TOWARDS UNDERSTANDING THE IMPACT OF PERSONALITY TRAITS ON MOBILE APP ADOPTION – A SCALABLE APPROACH

Research in Progress

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Abstract

Smartphones are the most personal devices. The kind of apps we install are therefore closely linked to our habits and personality. In this research-in-progress paper, we aim to provide two key contributions. First, we aim to advance the body of knowledge in technology adoption research by explaining adoption of specific mobile apps by using the Big Five personality traits. Second, we provide a scalable method of deriving personality traits based on easily accessible data. We show that it is possible to determine a user's personality in reasonable accuracy by evaluating her history of app installations and update events.

Keywords: Mobile App Adoption, Big Five, Adoption Research, Personality Traits.

1 Introduction

Smartphones are the most personal devices we own (Scornavacca and Barnes 2006) and carry around with us all day. The number of available mobile apps in the major app stores now easily exceeds one million – providing an app for almost any situation of our life (Statista 2014). Consequently, the kind of apps we install and use could be closely linked to our interest, demographics, and personality (Ryan and Xenos 2011; Seneviratne et al. 2014; Shen et al. 2015). As shown in other research fields (Bettman 1979; Sproles and Kendall 1986), personality traits can have a significant impact on our decision making. However, personality was largely ignored in information system (IS) adoption research but could have a significantly impact on explaining people's adoption behavior (McElroy et al. 2007). Researches in recent years have already shown some correlations between individuals' personality traits and their adoption of Internet (Landers and Lounsbury 2006; McElroy et al. 2007) and specific apps like Facebook (Ryan and Xenos 2011) and Foursquare (Chorley et al. 2015). As one of the first studies, we therefore aim to study the influence of personality on the adoption of different types of mobile apps.

Once the correlation between personality and the adoption of different types of mobile apps is identified, practitioners like app publishers will have a better understanding about whom to target in their marketing campaigns. However, each individual's personality traits remain unknown until being measured. Current questionnaire-based approaches to measure each individual's personality traits are limitedly effective and scalable (Montjoye et al. 2013). To cope with the vast amount of different mobile apps, we come up with a novel approach to derive personality traits by leveraging easily accessible mobile app data like a snapshot of one's mobile app installation and update events, because previous research shows that individual's app installation behavior has patterns and is predictable (Pan et al. 2011).

Therefore, the contributions of this work are two-fold: First, we provide insights into how the adoption of selected mobile apps can be explained by the Big Five personality traits. We use a state-of-the-art questionnaire-based approach for determining the personality traits. Second, we provide a scalable approach for determining the Big Five personality traits of a user based on her readily available mobile app data. We use the determined personality traits as ground-truth and show that the questionnaire-based approach can be replaced with this highly scalable and efficient method that is required to study mobile app adoption adequately.

The rest of the paper is structured as follows. Section 2 reviews related work on the impact of personality on IS adoption, as well as data-driven approaches to measure personality. Section 3 introduces the research method and Section 4 presents the results. Finally, the paper concludes with a discussion of the limitations and an outlook on future work.

2 Related Work

2.1 Previous Researches on IS Adoption and Personality Traits

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. The theories that are widely applied in adoption researches are the Theory of Reasoned Action (TRA) (Ajzen and Fishbein 1980), the Theory of Planned Behavior (TPB) (Ajzen 1985), Technology Acceptance Model (TAM) (Davis 1989), the Decomposed Theory of Planned Behavior (DTPB) (Taylor and Todd 1995), the Unified Theory for the Acceptance and Use of Technology (UTAUT) (Venkatesh et al. 2003; Venkatesh, Thong, et al. 2012), and the Innovation Diffusion Theory (IDT) (Rogers 1995).

Although these theories were developed from different perspectives, there are some overlaps and shared constructs. Venkatesh et al. (2012) compared these theories and listed all the core constructs that could influence adoption. Among all of these constructs, previous research on adoption of applications (Arts et al. 2011; Dwivedi et al. 2011; Moore and Benbasat 1991; Venkatesh and Susan 2001; Venkatesh, Brown, et al. 2012) especially the ones in the mobile context (Choudrie et al. 2014; Dass and Pal 2011; Hong et al. 2006; Verkasalo et al. 2010) indicated that constructs like relative advantage (Rogers 1995), 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) could have direct impact on the adoption of mobile apps.

