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Understanding the impact of personality traits on mobile app adoption – Insights from a large-scale field study

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ABSTRACT

The sheer amount of available apps allows users to customize smartphones to match their personality and interests. As one of the first large-scale studies, the impact of personality traits on mobile app adoption was examined through an empirical study involving 2043 Android users. A mobile app was developed to assess each smartphone user's personality traits based on a state-of-the-art Big Five questionnaire and to collect information about her installed apps. The contributions of this work are two-fold. First, it confirms that personality traits have significant impact on the adoption of different types of mobile apps. Second, a machine-learning model is developed to automatically determine a user's personality based on her installed apps. The predictive model is implemented in a prototype app and shows a 65% higher precision than a random guess. Additionally, the model can be deployed in a non-intrusive, low privacy-concern, and highly scalable manner as part of any mobile app.

1. Introduction

Smartphones are the most personal devices people own (Scornavacca & Barnes, 2006) and carry around with them all day. 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 (Statista, 2014). Consequently, the kind of apps people install and use could be closely linked to their interest, demographics, and personality (Ryan & Xenos, 2011; Seneviratne, Seneviratne, Mohapatra, & Mahanti, 2014; Shen, Brdiczka, & Liu, 2015). As shown in other research fields, personality traits can have a significant impact on an individual's decision-making process (Bettman, 1979; Sproles & Kendall, 1986).

While research on the impact of personality on information system (IS) adoption is scarce, first works already demonstrated the relevance of personality for explaining people's adoption behavior (McElroy, Hendrickson, Townsend, & DeMarie, 2007). Researchers in recent years find correlations between an individual's personality and her adoption of Internet usage (Landers & Lounsbury, 2006; McElroy et al., 2007) and specific apps like 'Facebook' (Ryan & Xenos, 2011) and 'Foursquare' (Chorley, Whitaker, & Allen, 2015). The high adoption rate of mobile devices and apps makes mobile apps a highly relevant and interesting field to study from a broader perspective than just from a single app. As one of the first studies, this work aims to study the influence of personality traits on the adoption of different types of mobile apps from a large-scale field study. Consequently, practitioners like app publishers could leverage the knowledge to boost adoption of their mobile apps as well as to conduct more efficient market segmentation.

However, information about each smartphone user's personality traits remains unknown to app publishers until being measured. The effectiveness and scalability of current questionnaire-based approaches to measure personality traits are limited (Montjoye, Quoidbach, & Robic, 2013). This work thus presents a scalable machine-learning approach to predict personality traits with information like app installations and update events (henceforth referred to as mobile app data) since they are suited as robust features (Pan, Aharony, & Pentland, 2011). Unlike previous studies, data used in our predictive models are openly accessible to any app developer. This makes it possible to integrate the approach into any mobile app. In addition, there is no extra burden on the user to fill out a questionnaire. The predicted personality traits can also serve other decision support systems and recommendation systems to conduct more precise user profiling, better customer relationship management, as well as more effective personalized marketing.

The contributions of this work are two-fold: First, it provides

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insights into how the adoption of different types of mobile apps can be explained by the Big Five personality traits. The state-of-the-art questionnaire-based approach is used to determine personality traits. Previous research typically has a small number of samples and focuses on specific apps like ‘Facebook’ and ‘Twitter’. Such limitation might influence the generalizability of the findings. Consequently, this work aims to classify a large number of apps into groups and analyze the impact of personality on each group to gain systematic knowledge.

Second, a scalable approach is generated to determine each smartphone user's Big Five personality traits based on her readily available mobile app data. A machine-learning algorithm is applied to solve the classification problem by using the Big Five-44 personality test as ground-truth for training, validation, and testing. The findings suggest that existing questionnaire-based approaches can be replaced by this highly scalable and efficient method. This enables a large-scale and cost-efficient exploration of mobile app adoption influenced by personality traits.

The rest of the paper is structured as follows. Section 2 presents related work on personality traits, user profiling, and IS adoption and Section 3 develops hypotheses. Section 4 introduces the research design in detail, which is followed by Section 5 that presents the empirical results. Finally, the paper concludes with a discussion of the limitations and an outlook on future work.

2. Related work

2.1. Personality traits

Five-factor models (FFM) (Mccrae & Costa, 1987) of personality emerged as a broader taxonomy for personality-related issues and are embedded in a rich conceptual framework for integrating all research findings in personality psychology (Digman, 1990). The most widely used five factor model is called the Big Five personality traits, which consists extraversion (E), neuroticism (N), agreeableness (A), conscientiousness (C), and openness to experience (O) (John & Srivastava, 1999). Extraversion is frequently associated with being sociable, gregarious, talkative, and active (Eysenck, 1947); Neuroticism includes traits like being anxious, depressed, worried, nervous, 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, broad-minded, and independent (Costa & McCrae, 1985). Personality traits can have a significant impact on an individual's decision making (Bettman, 1979; Sproles & Kendall, 1986). However, most research related to personality focus on job performance or career development (Penney, David, & Witt, 2011).

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

2.2. Automatic user profiling

Recent advances in information technology and machine-learning techniques have drawn the attention to data-driven and automatic approaches to overcome the limitations of the questionnaire-based approach. For instance, Kucukyilmaz, Cambazoglu, Aykanat, and Can (2006) were able to predict a person's gender by mining her chatting records. Ying, Chang, Huang, and Tseng (2007) predicted a user's gender from analyzing her online Web browsing behavior. In addition to gender, a person's age could also be predicted automatically. Nguyen, Smith, and Rosé (2011) concluded that a person's age was predictable through analyzing her blog texts, telephone conversations, and online forum posts. Guo, Fu, Dyer, and Huang (2008) and Han, Otto, Liu, and Jain (2014) detected a person's age and gender by leveraging face recognition technologies. Kosinski, Stillwell, and Graepel (2013) were able to predict a ‘Facebook’ user's gender, race and marriage status from investigating her Facebook Likes. Recently, researchers tried to predict not only demographics but also other user characteristics like personality traits. Pianesi, Mana, Cappelletti, Lepri, and Zancanaro (2008) extracted audio and video features from meetings and used them to predict each meeting participant's two personality traits, extraversion and locus of control. Wright and Chin (2014) predicted an author's Big Five personality traits based on the texts she had written. Similarly, researchers revealed a possibility to automatically predict a person's personality through analyzing her email content (Shen, Brdiczka, & Liu, 2013) and social network content like ‘Facebook’ and ‘Twitter’ (Bachrach, Kosinski, Graepel, Kohli, & Stillwell, 2012; Chin & Wright, 2014; Minamikawa, Fujita, Hakura, & Kurematsu, 2012). With the proliferation of smartphones, other researchers (Chittaranjan, Blom, & Gatica-Perez, 2013; Montjoye et al., 2013; Pan et al., 2011; Trestian & Nucci, 2009) started to use mobile metadata such as logs of phone calls, SMSs, and location information to predict a mobile phone user's personality traits.

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