LEVERAGING THE POTENTIAL OF PERSONALITY TRAITS FOR DIGITAL HEALTH INTERVENTIONS: A LITERATURE REVIEW ON DIGITAL MARKERS FOR CONSCIENTIOUSNESS AND NEUROTICISM

Research full-length paper

Track 12

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Abstract

Digital health interventions (DHIs) are designed to help individuals manage their disease, such as asthma, diabetes, or major depression. While there is a broad body of literature on how to design evidence-based DHIs with respect to behavioral theories, behavior change techniques or various design features, targeting personality traits has been neglected so far in DHI designs, although there is evidence of their impact on health. In particular, conscientiousness, which is related to therapy adherence, and neuroticism, which impacts long-term health of chronic patients, are two personality traits with an impact on health. Sensing these traits via digital markers from online and smartphone data sources and providing corresponding personality change interventions, i.e. to increase conscientiousness and to reduce neuroticism, may be an important active and generic ingredient for various DHIs. As a first step towards this novel class of personality change DHIs, we conducted a systematic literature review on relevant digital markers related to conscientiousness and neuroticism. Overall, 344 articles were reviewed and 21 were selected for further analysis. We found various digital markers for conscientiousness and neuroticism and discuss them with respect to future work, i.e. the design and evaluation of personality change DHIs.

Keywords: Digital health interventions, Personality traits, Personality recognition, Conscientiousness, Neuroticism, Digital markers, Behavioral features, Literature review.

1 Introduction

Non communicable diseases (NCDs), such as heart diseases, asthma, hypertension, diabetes or major depression, impose the greatest burden on global health (Krug, 2016; WHO, 2011; WHO, 2015). That is, a loss of US$ 47 trillion is expected between 2012 and 2032, which equals approximately 75% of the global gross domestic product in 2010 (Bloom et al., 2011). Any technology that helps make treatment more effective or efficient can potentially benefit humanity at a grand scale. Health information systems (HIS) have been identified as offering such potential (Agarwal et al., 2010; Fichman et al., 2011; Gupta and Sharda, 2013; Kohli and Tan, 2016; Lin et al., 2017; Lin et al., 2014; Martin et al., 2010). In particular, various digital health interventions (DHIs), i.e. HIS with the objective to support patients in their everyday life in contrast to hospital information systems, have been designed for NCDs such as diabetes (Block et al., 2015; Liang et al., 2011; Meyer et al., 2014; Ramadas et al., 2011; Young et al., 2017), asthma (Al-Durra et al., 2015; Huckvale et al., 2012; Merchant et al., 2016; Tinschert et al., 2017) and mental illness (Donker et al., 2015; Fitzpatrick et al., 2017; Kim et al., 2015; Wahle et al., 2017).

While there is a broad body of literature on how to design evidence-based DHIs with respect to health behavior theories (e.g. Health Action Process Approach or Health Promotion Model) (Marsch et al., 2014; Pender et al., 2010; Schwarzer, 2008; Schwarzer and Luszczynska, 2015), behavior change techniques (e.g. feedback on behavior or goal setting) (Abraham and Michie, 2008; Michie et al., 2013) or various design features (e.g. usability, aesthetics or tailoring) (Morrison et al., 2012; Wahle et al., 2017), targeting personality traits with health impact has been neglected so far in DHI designs. Indeed, there is evidence on the effect of two particular personality traits on health outcomes: conscientiousness and neuroticism.

First, individuals with low conscientiousness are less likely to follow medical prescriptions, which has been shown for chronically ill individuals in particular (Christensen and Smith, 1995; O'Cleirigh et al., 2007). Not following prescriptions can put patients suffering from chronic conditions at greater risks for complications that require hospitalization (Sokol et al., 2005). Thereby, they not only further increase the threat to their health and well-being but also multiply the financial burden placed on themselves and society.

Second, neuroticism is another significant predictor of health outcomes (Lahey, 2009). Alongside conscientiousness, it is predictive with respect to the long-term health condition of chronic patients (Brickman et al., 1996), and by itself it predicts somatic complaints (Rosmalen et al., 2007). Overall, high levels of neuroticism may contribute more to health costs than common mental disorders (Cuijpers et al., 2010).

