# Personalizing Smart Services Based on Data-Driven Personality of User

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**Abstract.** The article presents a research method of creating classification of users needs based on their personality (Big 5) determined on the basis of available digital data. The research is work in progress and is based on a specific use case which is a smart services (home environment) with users interface on a mobile phone. This paper includes the results of preliminary research on the needs of users, formulates research problems and discusses assumptions and the research methods. What distinguishes the proposed solution from others, is that the profile will be available for service just after installing, without the necessity of collecting data about user activity. The idea of data-based users classification, can be used at the early stage, which seems to be important in the adaptation process to any new smart service.

**Keywords:** User profiling · Service personalizing · Data driven services · Automatic personality recognition · Smart services

## 1 Introduction and Related Works

Nowadays, when the competitiveness and availability of services is very large, companies focus on adapting services to the user. Traces of digital activity of users are increasingly being used to collect information about the client, as well as profiling or classifying [1]. However, in the case of new and technologically advanced services using artificial intelligence (smart services), the risk of service rejection and discontinuation of using it, seems to be significant in the early beginning of contact with the service. A good illustration of this problem is the Amazon Alexa market research report, published in August 2018 that says "Of the people who did buy something using Alexa voice shopping, about 90% did not try it again" [2]. Moreover in the same report we can read that, despite the high sales success of the Alexa, users seem to limit themselves to using only a few basic functionalities like playing music, checking the weather or checking the news. Customers are not able to learn and use other, more advanced functionalities available in the service. As a result, algorithms based on history of usage are not appropriate, because people hardly get beyond what they know or do not


C. Debruyne et al. (Eds.): OTM 2019 Workshops, LNCS 11878, pp. 199–203, 2020.
https://doi.org/10.1007/978-3-030-40907-4_21

have history of usage. This article presents the idea and methodology of using automatically recognised personality as a classifier of needs. The research is in progress and all preparatory stages are finished. The creation of final statistical models and their validation is in the sphere of plans.

### 1.1 Personality

Personality is a psychological term, most often understood as a set of relatively constant psychical properties (attributes) for an individual, conditioning the constancy of its behavior and attitudes. There are a number of studies showing a strong relationship between personality and behavior, life satisfaction achievements and preferences e.g. [3].

For this research, the Big Five model is used to describe the personality of an individual. The model has been developed mainly by Costa & McCrae since 1978 and in the 90s it was conrmed in a large number of empirical studies [4,5]. Big 5 model basically claims that there are five dimensional factors of personality.

- **Openness** to experience describes tolerance for new and unknown.
- **Extraversion** describes tolerance for big quantity of stimuli and is also connected with social excintolerancehange.
- **Neuroticism** describes for stress.
- **Agreeableness** is about concentration to others need and willingness for co-operation.
- **Conscientiousness** is about intolerance for chaos and disorder.

### 1.2 Personality Detected from Digital Footprint

Many researchers have attempted to determine the user's personality based on digital data. Most of the attempts concerned data from social media (Facebook, Twitter) [6–8] or other personal data like call logs [9] or mobile applications [10]. Some of this kind of personality diagnosis were verified and the result was positive [11]. Models of indicating data-driven users' personality are mainly based on analysing of text (e.g. tweets or FB posts) [7,12]). In 2013 [7] researchers prove also that predicting personality based on telephone call logs data is possible. Tracking the digital footprint for detecting the users personality was also broadly investigated by researchers using various kinds of large data sets like text, profile photo, music, film preferences based on the FB likes or relations (SNA) for example: [6,7]. Except the analysing the profile photo in social media, all researches were based on the massive data, collected from the history of social service usage. Therefore, we are looking for methods that allow services for automatic personality recognition based on small amounts of data available at the time of service installation, when history of usage is not existed. Also the assumption refers to determining the personality of each user of the smart service, so the model should be based on the data available in each phone.

## 2 Research Objectives and Methodology

Taking into account the experience of the related works, as well as the business need, presented above, a research program was created, accompanying the project of creating user-oriented services dedicated to smart home environment. The main goal of the research is to propose **effective and accurate method of recognising the user's personality (Big 5), based on the data available at the moment of installation without having to wait for the data on the user's history to be collected**. An additional goal is to provide evidence that personality can be effectively used in smart services as a classifier. For the fulfilling research objectives, the following research scheme was designed (see Fig. 1):

