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Personality-Based Lexical Differences in Services Adaptation Process

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Abstract. In the near future, the reality we live in will undergo a significant transformation caused by the development of advanced information technologies. Artificial intelligence, robots, virtual agents, as well as advanced intelligent virtual services will become ubiquitous. Available digital data and technologies can be used to create new services that are actively adapting to the user. The results presented in the article come from preliminary research indicating how to use data available in digital services to both profiling users according to their personality, and providing them with personalised services. We will also present an idea how to use such analyses to create a personalized response from intelligent services. This can have a significant impact on lowering human-machine communication barriers and reducing technological exclusion. It can certainly improve the satisfaction and comfort of using services intelligent enough to be able to self-adapt to a user.

Keywords: user profiling · service personalizing · data based services · human-centred services · detecting personality based on digital data · smart services · sensitive services

1 Introduction and Motivation

Continuous digital transformation has been going on for several years. Customs and ways of performing tasks, as well as general functioning of people in the world are being gradually enriched with the growing number of helpful digital tools such as a smartphone. A new phobia of the lack of access to a smartphone - nomophobia [1] [2] has already been identified. This is tangible evidence of the revolutionary or even evolutionary changes that are taking place and will take place within us. However, despite the universality of the devices themselves, in the case of advanced digital services (e.g. smart home or virtual assistant/agent), the key is to reduce the barriers related to fears of artificial intelligence (AI), both in physical (robot) and purely virtual (application, program, virtual agent) form. Good determinants are being sought to diversified needs of users, so that the users can actively overcome these barriers. In today's world, old profiling methods fail. The deepening relationship between people and technology is the reason that profiling on the basis of easily accessible demographic features (such as gender, age, place of residence, education, economic status) proves to be inadequate and insufficient. However, the possibilities the digital world provides for analysing individual differences between people are constantly growing. In the context of the ongoing digital transformation, traces of the users' digital activity are increasingly utilized to collect information about the customer, as well as for profiling or classification. Nevertheless, it frequently takes a long time to collect user data. That is why our first motivation is to look for good classifiers of behaviour and needs that can be used from the first moment of using the service (see also [3], [4]), and the second one is to use this knowledge to actively match an AI-based service to the user. The high availability of digital data and the constantly increasing computing power of the simplest devices means that today it is easy to determine a user's personality profile, while 10 years ago this was possible only by the means of a personality questionnaire. The main purpose of this article is to present the results of preliminary research and analysis that are the confirmation of the legitimacy of such an approach. The article also shows the possibilities (though still limited) of using the available data for active profiling. We will present related research that confirms the proposed approach and discuss the challenges faced by researchers and developers of such services (ii). Finally, the analysis and conclusions from preliminary research will be shown (iii) and we'll discuss the results of the research in the context of their usefulness for creators of AI services (iiii).

2 Identified Challenges and Related Works

2.1 Personality driven from digital data

Personality has no single definition shared by all psychologists. In general, personality is a set of traits or characteristics, which are organised, relatively stable, and which influence the cognition and behaviour of individuals [5]. Within the existing personality theories one of the most influential and numerously validated ones is the Big 5 model. The model has been developed mainly by Costa & McCrae since 1978 and in the 90s it was confirmed by a large number of empirical studies [6], [7], [8], [9]. There is also a number of studies showing strong relationship between personality and behaviour, life satisfaction and achievements and preferences e.g. [10], [11]. Big 5 theory seems to have a dominant position and for many important reasons it is used for creating new Cybernetic Big Five Theory (see [12]). In this article a personality trait is defined as *probabilistic description of relatively stable patterns of emotion, motivation, cognition, and behaviour, in response to classes of stimuli that have been present in human cultures over evolutionary time*. The proposed Cybernetic Big Five is organised in the same way as the traditional Big 5 model and consist of five dimensional factors: **Extraversion** (tolerance for big quantity of stimuli and high need for socialising), **Openness to experience or Intellect** (tolerance for the new and the unknown), **Neuroticism** (intolerance for stress), **Conscientiousness** (intolerance for chaos and disorder, **Agreeableness**(concentration on others' needs and willingness for co-operation). In the past 10 years, many researchers and many companies have attempted to determine a user's personality based on different kinds of digital data. Most of the attempts concerned data from social media (Facebook, Twitter) [13], [14], [15] or other personal data like call logs [16] or mobile applications [17]. There is also evidence that this kind of data-based personality diagnosis is accurate [18], [19]. As far as the applied methods are concerned, models of indicating data-driven users' personality are mainly based on text analysis (e.g. tweets or FB posts), using statistical regression or simply r-Pearson correlation [20], [14]. It is worth noting that the availability of data from social media is now significantly more difficult than before. Therefore, in business practice, other sources that give insight into individual differences are sought. In 2013 [14] researchers proved that predicting personality based on telephone call logs data is also possible. There is also a proven case of detecting personality based on Sociometric Badges after collecting various kinds of data reflecting human behaviour for 6 months [18].

