Personality Based Data-Driven Personalization as an Integral Part of the Mobile Application

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Abstract. The article presents the results of the work on the method of intuitive UI and UX personalization of mobile applications. The method is based on the user's personality profile (Big 5) inferred from the available data on the user's phone at the time of installation. The user's personality model was created based on machine learning performed on data from 2,202 people. The proposed method enables personalization from the first contact of the customer with the application. Therefore, it is a significant advantage of the study. Moreover, the method ensures complete data privacy protection since no data about the user is uploaded outside the mobile phone.

Keywords: User · Service personalizing · Data based personalisation · Human-centred services · Detecting personality based on digital data

1 Introduction and Research Objectives

The digital revolution has made the smartphone the most used personal device, and a natural source of information about the user, which is confirmed by numerous studies [4]. The deepening dependence and coexistence with technology mean that profiling based on demographic characteristics is insufficient. Currently, digital data about users named "digital fingerprints" are commonly collected and used for profiling and classification. However, gathering users data is time-consuming and resulted in delaying product adjustment to the user preferences.

Therefore, the first motivation was to look for good classifiers that can be used from the first moment of using the application, right after installation (previous publications related to this research program are [12–14]). Then the insight about the user can be used for dynamic and automatic adaptation of services, e.g. smartphone application. The above motivation defines the main research problem analyzed in this publication, which is: how to define the personality profile of a mobile application user and personalize it to their needs from the moment the application is installed. To solve this problem, the following research

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questions were defined: (RQ1) Is it possible to create an automatic method to determine the user's personality based on the available mobile phone data during the app installation? (RQ2) Can this method be used in a mobile application for automatic application personalization?

The article presents the possibility of using telephone data for active profiling and automatic personalization of UX and UI. The first part will present research objectives, key findings from the review of related research, chosen research methodology and scheme. Then the results of research on the data personality model and the concept of personalizing a mobile application based on this profile will be discussed. In the end, conclusions will be presented, and the limitations and further plans for research and development of the concept will be discussed.

2 Research Methodology

The overall methodology chosen to carry out the required research is Design Science [6]. Following the Design Science framework, the presented research consists of the following steps presented in Fig. 1 The first step is identifying the existing problems in data-driven personalised personalisation. A literature review was conducted to search the possible existing solutions with a detailed analysis of available data. The summary of this stage is in section *Related Works*. Next, the research procedure consists of pre-research stages: interviews with customers, the psychometric procedure for creating required personality tools, preparing tools for data collecting and data collection. A summary of these pre-research studies is in section *Pre-research*. Then the primary research for the creation of artefact was conducted. The Hevner's Design Cycle: data processing and artefact development is presented in section *Research*.

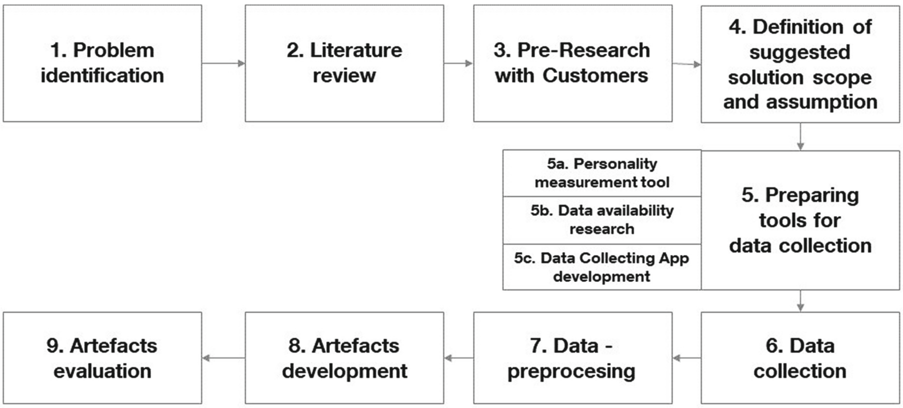

Fig. 1. Research steps defined according Design Science Research (own source)

3 Summary from Literature Review

The systematic literature review was conducted based on the method proposed by [15]. The primary keys used for the input search were: *determining personality based on (digital) data*, *personalization of services based on the user's personality*, *user's profiling based on data*, *customer-oriented services*; *mobile app personalisation*; *personality as a base of human-robot interaction.*

3.1 Prediction Personality from Data

Over the past ten years, many attempts have been made to define personality based on the digital footprint. The citations in this article are not exhaustive, and only examples are given to illustrate the conclusions from the more comprehensive literature review. Most of the research is concerned with determining personality from Social Media (SM) data, mainly through large text data-sets, available as open data on Twitter or MyPersonality App for training purposes (e.g. [2,10,11].

