically provide higher and more stable revenue, brands and manufacturers are moving from a good-dominant business towards a service-dominant business. Digitalization and the proliferation of smartphones make it possible to provide and consume services in an easy and ubiquitous manner. The number of available mobile apps in major app stores now easily exceeds one million – providing an app for almost any situation of our life [1]. Mobile apps are actually services as over 98% of Fortune 500 companies provide services through their mobile apps [2]. Therefore, how to improve consumers' adoption of these services becomes crucial to the success of brands and manufacturers.

User profiling is widely used in marketing and consumer analytics to classify consumers into similar groups thereby better understanding their behavior. Demographics such as age, gender, and salary are main focus in user profiling and their impact on technology adoption is well understood [3]. However, how demographics influence the adoption of mobile services is unclear. On the other hand, impact of other individual differences like personality traits on adoption is not well studied in previous literature. Recently, researchers claimed that personality traits could be correlated with people's adoption of new technologies like Internet and some specific mobile apps [4,5]. Consequently, we aim to provide a systematic overview of how individual differences impact mobile service adoption behavior with a large-scale field study.

Once the impact of a user's demographics and personality on her adoption of different mobile services is better understood, practitioners like app publishers and service providers could benefit from getting a better understanding about whom to target in their marketing campaigns. In contrast to user profiling in physical world where individual differences in age and gender can be guessed from look and feel, such knowledge remains unknown in digital world until being measured. Furthermore, a person'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. This might also explain why analyzing the impact of personality on consumer behavior is scare in both academia and practice. We thus present a novel approach to conduct user profiling by leveraging openly accessible mobile app data like a snapshot of one's app installations and update events because people's app installation behavior is a robust feature [6] and mirrors their interest, demographics, and personality [7,8].

The contributions of this work are two-fold: First, we provide insights into how the adoption of different types of mobile services can be explained by each user's demographics and personality traits. We use a state-of-the-art questionnaire-based approach for sampling demographics and determining personality traits. Previous research typically has a small sample size and focuses only on specific mobile services like location-based and social services. Such limitation could influence the generalizability of the findings. We instead aim to classify a large number of apps into mobile service groups and analyze the impact of demographics and personality on each group to gain systematic knowledge. Second, we provide data-mining models to conduct automatic user profiling based on her readily available mobile app data, which can be integrated into any mobile app. Based on our predictive models, practitioners will gain more knowledge about end-consumers in the digital world to enable more powerful personalized marketing, customer relationship management, as well as other business intelligence applications.

The rest of the paper is structured as follows. The related work is reviewed in Section II. Afterwards, we introduce our research design in Section III, which is followed by a section that states the implementation of the study in detail. Section V demonstrates the impact of individual differences on users' mobile service adoption behavior, while Section VI presents the accuracy of our data-mining user profiling approach. We discuss and conclude the paper in Section VII.

II. RELATED WORK

A. Categorization of Mobile Services

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 [9]". Because mobile devices provide ubiquitous and universal access to information as well as opportunity for providing highly personalized experiences, they are increasingly important to companies. As indicated by Scornavacca and Barnes [10], companies have opportunities to provide personalized services through leveraging mobile apps.

However, the classification of mobile services is not yet defined scientifically. Different types of mobile services were used in previous research. Pedersen [11] proposed a research model to understand what factors influence users' adoption of mobile services. He found that mobile purchasing, searching, alerting, reservation, gaming, entertainment, payment, and location-based services are most widely adopted by end users. Tojib and Tsarenko [12] generated a 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 Internet, 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 users. Similarly, Zhao et al. [13] evaluated a theoretical model to explain the mobile service adoption behavior of more than one thousand students. In the study, they defined 15 specific mobile services, including personalization, gaming, messaging, TV and music, newspaper, mobile pocket, location navigation, stock, and email services. Furthermore, Xu and Ilic [14] explored 27 different services along a typical product's life cycle and showed that consumers' intention to use these services will increase 22% on average if services can be accessed easily through smartphones. Services used in their study are recommendation, purchase, resell, reminder, registration, etc. Constantiou et al. [15] 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 [16] developed a prototype and conducted a user study with 109 undergraduate students to evaluate the use of the mobile learning and education service.

With the wide spread of mobile devices, some services that are previously interesting to researchers like SMS, email, note, GPS, and navigation & map services become ubiquitous and corresponding apps are typically pre-installed by smartphone manufacturers now. Therefore, these services are not targeted in this study. After reviewing previous literature, we focus on 16 mobile services in this work – namely mobile finance, reservation, transportation, product searching, shopping, recommendation, location-based service, chatting and messaging, media and video, music and audio, education and learning, gaming, photography, personalization, social, and news services.