On the other hand, researches in psychology showed that the five-factor model (FFM) (Mccrae and Costa 1987) of personality was a broader taxonomy for personality-related issues and it contributed a rich conceptual framework for integrating all research findings in personality psychology (Digman 1990). The most widely used five factors are called the Big Five personality traits, which consist extraversion, neuroticism, agreeableness, conscientiousness, and openness to experience (John and Srivastava 1999). Extraversion is frequently associated with being sociable, gregarious, talkative, and active (Eysenck 1947); Neuroticism includes traits like being anxious, depressed, worried, and insecure (Eysenck 1947); Common traits associated with the third dimension, namely agreeableness, refer to being courteous, trusting, cooperative, and tolerant (Norman 1963); Conscientiousness represents traits such as being careful, thorough, responsible, organized, and planful (Norman 1963); The last dimension, openness to experience, is typically associated with being imaginative, curious, broadminded, and independent (Costa and McCrae 1985). Personality traits can have a significant impact on our decision-making (Bettman 1979; Sproles and Kendall 1986). However, most research related to personality focus on job performance or career development (Penney et al. 2011).

2.2 Impact of Personality Traits on IS Adoption

Most IS adoption research on individual level focused on analyzing the impact of the above-mentioned constructs on different innovations. However, as revealed by Wejnert (2002), relatively little 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 studies, Menzel (1960) showed that self-confidence and risk-taking characteristic of individual actors affected their acceptance to novel information and applications. Similarly, multiple researchers (Agarwal and Prasad 1998; Brancheau and Wetherbe 1990; Leonard-Barton and Deschamps 1988) argued that personal innovativeness and openness positively influenced an individual's adoption of new technologies.

With the wide adoption of the Internet, more researchers tried to analyze the impact of the Big Five personality traits on general Internet adoption and use. For instance, extraverts prefer face-to-face interaction thereby spending less time on using the Internet (Landers and Lounsbury 2006), especially for online social activities like chat rooms (Hamburger and Ben-Artizi 2004). Nevertheless, they use the Internet as a tool to acquire information and share with others (Amiel and Sargent 2004). Conscientiousness 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 (Landers and Lounsbury 2006). People who are higher in neuroticism tend to limit their online time on playing games (Swickert et al. 2002) but spend extensive time on the Internet to gain a sense of belonging (Amiel and Sargent 2004). Agreeable people use emails less frequently than others (Swickert et al. 2002) but they on average spend more time online since they are more persistent in online investigations (Landers and Lounsbury 2006). Open-to-experience people are in general attracted to online activities because they are curious and frequently seek for new adventures (Tuten and Bosnjak 2001). McElroy et al. (2007) concluded that individual's personality traits explained more variances in her use of Internet and online selling behavior than her cognitive style. In addition to general Internet use, the authors called future research to focus on examining the impact of personality on more specific types of IS adoption and use.

Following the trend of proliferation of Smartphone apps, researchers started to investigate the correlation between personality traits and the adoption of specific apps. For instance, Ryan and Xenos (2011) claimed that extraverts are more likely to become "Facebook" users than conscientious individuals. Chittaranjan et al. (2013) found correlations between personality and the use of apps like "Office", "Calendar", "YouTube", "Mail", etc. Similarly, Chorley et al. (2015) revealed that the Big Five personality traits contributed to explain individual differences in using location-based social network like "Foursquare". The authors found significant correlation between conscientiousness, openness, neuroticism and the usage of "Foursquare". Nevertheless, regarding the large number of available apps, different types of apps need to be investigated to confirm the generality of those findings.

Personality was largely ignored in IS adoption research but could have a significant impact on explaining people's adoption behavior, research thus should examine the impact of personality on more specific types of IS adoption (McElroy et al. 2007). Consequently, our work tries to answer:

> ***RQ1:*** *How well can the adoption of a specific mobile app be explained by its users' personality traits?*

2.3 Data-Driven Approaches of Measuring Personality

An individual's personality traits like the Big Five are typically measured based on questionnaires (Barrick and Mount 1991; John and Srivastava 1999; Judge et al. 2002; Gosling et al. 2003). Instruments such as the NEO Personality Inventory, Revised (Costa and McCrae 1992), Trait Descriptive Adjectives (Goldberg 1992), 60-item NEO Five-Factor Inventory (Costa and McCrae 1992), and the Big Five-44 Inventory (John and Srivastava 1999) were developed for measurement. However, in spite of the ubiquity of questionnaires in research and practice, there are several implementation problems. 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 a questionnaire-based approach is only limitedly scalable.