There are attempts of predicting personality from SM profile picture [10,17]. The single studies in this topics, explore other than SM data, e.g. call logs [21], registry from mobile applications [26], eye movements [1], data from devices such as socio-badge [9]. It is worth noting that some of these studies are currently impossible to repeat due to the lack of availability of this data, but still they are valuable from a research perspective. This research relied on a large amount of data, either collected or possessed from service use history, with a few exceptions.

Based on a review of more than 35 studies on this subject, it can be concluded that the basic data for personality detection are text data from posts and tweets on SM platforms. It also seems that some researchers focus mainly on improving the ML methods themselves, without the specific purpose of using these models in practice. Despite the efforts, no cases describing the use of such a model for business purposes other than the personalization of SM were found [20,22]. Taking into account techniques of modelling, Machine Learning (ML) is currently the dominant approach for personality prediction from digital footprint [5,11, 16,23,24].

3.2 Personality Models

The Big Five Theory classifies personality traits along five dimensions: *Extraversion* (E), *Neuroticism or Stability (S)*, *Openness to Experience or Intellect* (O), *Conscientiousness* (C), *Agreeableness*(A). The Big 5 is one of the best experimentally tested personality models in psychology and it was confirmed in many empirical studies [3]. Many studies are indicating a strong relationship between Big 5 and behavior and preferences [8].

There is also another personality typology: the Myers-Briggs Type Indicator (MBTI) [7]. It is an array of 16 personality types, resulting from a combination of 4 binary dimensions: Introvert-Extravert, Intuition-Sensing, Thinking-Feeling, Judging-Perceiving.

Considering the attempts of data-driven personality, The Big 5 is used the most often (23 from 35 found out) while the MBTI is used about less frequently (7 from 35). The remaining 5 are single uses of other approaches. Regardless of the model used (Big 5 or MBTI), it can be stated that the personality model is treated as a set of discrete binary variables in most cases. This approach is coherent only with the Myer-Brigs Theory, a typology composed of a combination of 2-pole classes. Although using personality traits as a binary variable is convenient for building models (avoiding imbalance sample issue), it does not seem justified for personalizing products. For personalization, traits are for identifying those who differ significantly from the typical, average level of the trait. In the Big 5 model, traits are dimensions, and it is possible to define the typical users and the cut-off points of extreme groups. This fundamental difference affects both the interpretation and possible use of the result. Finally, the prediction of binary typology is less likely to differentiate behaviour [25].

3.3 Differentiation of Users Experience Based on Personality

There are some examples of using the personality for personalising advertisement execution [20] and recommendation systems [18]. Considering the creation of personality-aware service, valuable insight about the Big 5 personality impact comes from human-AI and human-robots interaction surveys. For example, the service adaptation process is more straightforward in the case of High E, High C, and High S [19]. However, highly neurotic (Low S) are not resistant to stress, accompanied by a higher level of anxiety and a lower ability to adapt to what can be crucial in brand new services based on advanced technology using Virtual Reality or Augmented Reality. In contrast, High O, when learning about and discovering new things feel satisfying, and such activity is beneficial for them. An additional incentive for people with High Openness is their intellectual involvement, so they have different adaptation paths. The research [27] confirms that High E prefers robots with extroverted behaviours and introverts with introverted ones. Therefore, it can be assumed that the inclusion of personality in the profiling of less advanced but interactive services like a virtual agent or other mobile application will bring benefits for users.

3.4 Identified Gap

The Big 5 approach seems to be adequate for service personalization purposes. Determining the personality is most often based on data collected while using a specific service (usually social media). Creating a profile requires time to record behaviours relevant to the model. Therefore, it is not practiced to calculate the user's personality profile at the time of service installation.

Little attention has also been paid to personalization based on the personality profile and its use in user-beneficial activities (not just tailoring marketing communication, ads, or content recommendation). Thus, there is a need to develop technology to enable much more reliable and people-friendly solutions and automatic personalization of UX and UI based on personality.