B. Impact of Demographics and Personality Traits on Adoption

As we have discussed in a previous paper [17], adoption and diffusion research focuses on a better understanding of various factors that lead to the adoption of some innovations or the rejection of others. In the field of technology adoption, previous research showed that demographics could have significant impact on people's adoption decision and behavior. For instance, researchers revealed that gender, age, and income have significant impact on people's adoption of online shopping [18] and electronic banking technology [19]. However, the impact of personality traits on technology adoption was scare, but recent findings indicate that they could also be influential and require more research in the future [5].

The most widely accepted personality model is called the Big Five personality traits, which is consisted of extraversion (E), neuroticism (N), agreeableness (A), conscientiousness (C), and openness to experience (O) [20]. Landers and Lounsbury [4] found that extraverts prefer face-to-face interaction thereby spending less time on using the Internet. Conscientious people are less likely to spend time online in leisure pursuits as they see them as unproductive activities. Nonetheless, they prefer to spend more time online to participate in academic activities [4]. In addition, agreeable people are found to use emails less frequently than others [21]. Chittaranjan et al. [22] found out correlations between the Big Five personality traits and the use of software like calendar and email.

As service adoption is similarly to technology adoption [11], users' demographics and personality could also have direct impact on the adoption of mobile services. For instance, Correa et al. [23] concluded that the adoption of social service is positively correlated with extraversion. Similarly, Chorley et al. [24] revealed that personality traits contribute to explain individual differences in using location-based services like "Foursquare". The authors found significant correlation between conscientiousness, openness, neuroticism and the use of "Foursquare". Several researchers [4,23] drew the same conclusion that conscientiousness has a negative impact on the adoption of social services.

However, researchers came to contradictory results regarding the adoption of other mobile services, which requires for further study. For example, some researchers found that extraversion has a negative correlation with the adoption of gaming service [22], while others draw a conclusion that extraversion positively influences game playing behavior [25]. Correa et al. [23] argued that agreeableness and openness have no impact on the adoption of mobile apps and services. Nevertheless, Butt and Philips [26] claimed that disagreeable individuals in general spend more time in using mobile personalization services like changing the ring tones or wallpapers. On the other hand, previous literature focused on analyzing the adoption of specific mobile apps like "Facebook" and "Foursquare", which failed to provide an overview of the full mobile service landscape. Further research is thus called to analyze the impact of user characteristics on a wide range of mobile services.

C. Data-Driven Approaches of User Profiling

User profiling used to be conducted by using questionnaires and interviews. Nevertheless, in spite of the ubiquity of the questionnaire-based approach in both research and in practice, its disadvantages are obvious: Answering a questionnaire is time-consuming, which makes the approach limitedly scalable [27]. Recent advances in information technology and data-mining techniques have drawn the attention to data-driven and automatic approaches of user profiling to overcome the limitations. For instance, researchers were able to predict a person's gender by mining her chatting records [28] or online Web browsing behavior [29]. In addition to gender, a person's age can also be predicted automatically, through analyzing blog texts [30], face recognition [31], or Facebook Likes [32]. Recently, researchers tried to predict not only demographics but also other user characteristics like personality traits. They predicted a user's Big Five personality traits based on mining her email content [8], social network content [33], and mobile meta-data like logs of phone calls, SMSs, and location information [6,27].

The data-driven approaches are cost-effective and scalable, and contribute to overcome the intention-behavior gap. However, while the results of these approaches are promising, they have a few drawbacks. First, 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. Second, part of the data used in the studies (like phone call and SMS records) is only available to phone manufacturers or telecommunication service providers. 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, leverage modern data-mining algorithms to conduct prediction. However, with a small number of samples in those studies, the result is not reliable and could overestimate the prediction accuracy due to over-fitting. Consequently, a large-scale empirical study that leverages a non-intrusive and highly scalable approach to conduct user profiling is required to fill these research gaps.

D. 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 [32], 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 are 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 [34].

In a typical research design, researchers collect data for one instantiation of a network (called observed network). However, there are many possible instantiation of networks 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 we do not know what stochastic process formed the patterns of the observed network [35]. To solve this problem, the Exponential Random Graph Model (ERGM) is 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 whether the estimates from our observed network are significantly different from the simulated network or not. If the difference is significant, then we can conclude that the network formation is resulted from some structural characteristics than by chance [32]. 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.

III. RESEARCH FRAMEWORK

A. Research Questions

To better understand the landscape of mobile service adoption as well as to fill the research gaps introduced in Section II, we thus aim to answer the following two research questions in this work:

RQ1: How individual differences like demographics and personality impact users' mobile service adoption behavior?

RQ2: How accurately can we leverage a user's mobile app data to conduct automatic user profiling?

