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 apps in the major app stores now easily exceeds one million – providing an app for almost any situation of our life. The kind of apps we install are therefore closely linked to our habits, personality, and interests. As shown in other fields (Sproles and Kendall 1986; Bettman 1979; Maynes 1976; Wells 1974), personality traits can have a significant impact on our decision-making. As one of the first studies, we therefore aim to study the influence of personality traits on mobile app adoption.

Technology adoption research is one of the most mature fields in information systems and has provided great insights into the key factors of explaining adoption decisions on different levels. However, the methods to measure the factors mostly depend on questionnaire-based approaches and pre-date the Smartphone age. In order to cope with the vast amount of different mobile apps, more scalable approaches are needed.

The contributions of our paper are therefore 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 installation data. We use the insights from the first study 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 in the fields of adoption research, personality traits, and data-driven approaches. Section 3 introduces the main research questions and methodology. Section 4 presents the results for the first research questions and second research question. Finally, the paper concludes with a discussion of the limitations and an outlook on future work.

2 Related Work

2.1 Previous Researches on Innovation Adoption

Adoption and diffusion research is regarded as one of the more mature research areas in the information system (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), 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 the above 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 researches 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 could have direct impact on the adoption of mobile apps.

Most adoption researches on individual level focus on analyzing the impact of those constructs on different innovations. Few researches revealed that personality and characteristics could also influence the adoption of innovation. For instance, 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 positively influenced an individual's adoption of new technologies. However, as revealed by Wejnert (2002), relatively few researches 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). Therefore, the impact of personality on adoption warrants further study.

2.2 Taxonomy and Measurement of Personality Traits

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 (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, is typically associated with being imaginative, curious, broad-minded, and independent (Costa and McCrae 1985).

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 like 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 the 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. Consequently, additional research is required to overcome the deficiencies of the questionnaire-based measurement of personality in a scalable and more efficient way.

2.3 Data-Driven Approaches of Measuring Personality

Researchers recently propose data-driven approaches to overcome the limitations of the questionnaire-based approaches. For instance, some researchers (Chittaranjan et al. 2013; Montjoye et al. 2013; 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). They also 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 of those approaches require the installation of additional data logging software on a mobile phone. Third, the approaches are requiring a long history of events (typically half a year) to provide reasonable results.

3 Research Method

3.1 Research Questions

To address the previously outlined research gaps, we propose a two-step model that is based on scalability of easily available data while being validated with a state-of-the-art questionnaire approach.

Based on the previous research, we have seen that individuals' personality and characteristics could have an influence on the adoption decisions (Weimann and Hans-Bernd 1994; Wejnert 2002). Hence different personality traits might lead to the adoption of different mobile apps. For instance, adopters of social media apps might be more social, talkative, and willing to share. Therefore, individuals with high extraversion traits are more likely to become adopters of such apps. Similarly, individuals with high conscientiousness might tend more to install personal finance apps because they are more organized and planful. Consequently, we try to answer:

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

As discussed in Section 2.3, current data-driven approaches have deficiencies in predicting individuals' personalities. Thus, we come up with a novel approach to derive personality traits by leveraging easily accessible information such as the mobile app installation data. However, the feasibility of using such an approach depends on the accuracy of modeling the Big Five traits with mobile app installation data. Thus, our research question is:

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

Figure 1 demonstrates the relationship between our two research questions.

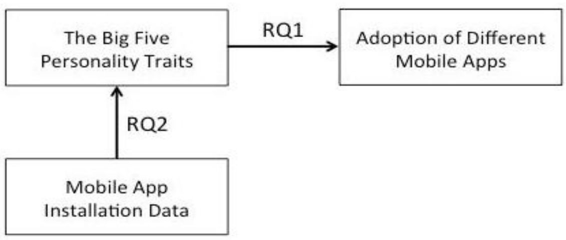

Figure 1. Relationship between Research Questions

3.2 Data Used to Answer Research Questions

The precondition to answer the research questions is to retrieve the mobile app installation data from each device. The mobile operation system Android provides a useful functionality in one of its standard APIs: It allows apps from third parties to retrieve information about app installation 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.