Determining the personality in most existing research does not ensure complete user privacy, i.e.the, the profile is calculated using sensitive data and outside the user's end device. Moreover, data, storage, and security were not usually discussed in the literature on determining the user's personality based on digital traces. Therefore, the question arises is it possible to design the counting of the personality profile with better privacy protection, for example, on the end device (e.g. smartphone).

4 Designing and Developing of Artefacts

The primary objective is to develop a novel method of personalizing interactive electronic services like smartphone applications. The design science stage of design and developing of the artefact is presented in Fig. 2.

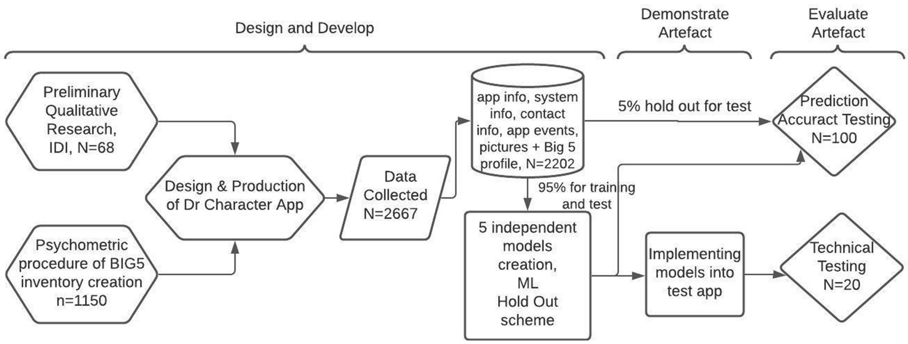

Fig. 2. Developing and evaluation of artefacts.

First, the preliminary qualitative study was carried out to identify needs and collect descriptions of discriminatory behaviour. Additionally, at this stage, users needs and expectations towards the personalization were defined, respectively, to each personality trait extreme groups. Consecutively, the psychometric procedure dedicated to creating the personality electronic assessment tool was executed.[1]). Then, the mobile application (named Dr Charakter) was developed, dedicated to collecting anonymous statistics from mobile phone together with the Big 5 assessment. The data categories processed on mobile phone: telco data (contact list statistics, call logs statistics, text messages log statistics, etc.), applications basic info, system info data, photos (structure of directories, number of photos, photos with faces, etc.), phone settings and statistics e.g. battery consumption, kind of security level. 2666 people were recruited. The participants installed app on the phone, answered Big 5 questions and received the

[1] The 25 items tool was created. Reliability, N = 3331: Alfa-Cronbach coefficient: E:.76, A:.58, O:.59, S:.72, C:.64). Accuracy: r-Pearson coefficients with IPIP-BFM-50: E:.85, A:.55, O:.62, S:.81, C:.76).

personality profile and basic statistics from mobile phone. During the filling the questionnaire, application calculates required statistics from the data available on the phone (with full transparency of what is done and an acceptance of the set of required by law consents). The only anonymous statistics were transferred from the respondent's mobile phone to analytic lab servers. Finally, the personality model was created (artefact 1) based on smartphone data, the same kind which can be available at the moment of any app installation. Finally, the model was implemented in the service prototype (artefact 2) and proceeding with the final validation. A novel method of personalizing smartphone applications.

5 Developing the Data Driven Model

5.1 Data Processing

2,667 people decided to participate in the study, including 1,303 men and 1,364 women. The average age was 31. Therefore, the final age distribution is similar to the characteristics of Internet users in Poland. In addition, the participants must possess skills sufficient to install the application on their own, agree with five consents and carry out the procedure by performing commands on the screen. Finally, the age distribution was: 44% aged 18–29, 32% aged 30–39, 24% aged 40 and higher. There were 250 raw data types, from which 143 were input for presented in this article modelling (Table 1). In the case of data collected by the *Dr Character* app, quality testing and data control have been performed.

Table 1. Descriptions of the data categories taken from the smartphone by Dr Character application

Data category	Examples of data	Definition and description
Standard android information (99)	device security, screen layout, color mode, font scale, keyboard parameters, battery level, rotation, alarm alert, tone/mute/vibrate ring	Current phone settings (during the test)
Contacts (33)	numbers with COE, with address, with e-mail, contacted last month, with name included family names from the list	List of contacts described in statistics. Number of contacts grouped according to 33 different criteria
Applications list (5)	package name, names, categories, found URL	Application general information such as the application list
Applications statistics (6)	package name, first timestamp, battery consumption, last timestamp, last time used, total time foreground	Application statistics - general information such as the date of instalment

The following cases were excluded: people who misplaced a personality questionnaire, installed applications on unused phones, cases with data incomplete or doubled due to the events of interrupted procedures (data transmission errors). After a pre-processing and filtering out records with errors, the model was built on data from 2202 unique participants (82,63% of the initial sample). Personality scores were normalized into the Sten scale. For the selected Sten scale, the unit of the standardized Sten scale is one sten. The number of units is 10. Thus, one sten covers 0.5 SD of the population (reference groups), and the mean of this scale is 5.5.