B. Experiment Design

Figure 1 illustrates our research methodology. A mobile app is developed for data collection. For RQ1, we determine each participant's personal profile with an in-app questionnaire. We use Big Five-44 questionnaire [20] to assess personality traits because it balances well the tradeoff between the complexity of a questionnaire and the reliability of measured result. As we plan to conduct the study in Germany, the full questionnaire is translated into German according to Lang [36]. Participants rate all the personality measurements on a 1 to 5 scale, where 1 stands for totally disagree while 5 stands for totally agree. The ratings are calculated according to [20] and serve as ground-truth to represent participants' scores on the Big Five dimensions.

To measure the impact of user profiles on mobile service adoption, we select the top 500 most frequently installed apps in our data set and classify them into different mobile service categories. If a user has installed more than one app in one category, she will be regarded as an adopter of that category. Two tests are applied to evaluate the impact. First, an independent-samples t-test is conducted to compare the differences between mobile service adopters and non-adopters in terms of their gender, age, salary, and each of the Big Five dimensions. Bonferroni correction is applied to solve the problem of multiplicity. Second, we conduct a network analysis to test how much variance in forming mobile service adoption network can be explained by both demographics and personality traits.

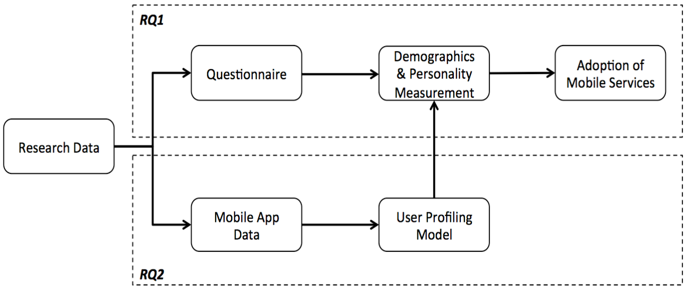


Figure 1. Overview of Research Design

For RQ2, we collect from each participant a snapshot of mobile app data. The Android operation system provides an API for developers to retrieve mobile app data from each device. The snapshot comprises four pieces of mobile app data for each app - the app's package name, when the app was first installed, when the app was last updated, and a string that represents the category the app belongs to on Google Play Store. Since the data snapshot is collected for each survey participant, we can use the data as independent variables to train a user-profiling model. The model can be applied in real-time to predict an Android user's demographics and Big Five personality traits.

In particular, we use the Random Forest algorithm [37]. It is suitable for our prediction model because the relationship between behavioral factors and personality traits are often non-linear. Random Forest is able to capture both linear and non-linear relationships and it usually performs better than other models in terms of prediction accuracy and model explanation. In addition, it almost cannot overfit [37], which makes models less sensitive to variance. We divide our data samples randomly into two sets: 70% samples in a training set and 30% samples in a test set to measure our model's prediction power. We used the statistic software R in our data analysis and applied Random Forest algorithm to generate the classification models. Ten-fold cross-validation is used to find out the optimal number of variables at each branch split.

C. *Input Features and Indicators of Predictive Models*

From reviewing the literature of current data-driven approaches of user profiling, we generate novel indicators that can be easily and directly computed from the four pieces of mobile app data introduced in the previous sub-section. The indicators that we believe would meaningfully represent potential difference in personality traits are described below. We emphasize that our focus in this study is not to understand the causality between these indicators and individuals' personality traits. Instead, we attempt to use readily accessible mobile app data to predict personality traits accurately.

Six genres of indicators can be calculated from the four pieces of mobile app data. The first genre is related to the number of app installs. Indicators are 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 [38]. The second genre is related to the number of app updates. The indicators of this genre are similar to those of the first genre. The third genre is related to the app install intervals. An install interval is defined as the number of days between two sequential app installation days. The indicators of this genre are the average install intervals, the standard deviation of install intervals, the entropy 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 forms the fourth genre of indicators.

The fifth genre is calculated based on the number of apps installed in each app category. The app categorization on Google Play Store on April 1, 2015 is taken as a standard. Google Play Store distinguishes between 44 categories (27 general and 17 game categories) which are taken as indicators in this study. The information about which category an app belongs to can be queried from a Google Play Store API with app package name as an input parameter. The last genre is the adoption of popular individual apps. From our data set, we picked up the top 100 most frequently installed apps and the top 100 most frequently installed games. If a user has installed an app, she will be regarded as an adopter of that app. In total, we come up with 78 indicators from the first five genres and 200 indicators from the last genre. All the 278 indicators can be easily calculated based on mobile app data and used for predicting a user's demographics and personality traits.