2.2 Personality as a classifier of user needs

In 2017 authors in paper [21] confirm that the use of psychological targeting allows to influence the behaviour of social media users by adapting the message to the psychological needs of recipients defined by personality (Big 5). But at the beginning of using a new type of AI services, such as a virtual/voice assistant, data from the history of usage will not be available.In the context of even better regulations on the protection of users' privacy, we are slowly moving towards a situation in which services will be limited to the use of own data, and data information systems will become more and more hermetic. Therefore, we are looking for methods that will allow services to detect user's personality based on even small amounts of data available at the time of service installation, e.g. from a mobile phone (apps used, history of usage, notes, calendar, photos, way of data storage). In this paradigm, the assumption refers to determining the personality of each user of a smart device (personal or home), so the model should be based on the data available on different smart devices. Therefore, we have excluded such types of data which do not apply to everyone (e.g. social media or other specific services or applications).

2.3 Continuous need for technological adaptation

Each subsequent technology and subsequent intelligent services will be increasingly complex and difficult to learn. It seems that the adaptation process will be more and more difficult. Understanding a user's personality at the beginning of the adaptation process seems to be crucial for the application of an appropriate activity to eliminate cognitive barriers. The adaptation process is easier in the case of high Extraversion, high Conscientiousness and low Neuroticism [22]. Highly neurotic people are generally not resistant to stress, accompanied by a higher level of anxiety and a lower ability to adapt, which stands in contrast to high Openness, as it is a beneficial feature when learning about and discovering new things. An additional incentive for people with high Openness to use such technologies is their intellectual involvement. According to [23], robots and virtual agents are simulating human behaviour better and better to facilitate contact and cooperation (rich communication, support, kindness, warm and deep contact). This promotes the anthropomorphization of virtualized entities. Interestingly, people with high Extraversion and emotional stability (low Neuroticism) anthropomorphize robots and virtual agents more often. They create emotional closeness which facilitates contact and cooperation [24]. This also works the other way round, robots with highly extroverted behaviors give a more positive impression than robots with introverted features [25], which can be a good solution in the absence of information about the user's presence. In turn, research [26] shows that contact with robots or other intelligence simulations can be facilitated by mapping user's personality. Extroverts prefer robots with extroverted behaviors, and introverts with introverted ones.

3 Research

3.1 Purpose of preliminary research

Before the main research, requiring large expenditures, a small preliminary study was carried out to verify the validity of the adopted assumptions and directions of research (see also [3], [4]). Below we present the results of analyses conducted on the basis of the material collected in these preliminary tests. The objectives for the initial study were as follows: (i) to verify personality according to the Big 5 theory as a sufficient classifier for the segmentation of attitudes in relation to intelligent services (virtual agent), (ii) to check statistical methods that can be automated in created services for personalised response.

3.2 Method of data gathering

The research was carried out on 60 users of mobile phones, residents of Warsaw. In order to emphasize the diversity among people resulting from their personality, the study was conducted on a very homogeneous group in terms of demographics (the aim was to reduce confounding factors). The age has been limited to 20-29, and groups for both sexes have been separated. The members of both groups were technologically advanced and using many functionalities of mobile devices. The study was multi-stage: first, filling out the personality questionnaire (Big 5), then monthly observation of behaviours concerning social profiles and the use of telephone, and finally in-depth interviews aimed at getting as much information as possible about behaviour patterns. Transcription of these interviews was used as the base for linguistic analysis (Natural Language Processing). The resources for NLP consist of over 11 000 sentences (59% of which were spoken by women) and almost 140 000 words (56% of which were spoken by women).