5.2 User's Initial Smartphone Personality Profile Model

User's Initial Smartphone Personality Profile (UISP) model was created in Python. All machine learning was conducting using *scikit-learn* library. In general, the model creation consists of the following stages: (1) Data set processing, (2) Creating Set of Additional Features, (3) Finding the best solution for the unbalanced sample problem, (4) Finding the best in the class model predicting personality (5) Creating the model on training sample (6) Validating model on the test sample.

For model creation, ensemble techniques were used. This technique is a combination of multiple machine learning algorithms or models. They are used because of the best controlling of the bias-variance trade-off, increasing model performance, and providing good model stability. There are 12 Machine Learning Methods chosen among others for tests: Random Forest Classifier (RF), k-Nearest Neighbor (KNN), Support Vector Machine (SVM), Logistic Regression (LR), Linear Discriminant Analysis (LDA), Decision Tree Classifier- CART, Gaussian Naive Bayes (NB), ETC = Extra Trees Classifier, Bagging Classifier (BC), AdaBoost Classifier (ADA), LGBM Classifier (LGBM), XGB Classifier (XGB). All of them were used to find out the best model fit for each dimension. The model was created using the standard hold out procedure, in which the data are divided into a training set (95%) the set for validation (5%) which is separate and not used for training. The training procedure is iterative and consists of a cycle of training (80% of the sample) and test (20%).

To evaluate the model quality is worth determining the "baseline" level of the prediction, i.e. the result to which the model's predictions will be compared. For regression problems, a random variable is often used, e.g., from 0 to 100, for comparisons. Considering the skewed distribution of 3 classes of trait level (low, medium, high), it will be approximately 33%-34% for the average baseline. The baseline for each of the models was defined in the context of the model usage (business perspective). So the assumed baseline is not using personality for personalization, which caused every user to receive the not-personalized service version (for average target). In this situation, the middle class is personalized with 100% precision and, for those with a High or Low level, precision is 0%. Based on that assumption, the baseline presented in the Table 3 was calculated. So far, a personality model is built based on 3 data categories of an Android mobile phone: Application Info, System Info, and Contacts. Of the 143 raw input