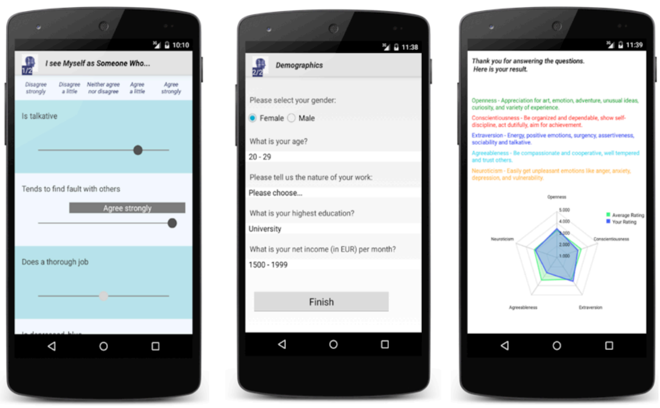
IV. IMPLEMENTATION

A. *Prototype*

We develop an app called "Persönlichkeitstest!" to collect the two types of data (questionnaire and mobile app data) at once. The app is described as a personality test game that presents the user after successful completion a feedback graph. Users give answers to the Big Five-44 measurement (as shown in Figure 2.a) and demographics (as shown in Figure 2.b) to compare her personality traits with the average of other people who have already participated in the game (as shown in Figure 2.c). The app presents a questionnaire as described above on the one hand and retrieves an Android device's mobile app data through the Google API on the other hand. Figure 2 shows the three main screens of the app.

When the app is opened for the first time, a random and unique string is generated to represent the corresponding participant. Meanwhile, a background process in the app is initiated, which reads the mobile app data from the device and sends it to our backend webserver. Once all the questions that measure personality or demographics are answered, the answers are transmitted immediately to our 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, we try to prevent users from providing their own devices to others who also want to do the test.

The app is listed on Google Play Store and we leverage Facebook pages, news feeds and posts to distribute the app. There is no monetary incentive for people to participant into the study. The only motivation to use the app is to compare one's own personality traits with the average of other people.



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

Figure 2. Screenshots of the Survey App

B. *Participants*

The 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 in Germany to recruit participants.

TABLE 1. CHARACTERISTICS OF PARTICIPANTS IN THE STUDY (N=2008)

Type	Range	In %	Type	Range	In %
Gender	Female	77.1%	Net Monthly Income (€)	>4000	0.8%
	Male	22.9%		3000-3999	1.6%
Age	10-19	21.7%		2000-2999	5.2%
	20-29	50.9%		1500-1999	13.2%
	30-39	17.9%		1000-1499	23.4%
	40-49	7.8%		500-999	23.2%
	50-59	1.4%		<500	17.9%
	N/A	0.3%		N/A	14.7%

During this period, our app promotion page was shown to 107,504 people and 2092 of them installed the app. The conversion rate for installation is around 2%. Among the 2092 people who installed the app, 2043 of them finished the full personality survey and 2008 of them completed in addition also the demographics questions. The distributions of the participants' demographics are shown in Table 1. The 2043 participants had on average 76 (S.D.=26) apps on their smartphones. Figure 3 (left) shows the distribution of the total number of apps installed per participant. After removing all the pre-installed apps, our participants had on average 31 (S.D.=22) apps installed by themselves on their smartphones. The distribution of apps that are not pre-installed per participant is shown in Figure 3 (right). In total, we observed 155,187 installed apps – out of which 63,688 were not pre-installed and thus eligible for our analysis.

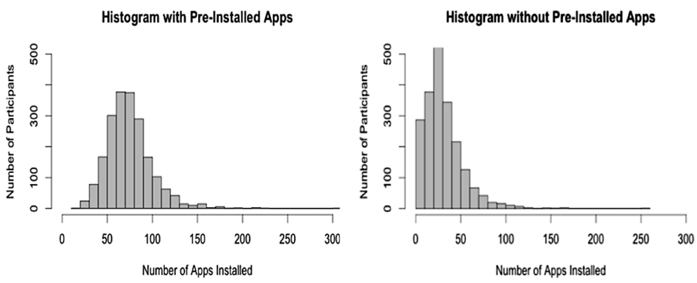


Figure 3. Distribution of Apps Installed per Participant (N=2043)

C. *Data Quality and Eligibility Checks*

To answer RQ1, participants who do not answer or select "No Answer" to the demographic questions are not taken into account when analyzing the impact of demographics on mobile service adoption. Similarly, participants who fail to answer all the questions that measure the Big Five personality traits were excluded in the personality related analysis to avoid inaccurate ratings. To generate a reliable prediction model to answer RQ2, three steps need to be further conducted. First, a lot of apps are pre-installed on by smartphone manufacturers. As such apps are not related to a user's behavior, they should be removed in the analysis. Second, users who install few apps or use her smartphone only recently should also be excluded because they have zeros on most of the indicators. Third, to make our results more interpretable, each quantitative data like age, salary, and the personality traits needs to be classified into several groups. To avoid problems generated from dichotomizing [39], we label quantitative values that belong to each personal characteristic as 'High', 'Medium', or 'Low' based on our sample distribution and suggestions from [39].