Researchers recently proposed data-driven approaches to overcome the limitations of the questionnaire-based approach. For instance, some researchers (Chittaranjan et al. 2013; Montjoye et al. 2013; Pan et al. 2011; Trestian and Nucci 2009) used mobile meta-data such as logs of phone calls, SMSs, and location information to predict a mobile phone user's personality, while others used acoustic measurements (Pianesi et al. 2008) and social network content (Chin and Wright 2014; Minamikawa et al. 2012) to conduct user profiling. Similarly, instead of sending out questionnaires, Han et al. (2014) leveraged face recognitions to estimate an individual's demographics. 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 very promising, they have a few drawbacks. First, part of the data used in the studies 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. Third, the approaches require a long history of events (typically half a year) to provide reasonable results.

As Smartphones are owned by individuals (Scornavacca and Barnes 2006) and the adoption and use of mobile apps could be correlated with individuals' personality traits (Ryan and Xenos 2011; Shen et al. 2015), we come up with a novel approach to derive personality traits by leveraging easily accessible information like app installation and update events (called mobile app data afterwards). However, the feasibility of using such an approach depends on the accuracy of modeling the personality traits with the mobile app data. Thus, our second research question is:

RQ2: *How accurate can mobile app data model a user's personality traits?*

3 Research Method

3.1 Data Used to Answer Research Questions

The precondition of answering the research questions is to retrieve the mobile app data from each Smartphone. The Android operation system provides an API to retrieve logs about app installation and update events on an Android device. No additional software like a system or network surveillance program needs to be installed on a device. Technically, a third party app neither needs any special system requirements, nor requires extra user permission (Seneviratne et al. 2014).

Three pieces of mobile app data are used in the study: A list of all the apps installed on a device, a timestamp for each app that indicates when the app was installed, and a timestamp for each app that indicates when the app was latest updated. By parsing and combining the three pieces of data, twelve variables can be calculated, which are: The total number of apps installed, the total number of apps installed per month, the maximum number of apps installed in a month, the number of months since when the first app was installed, the number of distinct days a user installs app(s), the number of days since when the latest app was installed, the number of days since the median installation day, the number of installation days per month, the number of distinct days a user updates app(s), the number of days since when the latest app was updated, the number of days since the median update day, and the number of update days per month.

Additional variables like the number of days since the first and third quartile of installation days can also be calculated to provide insight on the distribution of app installations over time. However, as a preliminary study with small sample size, adding more variables does not contribute to improve the prediction power of a model and it will increase the possibility of over-fitting (James et al. 2014). Therefore, only mobile app data that can be directly and easily computed are taken into account, which results to the scope of the above twelve variables. We emphasize that our focus is not to understand the causality between these variables and individuals' personality traits. Instead, we attempt to use easily accessible mobile app data to predict personality traits.

3.2 Research Design

In the first step, an Android app that collects mobile app data on the one hand, and presents a questionnaire to measure the Big Five personality traits on the other hand is developed. The Ten-Item Personality Inventory (TIPI) is used for the personality measurement because it well balances the trade-off between the complexity of a questionnaire and the reliability of measured result (Gosling et al. 2003). Participants rate all the measurements on a 1 to 7 scale, where 1 stands for totally disagree while 7 stands for totally agree. The ratings are calculated according to Gosling et al. (2003) and used as ground-truth to represent participants' scores on each of the Big Five dimensions. Furthermore, demographics like age, gender, salary, educational level, household size and average hours spent on mobile apps are also collected. We confirm to the participants that all data will be analyzed anonymously. We recruit participants and distribute the app installation file to them through sending out group-emails to students in several universities in both Switzerland and Germany. Each participant has to install the app (to provide her mobile app data) first, and then answer the questionnaire (to provide ground-truth of her personality traits) to finish the process. When the questionnaire is finished, both pieces of data will be transmitted to a backend server with a random but unique code generated in the app to represent each participant.

After the data collection phase, we select several apps and compare the differences between app adopters and non-adopters on their personality traits to answer RQ1. We choose the most popular apps on the Android market and then exclude all preinstalled apps as well as non-internationally used ones to cope with potential selection biases. In addition, we exclude all apps whose number of adopters is less than 20% of non-adopters to have a more balanced ratio of adopters and non-adopters. We then use each participant's mobile app data to model her Big Five personality traits to answer RQ2. Linear regression method is used to test the modeling accuracy. The twelve variables described in Section 3.1 are included in the modeling. As using too many independent variables will lead to an over-fitted model thereby lessening the model's ability of making prediction, the backward regression approach is used instead (James et al. 2014) in the data analysis.