3.3 Differentiation of attitudes towards intelligent services

Qualitative analysis of respondents' statements confirmed the wide variation in attitudes towards intelligent services between people with different Big 5 profiles.A short summary of these declared attitudes is presented in (Tab. 1). It shows mainly qualitative differentiation of attitudes and expectations of mobile phone users towards virtual agents and services based on AI. The differences

Table 1. Different attitudes and expectations connected with virtual assistant (VA) contingent on personality dimensions (Big 5)

Personality dimension	High level	Low level
Extraversion	rejection of VA, but can be considered if adapted to the user expectations (no advertisements)	rejection based on privacy (need for high protection), VA in role of an invisible friend
Openness to experience	the repeatability based on usage history is irritating, but the idea of a smart, proactive VA searching for all they need is attractive, they would be first to try it, their interest is changing and evolving	they expect to do something easier and faster - but still only when they need it (they initiate the action) - their interests are rather stable.
Conscientiousness	the only group which likes personalisation, VA for them can be a useful tool to control themselves, keep schedule and order	they are aware of their own problems, so they want the functionalities that help them avoid errors due to lack of systematic or discretionary decision-making etc.
Neuroticism	they appreciate the convenience of this solution (it limits forgetting, helps), but are skeptical about the data transfer and the risk of "manipulation"	if they have enough time for adaptation, they can go with it (the value for them is the effectiveness in real life))
Agreeableness	they are afraid, but if it becomes popular (recommended by friends), they will accept it	their main motivation are pragmatic needs (usefulness in everyday life).

concern mainly the function of a virtual assistant and are a simple derivative of the diversity of needs. At the same time, it can be seen that attitudes polarize according to personality dimensions. For example, people who are open to experience expect non-standard content, have a high level of cognitive needs and a 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 another dimension, individuals with a high level of Conscientiousness use mainly the functionalities that help in the implementation of the need for control, which mainly manifests itself in the control of time and in scrupulous planning. On the other hand, people with a low level of Conscientiousness, who accept life in chaos and disorder, need only very basic control functionalities and will never be interested in using advanced calendar or notebook functions.

3.4 Results of statistical analyses (NLP)

The basic hypothesis was the question whether there is a connection between the personality of participants and the diversification of their language. The Big 5 theory assumes that people have five personality traits. Consequently, the comparison of linguistic differences of groups with e.g. high and low Extraversion must also take into account Openness, Conscientiousness, Agreeableness and Neuroticism. To verify the hypothesis, six distance matrices of equal dimensions were constructed.

Procedure of creating distance matrix for language differences Every document (text of discussion for each group) was pre-processed using UDPipe in Orange Data Mining software. (See ([29])([30])([31])) – tokenization and lemmatization for Polish language. After tokenization and lemmatization for Polish language, Bags of Words were constructed (TF - Smooth IDF parameters). The next step was to calculate the differences between each document, which created a matrix with 20 rows and 20 columns. The distance measure was based on cosine similarity (1-cosine of angle between vectors assigned by Bags of Words). The maximum distance between documents was 0.43, minimum was 0.22.

Procedure of creating distance matrices for personality differences It was assumed that personality profile of the group will be measured as a mean result of participants. The profiles of each group were compared against one another for every BIG 5 trait. This created 5 matrices with 20 rows and 20 columns. The maximum distance between trait levels equalled 0.83 between women (Openness), 0.76 between men (Conscientiousness) and also 0.76 between men and women (Conscientiousness).

The described procedures led to creation of the merged comparison of linguistic and personality differences – 45 cases for men and women respectively. This gave an opportunity to measure simultaneous impact of BIG 5 traits (independent variables) on the language which was used by the study participants. For statistical analysis of the relation between BIG 5 and language, multiple regression algorithm in SPSS (See [32]) software was used. In the first step all BIG 5 traits were used for exploration as independent variables (regression with entry method). It turned out that for women all trait differences between groups, apart from Openness, are significant predictors. On the other hand, for men Extraversion is the most important in explaining differences in language. Because of the correlation of traits variability for women (especially Extraversion and Neuroticism) (Fig. 2) and low number of cases (n=45) for men and women, stricter conditions were applied (regression with stepwise selection and p-value test of 0.01 value).(Fig. 1). This caused only one BIG 5 trait for each group to enter their regression model – Conscientiousness for women and Extraversion for men. Conscientiousness explains 22% of language variance, while Extraversion explains 31% of language variance.