Three pieces of mobile app installation 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: 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, and number of update days per month.

Additional variables like number of days since the first and third quartile of installation days can 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. Thus, we limit the mobile app data in this study to the scope of those twelve calculated variables.

3.3 Research Design

In the first step, an Android app that collects mobile app installation data (the bottom box in Figure 1) is developed. A questionnaire that measures the Big Five personality traits (the middle box in Figure 1) is then integrated in the app. The Ten-Item Personality Inventory (TIPI) is used for the personality measurement because it is brief and still provides acceptable reliability (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, household size and average hours spent on mobile apps are also collected. Although mobile app installation data is 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 emails. Each participant has to install the app (to provide her mobile app installation 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 our backend server with a unique code generated in the app to represent each participant.

After the data collection, 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 with small number of adopters in order to have a more balanced ratio of adopters and non-adopters. We then use each participant's mobile app installation data to model her Big Five personality traits to answer RQ2. Linear regression method is used to test the modeling accuracy. The 12 variables described in Section 3.2 are directly retrieved or calculated from the raw mobile app installation data, therefore, all of them can be used to model each individual's personality traits. However, using too many independent variables will lead to an overfitted model thereby lessening the model's ability of making prediction. To cope with the problem, 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. We recruited participants through sending out group-emails to students in several universities in Europe. Recipients were encouraged to forward the email to their friends. The Android app installation file was attached in each email. A participant needs to install the app on her Android phone, open the app and then answer the questionnaire. 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%			Total	100%
Gender	Male	77%		*Net Monthly Salary (€)*	> 5000	9%
	Female	23%			4000 – 4999	14%
	Total	100%			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%
	Total	100%			Total	100%

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

4.2 Explain Adoption with Personality Traits

Based on the selection criteria described in Section 3.3, thirteen apps were selected in the study. Table 2 illustrates 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 correspond to the t-values. The personality traits are extroversion (E), neuroticism (N), agreeableness (A), conscientiousness (C) and openness (O).

The most popular app is "Whatsapp", which enables user to send free text and voice messages as well as pictures, videos or location information to contacts given they have an active Internet connection. The second most adopted app is "Facebook", followed by "Skype" and the "Facebook Messenger".

There are a couple of interesting observations in the result. First, adopters of "Whatsapp" tend to be significantly less emotionally stable but much more agreeable. Or 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 resisting. Another interesting and statistically significant observation is that adopters of the "Facebook Messenger" app tend to be more extroverted than non-adopters. 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, 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 at the 5% level while the former is pretty near to being significant at the 5% level. Furthermore, users of "Instagram", a photo sharing community, are on average significantly more extroverted, 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.

Table 2 provides clear evidence that the adoption of specific apps could be explained by users' personality traits. Thus, RQ1 is addressed. We recognized that in our current sample the majority of the popular apps were social apps, which could lead to a bias in the analysis. Consequently, we plan to increase our sample size and enlarge the types of apps under consideration in a future study.

App ($N_{adopter}$, $N_{non\text{-}adopter}$)	***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 13 Selected Apps (N=22, Sig. (2-tailed): * significant at p<.05; ** significant at p<.01)*

4.3 Accuracy of Modeling Personality Traits

Table 3 shows the result of modeling participants' personality traits with their mobile app installation data by using the backward regression approach. The model with the least adjusted R-squared was selected and each variable used in that model is represented as a black circle. The corresponding R-squared and adjusted R-squared were also reported.

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 13 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 an individual's personality traits based on her history of app installations 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, they can leverage the 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. 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). As a result, 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. They should also give users the right to opt-in for providing the mobile app installation data and receiving personalized in-app recommendations and promotions.

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 1000 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 installation data. With a larger sample in the planned future study, more sophisticated data mining methods like Support Vector Machine (SVM) or neural networks can be applied to increase the model fit. Cross validation can 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 detected 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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