V. IMPACT OF DEMOGRAPHICS AND PERSONALITY

A. *Statistical Analysis*

After reviewing the top 500 most popular apps and categorizing them into the 16 pre-defined services, we assigned 1s and 0s to all the users to distinguish mobile service adaptors from non-adopters. Then we applied the independent-samples t-test with Bonferroni correction to test whether significant differences exist between adopters and non-adopters in their demographics and personality traits. The result is shown in Table 2. Each cell in the table represents the difference of mean ratings between 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 service adopters than men. Personality is measured on a 1 to 5 scale as described in Section III. 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.

Regarding demographics, gender has significant impact on the adoption of four services. Male in general is more likely to use recommendation, video, and news services but less likely to use photography service. Age is the most influential factor as it has significant impact on 11 out of the 16 mobile services. Young people are more involved in education and they typically spend more time on leisure activities like listening to music and polishing photos (especially for young woman). As they tend to travel around more frequently, they are also more likely to use transportation services. On the other hand, old people tend more to do budget planning or to use mobile banking services, and they usually spend more time on reading newspapers and magazines. In addition, salary has significant impact on six services. People with higher income are more likely to adopt mobile finance and mobile shopping services. Also, they tend more to use mobile recommendation services and news services, but less likely to use public transportations.

TABLE 2. DIFFERENCE BETWEEN ADOPTERS AND NON-ADOPTERS (N=2043)
(Sig. (2-tailed): * significant at p<.05; ** significant at p<.01)

Mobile Service	**Gender** (0-female; 1-male)	**Age** (years old)	**Salary** (€ per month)	**Personality** (rated on a 1-5 scale)
Finance	.02	3.62**	189.66**	.05 (C)
Reservation	-.04	.44	78.32	.07 (C)
Transportation	-.03	-2.23**	-106.62*	-.08* (C)
Product Searching	.00	.81	128.12*	.06 (C)
Photography	-.15**	-1.37*	-56.3	.11** (N) -.08* (C)
Recommendation	.07*	2.99**	196.2**	-.07 (A)
Location-based	.06	-1.83**	-57.41	-.11** (C)
Chat Messaging	-.07	1.96**	92.99	.09 (N)
Media & Video	.10**	-1.93**	13.73	-.08* (C)
Music & Audio	.05	-1.73**	-75.30	.07 (E)
Gaming	-.02	.42	-53.26	-.11** (E)
Shopping	-.05	2.47**	97.73*	-.07 (A)
Personalization	-.01	1.49*	-11.35	.13** (N) -.10** (E)
Social	-.03	1.09	57.53	-.06 (C)
News	.07*	1.98**	184.53**	.04 (A)
Education	.04	-1.73**	-75.30	-.09 (E)

Regarding the impact of personality traits, Conscientiousness has negative and significant effect on the adoption of services like photography, media & video, and location-based services. The results are consistent with the findings of previous research [4,22] that conscientious people are goal-driven thereby being less willing to use leisure services to have fun. Although transportation services are not leisure pursuits, we find that conscientious individuals still tend not to adopt them on mobile. It could be that more conscientious people travel less often, or they prefer to use such services on computers instead of on mobile devices. As an exploratory study, understanding the psychological reasons behind the adoption behavior is beyond our scope and requires future research. Previous research has contradictory findings regarding the impact of extraversion on game playing. Our result reveals a significant and negative correlation between them with a large sample size. Also, extraversion is negatively correlated with the adoption of mobile personalization service that is typically related to changing wallpapers, ring tones, icons and fonts. One explanation could be that less extraverted people tend to avoid social interactions thereby spending more time on personal activities. We also find that neuroticism is significantly and positively correlated with the adoption of mobile photography and personalization services. According to Devaraj et al. [40], neuroticism is negatively associated with perceived usefulness. Therefore, smartphone users with high neuroticism tend to become adopters of mobile services that are not perceived as useful, such as changing wallpapers and polishing pictures. On the other hand, openness to experience and agreeableness have no significant effect on smartphone users' mobile service adoption behavior.

Previous research reported significant correlation between personality traits and the adoption of finance, chatting and messaging, education, and music services. These relationships are also supported by our result if a normal independent-samples t-test is conducted without Bonferroni correction. To stay more rigorous and conservative, we do not report these findings. In the end, six out of the 16 mobile services have significant difference on at least one of the Big Five personality traits between adopters and non-adopters.