Regression - method: Enter

female

	B	Beta	Sig.	R Square
O	0,02	0,15	0,26	0,53
C	0,08	0,53	0,00	
E	0,10	0,51	0,00	
A	0,06	0,31	0,02	
N	-0,06	-0,34	0,01	

male

	B	Beta	Sig.	R Square
O	-0,05	-0,24	0,12	0,43
C	0,02	0,12	0,47	
E	0,12	0,50	0,00	
A	-0,01	-0,04	0,77	
N	-0,05	-0,22	0,15	

Regression - method: Stepwise, p-value in = 0,01

female

	B	Beta	Sig.	R Square
O	*removed*	*removed*	*removed*	0,22
C	0,07	0,47	0,00	
E	*removed*	*removed*	*removed*	
A	*removed*	*removed*	*removed*	
N	*removed*	*removed*	*removed*	

male

	B	Beta	Sig.	R Square
O	*removed*	*removed*	*removed*	0,31
C	*removed*	*removed*	*removed*	
E	0,14	0,56	0,00	
A	*removed*	*removed*	*removed*	
N	*removed*	*removed*	*removed*	

Fig. 1. Results of Regression Analyses

Correlations

female	cosine distance	O	C	E	A	N
cosine distance	1	-0,13	**,47****	,33*	0,17	-0,23
O	-0,13	1	-,31*	-0,15	-0,23	-0,11
C	**,47****	-,31*	1	0,07	-0,23	-0,07
E	,33*	-0,15	0,07	1	-0,12	,46**
A	0,17	-0,23	-0,23	-0,12	1	-0,24
N	-0,23	-0,11	-0,07	,46**	-0,24	1

Correlations

male	cosine distance	O	C	E	A	N
cosine distance	1	-0,29	0,17	**,56****	-0,19	-0,23
O	-0,29	1	-0,16	-0,19	-0,14	-0,25
C	0,17	-0,16	1	-0,14	-0,27	-,33*
E	**,56****	-0,19	-0,14	1	-,31*	-0,07
A	-0,19	-0,14	-0,27	-,31*	1	-0,03
N	-0,23	-0,25	-,33*	-0,07	-0,03	1

Fig. 2. Results of Correlation Analyses

From the above analysis it can be concluded that language diversification is influenced by a disparate trait for each sex.For groups with high and low Conscientiousness (women) and high and low Extraversion (men) analysis of most popular words was conducted (words were reduced to the basic form – a token). During the discussion in qualitative study extraverts used 8% more tokens than introverts. Among 100 most popular words, the first 5 tokens are generating 26% of words, whereas for introverts this equals 21%. The differences between the usage of statements for 10 most popular words are shown on the chart (see Fig. 3). The maximum dissimilarity was 5.4% between high and low Extraversion.(see Fig. 3).