4 Result Analysis

4.1 Participants

The study was conducted in November 2014. A total of 22 people participated in the study and distributions of their characteristics are shown in Table 1.

Respondents	***Range***	***In %***		***Respondents***	***Range***	***In %***
Age	M=27.7 (SD=4.6)	100%		*Highest Education*	University	73%
Household Size	M=2.7 (SD=1.8)	100%			High School	27%
Daily Online Hours	M=7.0 (SD=4.5)	100%		*Net Monthly Salary (€)*	> 5000	9%
Gender	Male	77%			4000 – 4999	14%
	Female	23%			3000 – 3999	5%
Job Type	Full-time	50%			2000 – 2999	14%
	Part-time	9%			1000 – 1999	31%
	Self-employed	9%			< 1000	23%
	Student	32%			No Answer	4%

Table 1. Characteristics of Participants in the Study (N=22)

4.2 Explain Adoption with Personality Traits

Based on the criteria described in Section 3.2, thirteen apps were selected in the study. Table 2 shows the results of an independent sample t-test of the Big Five dimensions between adopters and non-adopters of the selected apps. The numbers in each cell refer to the t-values. The personality traits are extroversion (E), neuroticism (N), agreeableness (A), conscientiousness (C) and openness to experience (O).

App ($N_{adopter}$, $N_{non-adopter}$)	***E***	***N***	***A***	***C***	***O***
Whatsapp (15, 7)	1.564	**2.525****	**3.898****	0.008	1.306
Facebook (15, 7)	-0.548	-1.475	-1.152	-0.747	-1.572
Skype (11, 11)	0.963	-1.430	-0.528	0.087	0.900
Facebook Messenger (10, 12)	**2.286***	-0.384	1.168	0.956	0.323
Twitter (8, 14)	-1.084	0.119	**-2.810****	-0.164	-2.036
Evernote (7, 15)	0.708	-0.174	0.215	**2.040**	-0.413
Adobe Reader (7, 15)	-0.708	-0.174	-0.694	1.355	0.867
LinkedIn (6, 16)	1.548	1.463	0.193	**2.688***	0.261
Tripadvisor (6, 16)	0.999	-0.021	-0.043	1.392	1.690
Shazam (5, 17)	1.984	0.148	0.171	1.456	1.295
Instagram (4, 18)	**2.607***	1.202	0.988	1.836	1.764
Telegram (4, 18)	-0.188	**1.844**	-0.675	0.578	0.630
eBay (4, 18)	1.374	0.347	-0.397	1.300	0.895

*Table 2. Personality Difference of Adopters and Non-Adopters on Popular Apps (N=22, Sig. (2-tailed): * significant at p<.05; ** significant at p<.01)*

Adopters of "Whatsapp" tend to be significantly less emotionally stable *[t(20)=2.525, p<.05, r=.49]* but much more agreeable *[t(20)=3.898, p<.01, r=.66]*. In other words, people who have not installed "Whatsapp" tend to be more relaxed and stable but also more egocentric and skeptical towards others. This is consistent with the fact that "Whatsapp" being the primary mobile communication platform in most European countries with non-adopters being the exception. Thus peer pressure and network effects can force most users into adopting "Whatsapp" with only egocentric and skeptical people remaining resistant. Adopters of the "Facebook Messenger" app tend to be more extroverted than non-adopters *[t(20)=2.286, p<.05, r=.45]*. Facebook has recently disintegrated the messaging feature from its app. Actual adopters of the new stand-alone messaging app tend to be more extroverted, communicative and active. In addition, "Twitter" adopters tend to be less agreeable and more egocentric *[t(20)=-2.810, p<.01, r=.53]*, while users of "Evernote", a cloud based note-taking software, and especially "LinkedIn", a professional business social network, are much more organized and considerate, with the later value being significant *[t(20)=2.688, p<.05, r=.52]* while the former is near to being significant at the 5% level *[t(20)=2.040, p=.055, r=.42]*. Furthermore, users of "Instagram", a photo sharing app, are on average more extroverted *[t(20)=2.607, p<.05, r=.50]*, thus feeling a stronger need for sharing pictures with family and friends than non-adopters. Although not significant, people who use the "Telegram" app, a supposedly more secure messaging alternative to "Whatsapp", tend to be more concerned, nervous and insecure *[t(20)=1.844, p=.08, r=.38]*. Table 2 provides evidence that the adoption of specific apps could be explained by personality. Thus, RQ1 is addressed.