B. *Network Analysis*

Statistical analysis indicates what characteristics are significantly different between service adopters and non-adopters. Although demographic differences impact a larger number of mobile services than personality differences, we cannot conclude that demographics are more powerful than personality traits in explaining users' service adoption behavior. In order to test which individual difference is able to explain more variance exists in forming the patterns of users' mobile service adoption behavior, we in addition applied ERGM on a network that is generated from our collected data. The network is a two-mode network represented by a table with rows (the first mode) being all the users and columns (the second mode) being the 16 services. If a user has adopted a specific mobile service, the corresponding cell is set to 1 otherwise 0. We attached eight attributes (gender, age, salary, and the Big Five personality traits) to each user to understand which one contributes to explain the network structure, such as who use what services, and who is close to whom in terms of their service adoption patterns. After removing all the missing data and "No Answer" choices, we used data from 1711 users in the analysis.

The network density is 0.8%, which mirrors the current low adoption of mobile services among smartphone users. To get a better understanding of the network structure, we randomly picked up 100 users and plotted the corresponding network graph as shown in Figure 4 (left). The blue dots represent the 16 services while each red dot represents a user. The distance between two dots indicates the closeness between them. In the mobile service context, the closer the two red dots, the more similar their service 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 several mobile services, while other users have adopted only one or two services. Two users who are located on the edge of the graph are isolated – they have adopted none of the 16 mobile services.

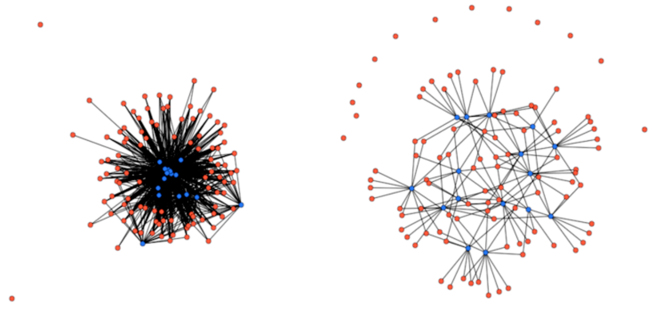


Figure 4. Comparison of Network Structure between Service Adoption Network and a Random Network

The right graph in Figure 4 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' service adoption network and the formation of such a network is not a random process.

TABLE 3. COMPARISON OF FIVE ERGM MODELS

(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	.184***	.913***	1.106***	.712**	1.288**
Isolates		18.11***	17.32***	15.62***	13.84***
Degree		15.16***	14.55***	13.05***	11.45***
Gender			-.325***		-.297***
Age			-.005***		-.006***
Salary			.001***		.002***
O				-.205***	-.188***
C				-.181***	-.254***
E				.100***	.102***
A				.183***	.167***
N				.106***	.085***
AIC	37953	36446	35982	35659	35265
Variance Explain	0.00%	4.04%	5.28%	6.14%	7.19%

We generated in total five ERGM models to explain the formation of the service adoption network. The result is presented in Table 3. Model 1 has only edges as its predictor and it serves as the null model. Model 2 takes the isolated users and the degree of all nodes as its predictors and it is able to explain 4.04% of the variance in the service adoption network. In addition to the endogenous variables, Model 3 includes the demographics of users as predictors and it is able to explain 5.28% of the total variance. On the other hand, Model 4 removes the demographics attributes but adds the Big Five personality traits as predictors. Consequently, it is able to explain 6.14% of the total variance. Model 5 includes all the endogenous and exogenous variables, and it can explain 7.19% of the variance exists in the network formation process. Both endogenous and exogenous variables are statistically significant in all the five ERGM models.

The network formation is a structured and stochastic process. Consequently, our models are not able to explain a lot of the variance exists in the network. Nevertheless, the percentage of variance explained is still on the same level of similar previous research [5]. Furthermore, the result shows that users' demographics and personality traits have significant impact on the formation of a service adoption network. More important, although not being focused in previous research, we conclude that personality traits are actually more powerful than demographics in explaining users' mobile service adoption behavior. RQ1 is thus addressed.

VI. AUTOMATIC USER PROFILING

According to the sample distribution, the majority of our users are between 20 and 29. Therefore, we classify them to be medium in age in our prediction. Consequently, users under 20 years old are labeled as 'Young' while users above 30 years old are labeled as 'Old'. Based on the sample distribution as well as the net income distribution in Germany, we labeled users who earn less than 1000 EUR per month to be in the 'Low' salary group, while users who earn more than 2000 EUR per month are classified to the 'High' salary group. The remaining users are labeled as 'Medium' in net salary per month. Each user is also classified into 'High', 'Medium', or 'Low' groups on each of the Big Five dimensions according to [39]. In addition, we cleaned our data set according to the approach described in Section 4.3. This results to 1531 useable data points (one represents a participant). We randomly assigned 70% data points into a training data set and the remaining 30% data points into a test set.