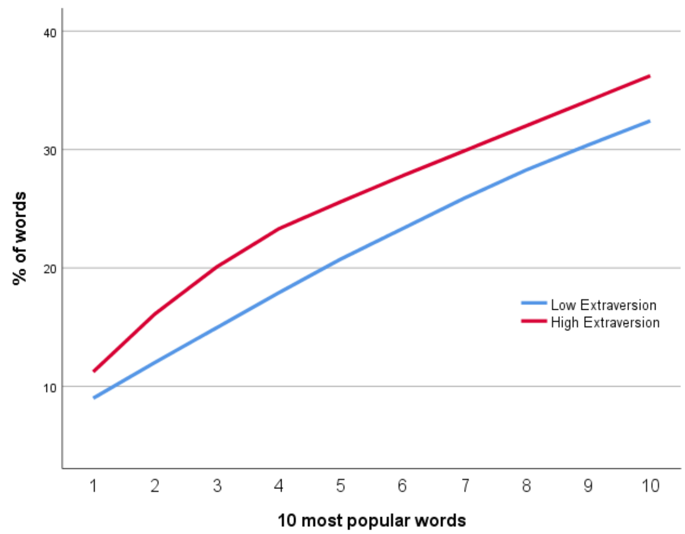

Fig. 3. Comparison of frequency of words between Extraverts and Introverts

When considering the basic parts of speech in vocabulary, in both groups nouns outweigh others categories (for high Extraversion – 53 different tokens, for low Extraversion – 49 different tokens). The fraction of nouns used in discussion is significantly different between groups (based on chi-squared test). Nouns served as 56% of used words for extraverts and 50% for introverts. Differences can also be seen for adjectives and adverbs – among 100 most popular words extraverts use 13 different words from this category, introverts 21. The latter also use them more frequently – 13% vs 7%. The distribution of verbs is more balanced, both groups use them as 37% of words, but extraverts have a little more verbs in their vocabulary – 34 tokens vs 30 for introverts. Participants with low extraversion use a little bit more terms connected with time and use them more frequently than extraverts – 8 tokens vs 5 tokens and 8% vs 5% among 100 most popular words. Terms connected with people are more evenly distributed - 4 tokens for introverts and 4 tokens for extraverts, 8% and 5% accordingly for 100 most popular words.(Tab. 2)

Considering groups with low and high Conscientiousness, there is a gap in the number of words that were used. Less conscientious people used 29% more tokens than high-conscientious people. Among 100 most popular words for high Conscientiousness the first 5 tokens generate 27% of words, whereas for low Conscientiousness this equals 23%. The differences between the usage of state-

Table 2. Table: statistics for words - Extraversion

	High Extraversion		Low Extraversion	
	% of distinct tokens	% of spoken	% of distinct tokens	% of spoken
verb	34%	37%	30%	37%
adjective/adverb	13%	7%	21%	**13**%
noun	53%	**56**%	49%	50%
time	5%	5%	8%	8%
people	4%	8%	4%	7%

ments for 10 most popular words are shown in Figure 4. The maximum revealed dissimilarity was 4.1% between high and low Conscientiousness (see Fig. 4)

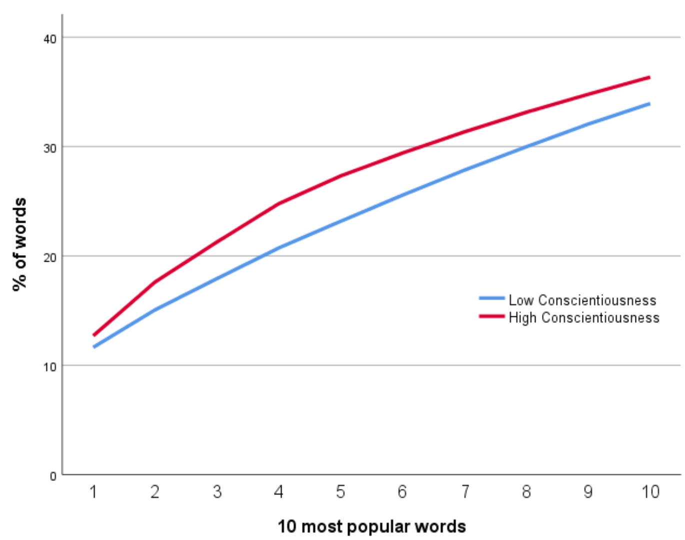

Fig. 4. Comparison of frequency of words between High and Low Conscientiousness

When compared to Extraversion, Conscientiousness does not seem to differentiate between parts of speech in 100 most popular words. The results of both low and high Conscientiousness groups are similar. The frequency of usage is less balanced – nouns used by the high level group constitute 50% of most used words, for low level group it equals 47%. The differences in other categories are less significant.