Table 2. Features Importance for the best in class model

Feature	E	A	C	S	O	Feature	E	A	C	S	O
Contacts mobile	7.4	2.3	2.7	3.3	2.4	Emails	1.3	0.7	1.4	1.4	1.4
Contacts	5.4	1.9	3.2	3.8	2.4	Contacts type work	1.1	0.7	0.7	0.7	1.4
Contact one month	4.3	4.0	2.8	2.5	2.2	Min install	1.1	1.1	1.9	2.1	2.1
Weekend ratio	4.1	2.7	2.7	2.9	2.1	Contacts photo	1.0	1.5	1.2	1.4	1.5
Battery level	3.6	3.6	3.3	3.5	2.4	Dtmf tone when dialing	1.0	0.2	0.4	0.4	1.8
Mean day	3.3	4.9	3.1	3.2	2.1	Ratio days per app	0.9	1.1	2.5	2.6	2.4
Boot count	3.2	3.9	2.8	3.1	1.8	Mobile net code	0.8	0.8	1.1	1.3	1.8
Contact six months	3.2	2.3	3.0	2.3	2.4	Density dpi	0.8	1.0	1.4	1.2	1.8
Max app install	3.2	4.4	3.6	3.5	2.3	Free size sd	0.8	0.8	2.9	2.9	2.3
Contact three months	3.1	2.8	2.6	2.7	2.3	Contacts type home	0.7	0.6	0.8	1.0	1.2
Screen brightness	3.1	3.5	3.5	3.1	2.0	Contacts ICE	0.5	0.3	0.2	0.3	0.7
User apps	3.1	3.7	3.0	3.1	2.0	UI mode	0.5	0.7	0.5	0.5	1.2
Work period ratio	3.0	5.3	3.3	3.1	2.2	Mute streams affected	0.4	0.3	0.6	0.6	1.7
App diff days	3.0	3.0	2.8	2.6	2.1	Data roaming	0.4	0.2	0.4	0.6	1.7
System apps	2.9	2.6	2.8	2.7	2.1	Font scale	0.4	0.8	1.7	0.9	1.6
Contact one week	2.9	3.4	3.5	3.5	2.2	Mobile data enabled	0.4	0.6	0.4	0.4	1.7
Available size sd	2.6	2.9	2.9	2.7	1.9	Color mode	0.4	0.4	0.5	0.6	1.4
Total size sd	2.5	2.9	2.5	2.8	2.0	Time mode 12 24	0.4	0.4	0.4	0.4	1.5
Contacts foreign	2.4	1.5	1.7	1.6	1.8	Contacts shared cost	0.3	0.4	0.6	0.5	1.5
All apps	2.4	3.1	2.8	2.7	2.1	Contacts type unidentified	0.2	0.2	0.2	0.2	0.9
Ratio apps per day	2.4	2.9	2.6	2.7	1.8	TTS default pitch	0.2	0.3	0.4	0.2	0.6
Duplicated contacts	2.3	2.1	1.9	1.8	1.7	Screen layout	0.2	0.5	0.2	0.3	0.8
Contact two weeks	2.2	2.5	2.6	2.4	2.2	Contacts address	0.2	0.4	0.5	0.6	1.1
Screen off timeout	2.2	1.4	1.5	1.4	2.0	TTS default rate	0.2	0.3	0.3	0.2	0.7
Contacts type mobile	1.8	2.6	3.0	3.6	2.6	TTS default synth	0.1	0.2	0.3	0.3	1.1
Contacts family	1.7	1.8	2.0	2.1	2.2	Battery saver mode	0.0	0.2	0.3	0.2	1.0
Contacts unknown	1.6	2.3	2.1	1.8	2.1	Contacts toll free	0.0	0.1	0.5	0.3	0.7
Contacts fixed	1.5	3.7	2.0	2.1	2.3	Contacts ussd	0.0	0.2	0.2	0.2	0.6
Contacts short number	1.5	1.2	1.5	1.3	2.1		100	100	100	100	100

data features, the presented model was built on 57. The remaining collected data (apps events, pictures, call logs) has not yet been used. The parameters of the best-performed models based on the three categories of android data are shown in Table 3. The final five models were evaluated on the test group (N = 100) against the assumed baseline. LGBM proved best for E and C, RF for A and O, ETC for S. Compared to the baseline, the best model is E and O. The model for A turned out to be the weakest - it was not possible yet to go beyond the assumed baseline. The specificity of the agreeableness dimension relating to the sphere of interpersonal contacts would require data related to such contacts. Perhaps the improvement will be brought by expanding the features with statistics from call logs and SMS.

Considering the importance of particular data types for creating the model itself, the system's information (e.g. battery level, screen brightness, and the amount of free memory) seems to be most significant Fig. 2. Information about installed applications comes second. Interestingly, there is little differentiation among the top 10 most important features. Lack of differentiation means there

Table 3. Comparison of best in class models performance with baseline (on hold out test sample N = 100)

The best in class:	LGBM	LGBM	RF	ETC	RF
Dimension:	E	C	A	S	O
Precision baseline	0.52	0.55	0.49	0.52	0.58
Precision model	**0.75**	**0.68**	**0.62**	**0.81**	**0.74**
F1 score baseline	0.61	0.63	0.58	0.60	0.66
F1 score model	**0.76**	**0.65**	**0.61**	**0.65**	**0.69**
Accuracy baseline	0.72	0.74	0.70	0.72	0.76
Accuracy model	**0.79**	**0.75**	0.70	**0.74**	**0.78**

are no unique traits to a given personality trait. Since these most critical traits are repeated for all dimensions of personality, these features are most related to user behaviour.

5.3 Method of Personalisation Based on UISP Model

The proposed concept of data-driven personalisation is investigating by implementing the user's personality data-driven model into the android application. The diagram (Fig. 3) shows the process flow. The user installs the application with implemented UISP model on the smartphone. The application counts the 57 statistics needed to calculate the profile. Furthermore, the services automatically adjust the appearance of the service, functionality, and communication to the user's personality profile. The profile remains secret and private because it is not shared with the application back-end and not send outside the device.