As illustrated in Table 2, demographics and personality traits have positive or negative impact on the adoption of different mobile services. Because more than half of the participants belong to the 'Medium' group in age and salary, as well as in each of the Big Five traits, a model that focuses 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 of more interest because they behave differently from the majority. Take our participants for example, the proportion of adopters of mobile personalization service among people who are high in neuroticism is 35% higher than that who are medium or low in neuroticism.

Consequently, instead of treating 'High', 'Medium', and 'Low' groups equally, we focus our Random Forest model on accurately classifying people in the 'High' and 'Low' groups of age, salary, and Big Five dimensions. Thus, in addition to female and male, we have in total 14 groups to model in our prediction, which are 'Low' in age (LiAge), 'High' in age (HiAge), 'Low' in salary (LiS), 'High' in salary (HiS), 'Low' in extraversion (LiE), 'High' in extraversion (HiE), 'Low' in neuroticism (LiN), 'High' in neuroticism (HiN), 'Low' in agreeableness (LiA), 'High' in agreeableness (HiA), 'Low' in conscientiousness (LiC), 'High' in conscientiousness (HiC), 'Low' in openness to experience (LiO), and 'High' in openness to experience (HiO).

TABLE 4. COMPARING PERFORMANCE OF PREDICTION MODELS

Target Group	Precision			Recall		
	Random Guess	Random Forest	Improve	Random Guess	Random Forest	Improve
Demographics						
Female	50.0%	90.9%	81.8%	50.0%	93.3%	86.6%
Male	50.0%	88.9%	77.8%	50.0%	27.9%	-44.2%
LiAge	32.2%	49.0%	53.1%	33.3%	58.5%	75.7%
HiAge	14.8%	35.7%	141.2%	34.6%	63.6%	83.8%
LiS	46.7%	53.3%	14.1%	38.3%	61.2%	59.8%
HiS	8.5%	42.9%	404.7%	33.3%	18.2%	-45.3%
Personality						
LiO	23.5%	29.1%	23.8%	32.1%	26.8%	-16.5%
HiO	27.5%	33.5%	21.8%	28.4%	60.0%	111.3%
LiC	28.1%	38.0%	35.2%	30.1%	48.5%	61.1%
HiC	27.5%	41.4%	50.5%	31.3%	45.6%	45.7%
LiE	21.5%	33.3%	54.9%	30.6%	21.6%	-29.4%
HiE	26.1%	38.3%	46.7%	31.3%	44.5%	42.2%
LiA	23.4%	27.5%	17.5%	34.6%	54.2%	56.6%
HiA	29.4%	36.8%	25.2%	31.9%	45.2%	41.7%
LiN	26.8%	33.5%	25.0%	34.5%	43.9%	27.2%
HiN	23.0%	31.7%	37.8%	33.3%	34.2%	2.7%
In Total						
Avg.	28.7%	44.0%	69.4%	34.9%	46.7%	34.9%

Table 4 demonstrates the prediction accuracy. There are in total 16 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 is random guess, which is defined as randomly allocating each user in the test set into one of the three groups ('High', 'Medium', or 'Low') with the same probability because prior probability distribution is unknown in many business settings. Our definition of random guess is similar to that of previous research [33].

Take the target group LiO for example, a random guess has a precision of 23.5% and a recall of 32.1% on the test data set. This means that, among all the users who are classified as 'Low' in openness to experience, only 23.5% of them are actually low while the remaining 76.5% are either medium or high in openness. On the other hand, the random model correctly identified 32.1% of all the users who are actually low in openness. Compared to the random model, our Random Forest prediction model is able to improve the precision by 23.8% to 29.1% at the cost of reducing the recall by 16.5%.