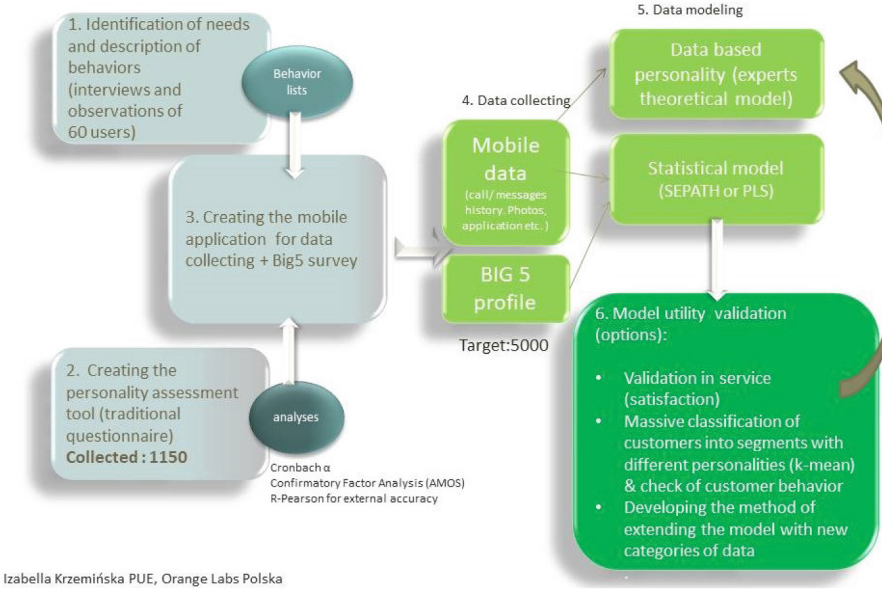


**Fig. 1.** Research Scheme & Methods

**1. Preliminary qualitative research** Carried out to identify needs and collect descriptions of discriminating behavior. Survey conducted in 2018 (own research[1]), delivered clear evidence that personality dimensions are good enough for discriminating users needs and expectations. For example, people

[1] The research was carried out in 2018, on 60 users of mobile phones, aged 20–29, men and women, (homogeneous group due to emphasize the diversity resulting from personality). The study was a multi-stage: filling of the personality questionnaire (Big 5), monthly observation of behaviors in social profiles and in the use of telephone, in-depth structured interviews aimed at getting as much information as possible about behavior patterns. The results of these studies were behavioral metrics for each of Big 5 dimensions.

who are open to experience (high openness) expect non-standard content, have a high level of cognitive needs, and high need to explore (curiosity). In turn, people with low openness expect only a sense of comfort in a world that is well known to them (they like only what they know, they are afraid of unknown). For high on conscientiousness people important are those functionalities that help in the implementation of the need for control. On the other hand people with a low conscientiousness, who accept life in chaos and disorder, need only very basic control functionalities and will never be interested in the use of advanced calendar or notebook functions. Moreover, respondents confirm that the services based on artificial intelligence are currently not adapted to them and this is the primary reason for their rejection or dissatisfaction with available services.

**2. Creation the personality assessment tool** which can be used for this specific research (low number of questions (25) and tool tested and created for online or mobile app usage). All standard psychometric procedures are applied.

**3. Developing the mobile application** dedicated for collecting data from mobile phone and Big 5 assessment (25 questions from stage 2). So far the data from the following user activities (sources) are collected and analyzed on a mobile phone of a user: telco data, application data, Photos, phone settings and statistics.

**4. Main research fieldwork** is data collecting required for creating the model, planned 5000 participants. Research is in this stage now. The data collected are: mobile phone data, available in the moment of service installation (single drop without additional logging the activity) and Big 5 metrics.

**5. Creating the personality model** There is an idea to create 2 models. The first will be theoretical model coherent with psychological Big 5 theory. The second will be pure statistical model based on SEPATH (structural equations path modelling) or PLS (partial least squares path modeling).

**6. Validation stage** e.g in interactive service which allow experimental manipulation based on personality adapted service. Or in laboratory simulation way comparing satisfaction metrics or checking the purchasing behaviour after massive classification of whole data base of mobile customers.The final shape will highly depend on the phase of maturity of the created parallel service as well as on the availability of data on service platform.

The stages 1, 2 and 3 are finished. The research is now on stage 4 (collecting data for statistical models). The future works concern the stages 5 and 6. The validation stage (6) is now rather a list of proposals and is not completely defined. Stage 5 and stage 6 will run cyclically until satisfactory results are achieved. It will also be repeated if the data-set is expanded or the assumptions changed.

## 3 Conclusion and Future Work

The presented user-oriented research program is conducted simultaneously with service development. It seems that extending the list of variables describing users with features related to, personality and creating universal methods measuring these features is a natural step in the development of intelligent and smart services. It can be new approach for user-oriented services designing. The challenge for researchers will also be an attempt to verify which of created models is more effective in predicting behavior and personalising the smart services. The solution can be also developed towards a faster and automatic diagnosis of a given person (e-health). Also can be easily transfer to other areas of business, such as creating applications and user interfaces which will be automatically adapted to users' personality.

Considering the desired direction of further research, they are mainly related to the measurement of the impact of service personalization on user satisfaction and the creation of a system monitoring the accuracy of the personality model based on data about user activity in the service. The entire system should also be refined in terms of expanding the data set on which the model is created with new categories of data, e.g. smartwatch devices or sensors installed in a smart home that reflect better the more physical spheres of behavior (eg meals, leaving home, home activities, e.t.c.).

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