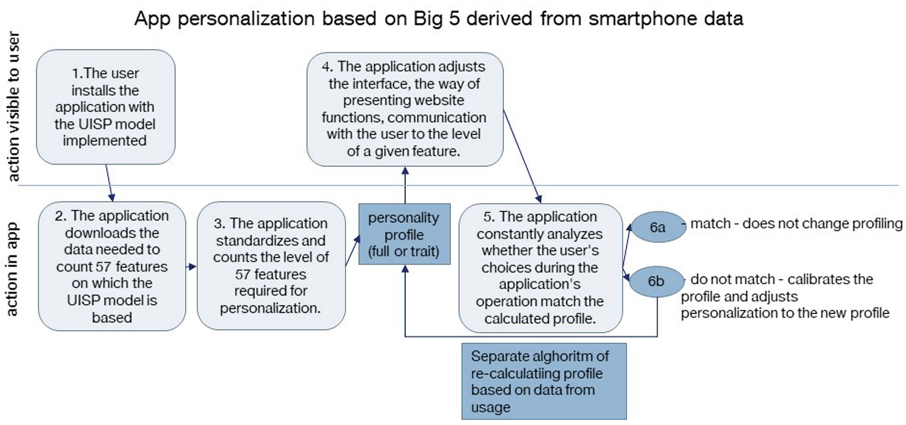

Fig. 3. General flowchart of personalization based on the personality profile (from UISP model) in the service

It is available only for this mobile application. The application has the same functionalities for everyone, but the service is delivered differently to the various users, thanks to the profile. Based on the Big 5 Theory, Introverts should receive an interface with fewer elements and subdued colours, while Extraverts receive an animated, more stimulating interface. The application adapts to the user's capabilities, e.g. to those with Low C, and it provides more messages reminding about the actions to be performed. The reinforcements (feedback) from the app are tailored to the needs of each user. For example, extroverts need more social-oriented communication. High C is related to the purpose and appreciation of the tasks. Adapting the service to different profiles requires additional research, which is developed for specific service functionalities.

The final UISP model (artefact 1 and personalisation logic (artefact 2) was implemented in the lab prototype application to allow evaluation. The user's personality profile, calculated automatically based on statistics from android data, is available immediately after installing the service (the calculation last c.a. 2 s). It was checked on twenty different handsets. This model implementation in the app is a sound basis for further research into determining personalisation preferred by different personality types.

The idea of personalising method (Fig. 3) is also assumed constant analyses of the user's choices during the application's. Based on the results of this analysis, the application will decide whether to continue profiling based on the initial profile or to run the profile re-calculation based on data from the service usage. Additionally, for personalisation purposes, it is enough to classify users into a low, medium, and high class of a given trait. Finally, since various personalised elements in the service are adjusted independently, potentially, the entire profile does not have to be included in the service. The five models can be created and used independently, e.g. adjusting interface graphics is significant high Extraversion and Openness. Thanks to that, no information about the user is transfer and stored outside the handset. All the data and the profile itself are stored locally.

6 Conclusion and Discussion

The article presents the work results aimed at creating a model for calculating the personality profile based on the data available during the installation of the service in a mobile phone. Furthermore, the concept of automatic personalisation of the service was also presented, and the mechanisms implemented in the smartphone app itself (front-end layer). The presented research resulted in the successful creation of both defined artefacts (1 and 2), although both require to be finally validated in UX tests. The new contribution of this study consists mainly in the fact that the possibility of calculating the personality profile from anonymous statistics available on the phone during the installation of the application has been shown and, it can be done with accuracy comparable to models based on large amounts of data despite distinguishing narrowly defined high and low class for personality traits. Therefore, this approach is more accurate for service-personalisation purpose. Furthermore, it also proposed using such an in-app model to personalise any service, which can be a base for new kind of user's personality-aware services.

The research was also aimed at confirming the suitability for profiling based on data from the moment of service installation, without the need to collect data logs from the services and test automatic analytic that can be implemented inside the service. Work on both the UISP model (extension with new data categories) and the first test application that uses the UISP model for personalisation is ongoing but is nearing completion.

Another UX research, in the experimental model, is planned to confirm the usefulness and value of the proposed solution for users. Currently, personalisation is determined based on theoretical descriptions of features that contain basic behavioural guidelines. Subsequent tests should be dedicated to the verification of the business use of such profiling.

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