People from low Conscientiousness group use more terms connected with time and use them significantly more often than the high Conscientiousness group – 15 tokens vs 9 tokens and 15% vs 10% among 100 most popular words. Terms connected with people are more balanced - 9 tokens for low Conscientiousness

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Table 3. Table: Statistics for words - Conscientiousness

	High Conscientiousness		Low Conscientiousness	
	% of distinct tokens	% of spoken	% of distinct tokens	% of spoken
verb	34%	39%	34%	41%
adjective/adverb	17%	11%	18%	12%
noun	49%	50%	48%	47%
time	9%	10%	15%	**15%**
people	10%	10%	9%	10%

and 10 tokens for high Conscientiousness, 9% and 10% accordingly for 100 most popular words.(Tab. 3)

4 Idea for Research Utilisation

The presented set of lexical analyzes can be automated and used directly in a service that interactively communicates with the user. The diagram presents an example for data flow using similar analyzes (see Fig. 5). A separate layer in architecture is used for general analytic. These profiles and variations created

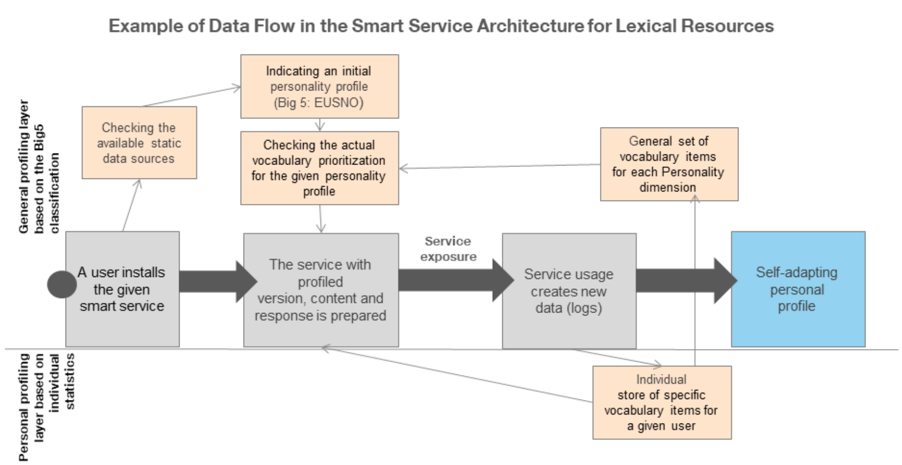

Fig. 5. Example of Data Flow in the Smart Service Architecture for Lexical Resources

for groups with a specific personality profile would be used to personalize the service at the beginning of use. When data from a specific user is still missing. Over time and the collection of data about a specific user, profiling will change to more individual, tailored to one user (not to a group of people with a similar personality profile). Data collected for groups with a specific personality could still be used to change the behavior of e.g. a virtual agent or robot if the performance of a specific task can be improved by co-operation with an agent with a different personality than the user's personality. Over time and the collection of data about a specific user, profiling will change to more individual, tailored to one user (not to a group of people with a similar personality profile). Data collected for groups with a specific personality could still be used to change the behavior of e.g. a virtual agent or robot if the performance of a specific task can be improved by co-operation with an agent with a different personality than the user's personality.

5 Conclusion and Future Works

The presented preliminary research was carried out in order to obtain insight about undertaking further, more advanced research concerning the creation of user-oriented services. It was a part of a research program conducted simultaneously with Smart Home service and Personal Virtual Assistant development.

The research was to confirm the usability for profiling of personal data obtained without the necessity of collecting data logs from services, as well as to test automatic analytic which can be implemented inside service back-end. It also seems that personality-based lexical differences can be useful in creating personalized service response in communicating with an intelligent service. On the other hand, the service constructed in this way will be able to collect data to simulate any desired personality of the virtual agent.

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. The results of this research confirm that Big 5 profile is a good classifier influencing the way, the style and the barriers connected with human-virtual agent (or robot) interactions. It can be a new approach to the design of user-oriented services based on the insight from the available data. An attempt to verify which of the created models is more effective in predicting behaviour and personalising smart services will also be the challenge for researchers. Of course, every model based on the simplification connected with clustering (assignment to group of comparable needs) will be useful only during an early adaptation process. This will prevent the service from being rejected at the initial stage of usage. As the service is being used, each model becomes tailor-made for a given user. However, this requires time and is directly contingent on the use intensity. In situation of occasional usage of the service, it can last unacceptably long. However, the proposed approach to profiling may become attractive when adding more features of the service that does not yet have any usage history. It can also be easily transferred to other areas of business, such as creating applications and user interfaces which will be automatically adapted to users' personality.

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