TABLE 5. PREDICTORS USED FREQUENTLY IN PREDICTION MODELS

Model	First Mostly Used	Second Mostly Used	Third Mostly Used
Demographics			
Female	# Apps in Sports	# Apps in Casual Game	# Apps in Photography
Male	# Apps in Sports	# Apps in Photography	# Apps in Casual Game
LiAge	Entropy Category	Entropy Monthly Update	Entropy Monthly Installs
HiAge	Entropy Category	Adoption of Snapchat	S.D. Install Interval
LiS	Entropy Category	Entropy Monthly Update	Entropy Monthly Installs
HiS	Entropy Monthly Update	Entropy Category	Maximum Update Interval
Personality			
LiO	# Apps in Photography	# Apps in Puzzle Game	# Apps in Music Game
HiO	Entropy Monthly Installs	Max Monthly Install	Entropy Monthly Update
LiC	Entropy Monthly Update	Average Update Interval	Entropy Category
HiC	Max Monthly Install	Entropy Monthly Update	Average Update Interval
LiE	# Apps in Education	# Apps in Education Game	# Apps in Shopping
HiE	Entropy Category	Average Update Interval	Entropy Monthly Installs
LiA	Mean Install Interval	Average Install Interval	Mean Monthly Update
HiA	# Apps in Music Audio	# Apps in Shopping	# Apps in Books Reference
LiN	Entropy Category	S.D. Update Interval	Entropy Monthly Update
HiN	Entropy Monthly Update	Average Update Interval	S.D. Update Interval

Our random forest models are able to improve the prediction precision by 69.4% and improve the recall rate by 34.9%. Our models perform extremely well in predicting demographics, especially for old people and for people with high net income. Regarding the prediction of personality traits, conscientiousness and extraversion can be most accurately predicted. In terms of recall rate, our models perform best on predicting age, agreeableness, and conscientiousness. Overall, our proposed models are able to achieve a similar or higher level of precision and recall compared to that of previous studies [22,27].

To get an overview about what predictors are important in our predictive models, we present the top-three most frequently used indictors in each of the 16 models in Table 5. As shown in the table, some specific types of apps are most frequently used in distinguishing female from male. Regarding the prediction of other groups, the entropy of app categories, monthly app installs and updates, as well as the app installation and update intervals are the most frequently used features by our models in the classification. Thus, RQ2 is answered.

VII. DISCUSSION AND CONCLUSION

As one of the first large-scale studies, we showed that users' demographics and personality traits have a significant impact on their mobile service adoption behavior. In addition, we revealed that although neglected in academia and practice, personality traits are more powerful in explaining the variance of people's mobile service adoption behavior than demographics. Previous literature that analyzes the impact of personality on mobile service adoption typically has a small number of samples with a limited number of apps under study. This might be the reason why researchers drew contradictory results in similar settings. Our large-scale field study provides reliable arguments to the support of some previous findings and the rejection of others. It goes beyond intention and leverages actual behavioral data of app installation logs to examine mobile service adoption.

Also, we provide a feasible, scalable and automatic data-mining approach for user profiling based on readily available information like a user's snapshot of app installation and update events. By leveraging our approach, demographics and personality traits become predictable for everyone who uses a smartphone without the pains of answering survey. On average, our predictive models perform around 70% and 35% better than random guess in terms of precision and recall, respectively. Our approach can be integrated into any mobile app without asking for additional user permission and it complies with privacy laws and regulations in Europe.

For practitioners, the contributions of our work are also two-fold. First, depending on the type of a mobile service, companies will know who are the potential adopters of the service in real-time. For instance, an app that provides mobile education service should target on less conscientious young people whereas a mobile financial service app should set old people with high net income and high conscientiousness as its target group. Second, our predictive models can serve as a tool to enable other business intelligence applications. For instance, based on the result of automatic user profiling, app publishers are able to conduct more effective personalized marketing as well as to cross-sell other apps to potential adopters. Moreover, different persuasive technologies and/or human-computer interaction design principles could be used based on different demographics and personality traits to further improve adoption.

Although powerful, both retrieving mobile app data and conducting personalized marketing might trigger users' concern about privacy. We suggest app publishers who leverage our approach to state explicitly to 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 to enable personalized in-app recommendations and other types of user interaction. Nevertheless, compared to existing approaches that require the installation of specific surveillance apps to trace the content of emails and social activities, our approach should lessen users' privacy concerns because we use only a snapshot of app events and do not trace the content of each user's activity in an app.

There are several limitations of this paper, which provides opportunities for future research. First, although we have a large sample size compared with previous research, the samples are unbalanced in terms of age, gender and income. Future research is thus called to confirm our findings with more representative samples. Second, we use the installation of apps to determine whether a user is a mobile service adopter or not. However, it could happen that some users have installed specific 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 service 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. Third, we find some interesting associations between a user's characteristic and her adoption of different mobile services. Some findings are consistent with previous research while others are counter-intuitive. As an exploratory study, we do not focus on the psychological reasons behind the relationships, but future research could address the gap to provide more solid understanding about mobile service adoption. Furthermore, we used the top 100 most popular mobile apps and games to generate user-profiling models. Due to the fact that the list of popular apps changes over time, our model needs to be retrained periodically. Future research could investigate into the retrain interval and examine how it influences the prediction accuracy. Whether it is possible to get rid of the impact of specific apps and to further improve the prediction accuracy is also an interesting topic that calls for future research.

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