4.3 Accuracy of Modeling Personality Traits

Table 3 shows the result of modeling participants' personality traits with their mobile app data by applying the backward regression approach. The model with the least adjusted R-squared was selected to prevent over-fitting and each variable used in that model is represented as a black circle.

Variables Calculated from Mobile App Installation Data	***E***	***N***	***A***	***C***	***O***
Total number of apps installed	•				•
Total number of apps installed per month	•			•	•
Maximum number of apps installed in a month	•	•	•	•	•
Number of months since when the first app was installed	•				•
Number of distinct days a user installs app(s)	•			•	•
Number of days since when the latest app was installed		•	•	•	•
Number of days since the median installation day		•	•		
Number of installation days per month	•			•	•
Number of distinct days a user updates app(s)		•			
Number of days since when the latest app was updated		•			•
Number of days since the median update day		•	•		•
Number of update days per month	•		•	•	•
R^2	.688	.748	.592	.888	.709
Adjusted R^2	.532	***.647***	.464	***.843***	.444

Table 3. Result of Modeling Personality Traits with Mobile App Data (N=22)

The result showed that conscientiousness was well modeled with around 85% of the variance being explained, followed by neuroticism with 65%. Compared to other traits, the accuracy of modeling openness and agreeableness was lower, but it could still explain around 45% of the variance. Regarding the usage of the variables in the models, the maximum number of apps installed in a month was used in every model, followed by the number of update days per month and the number of days since the latest app installation. The number of distinct days when a user updates her apps was used only once in modeling neuroticism.

With a small sample size, it is difficult to confirm the predictive power of our models through cross-validation. However, the result strongly indicates the potential of using mobile app installation data to predict personality traits, especially conscientiousness and neuroticism. Thus, RQ2 is addressed.

5 Discussion, Limitation and Future Work

By comparing the personality traits of adopters and non-adopters of thirteen mobile apps, our work sheds light on explaining adoption of specific apps by using the Big Five personality traits thereby advancing the body of knowledge in adoption research. Furthermore, we provide a feasible and scalable way to estimate one's personality traits based on a snapshot of her app installation and update events.

For practitioners, our work provides an opportunity of identifying potential adopters of specific apps by predicting their personalities with easily accessible data. Take app publishers for example, who can leverage this approach to better understand current app users thereby conducting more effective personalized marketing (Dorotic et al. 2012) as well as cross-selling other apps to potential adopters. In addition, different persuasive technologies and/or human-computer interaction design principles could be used based on different personality traits to further improve adoption (Brinkman and Fine 2005; Halko and Kientz 2010). 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). We suggest app publishers that leverage the approach to 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 installation data and receiving personalized in-app recommendations and promotions. However, compared to existing approaches that trace the installation of specific apps and phone call logs, our prediction model should lessen privacy concerns because only aggregated data like the total number of apps installed and the frequency of installation is used in our approach.

There are several limitations of this paper, which provides opportunities for future research. First, we acknowledge that the sample size of this work is relatively small and participants are not representative of the population in terms of gender, age, and salary. In a next step, we plan to recruit more than thousand participants in Europe to provide more valid and reliable results. Second, current work uses a simple regression method to model personality traits with mobile app data. With a larger sample in the planned future study, more sophisticated data mining methods like Support Vector Machine (SVM) or neural network can be applied to increase model fit. Cross validation should be applied to estimate the prediction power of the resulting models. Furthermore, although limited by a small number of samples and apps, our work already showed the potential impact of personality traits on the adoption of different types of mobile apps. However, further research is called to systematically categorize apps into different groups and then analyze what personality trait can influence the adoption of what type of apps. Moreover, previous research revealed that personal characteristics like innovativeness have stronger impact on early adopters than later adopters (Brancheau and Wetherbe 1990). Consequently, we suspect the influence of personality traits on a specific app would change over time. Such change is also interesting and worth being studied in depth in the future. A final limitation is that we used the TIPI to measure each participant's Big Five scores. When analyzing the data, we noticed that few participants rated inconsistently on the two questions that measure the same dimension. To further enhance the reliability of our ground-truth on personality, we will use a more reliable Big Five-44 measurement (John and Srivastava 1999) in our planned large-scale study.

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