Although a traditional view states that personality traits are stable in adulthood and thus per se not adjustable (McCrae and Costa, 1996), recent research in psychology has highlighted the possibility that personality is changeable by appropriate interventions (Allemand and Flückiger, 2017; Mroczek, 2014). First steps have been explored both for conscientiousness (Magidson et al., 2014) and neuroticism (Armstrong and Rimes, 2016; Barlow et al., 2013). Neuroticism has emerged as a target for intervention in the treatment of anxiety and other emotional disorders (Barlow et al., 2013). A recent study has found promising experimental support for the malleability of neuroticism (Armstrong and Rimes, 2016).

Sensing these personality traits with the help of digital markers, i.e. behavioral indicators derived from online sources or smartphone sensors and interactions such as communication patterns in social networks or usage patterns of mobile applications, and providing corresponding personality change interventions, i.e. to increase conscientiousness and to reduce neuroticism, may be an important active and generic ingredient for various DHIs.

With recent advances in information and communication technology, it becomes more and more reasonable to automatically and unobtrusively draw conclusions about an individual's personality, since a variety of digital markers can efficiently be collected and analyzed (Allemand and Mehl, 2017; Chittaranjan et al., 2011; Xu et al., 2016). For example, smartphones can record information such as movement patterns, geographic location, sounds, phone calls, or data from Bluetooth connected medical devices, for example, to measure adherence to pre-defined blood glucose meter events (Miller, 2012; Xu et al., 2016). Moreover, individuals use Facebook, Twitter, WhatsApp, Instagram among other social media platforms. In accessing these services, users provide personal profile data, connect with others, and create message streams, which are all potential digital markers reflecting various personality traits (e.g. Golbeck et al., 2011b).

Against this background and as a first step towards the design of personality change DHIs, we state the following research question: *Which digital markers can be measured unobtrusively and are related to conscientiousness and neuroticism?*

We answer the research question by conducting a systematic literature review. To the best of our knowledge, the current research is the first literature review on unobtrusive recognition of personality traits with health impact that employs a systematic search process (Okoli and Schabram, 2010; vom Brocke et al., 2009; Webster and Watson, 2002). We therefore see the contribution of this paper as a foundation for the design of personality change DHIs.

The remainder of the paper is structured as follows. Next, we discuss related work with respect to personality traits, the relation of conscientiousness, neuroticism and their impact on health outcomes, and automatic personality recognition. This allows us then to derive relevant selection criteria for the literature review. Subsequently, we describe our search strategy and present the results. To conclude, we discuss the findings and outline future work, i.e. the design and evaluation of personality change DHIs.

2 Related Work

2.1 Personality Traits

Personality traits are defined as relatively enduring patterns of behavior, thought, and feeling that are consistent across a wide variety of situations and contexts (Roberts, 2009). Traits describe the most basic and general dimensions upon which individuals are typically perceived to differ. These individual differences are often organized within the conceptual framework of the Big Five (John et al., 2008) or Five-Factor Model (McCrae, 2008) and include five broad traits: extraversion, openness to experience, agreeableness, conscientiousness, and neuroticism. Extraversion refers to individual differences in the propensity to be sociable, active, assertive, and to experience positive affect. Openness to experience refers to individual differences in the proneness to be original, complex, creative, and open to new ideas. Agreeableness refers to traits that reflect individual differences in the propensity to be altruistic, trusting, modest, and warm. Conscientiousness reflects the propensity to be self-controlled, task- and goal-directed, planful, and rule following. Finally, neuroticism, or conversely, emotional stability, contrasts even-temperedness with the experience of anxiety, worry, anger, and depression.

2.2 Conscientiousness, Neuroticism and their Relation to Health Outcomes

We now provide further details on conscientiousness and neuroticism and present their relation to health-related outcomes. Conscientiousness and neuroticism can be divided into three facets for each trait (Soto and John, 2016). Conscientiousness as a personality trait includes the three key facets of organization, productiveness, and responsibility. Organization or orderliness represents a preference for order, structure and tidiness. Productiveness or industriousness represents a more proactive facet of conscientiousness and addresses the degree of persistence a person shows while pursuing goals and the work ethic of someone. Responsibility as a facet of conscientiousness stands for commitment to meeting duties and obligations and represents the prosocial component of conscientiousness, which is capturing the degree to which a person can be depended upon by others. The personality trait of conscientiousness has been linked to a myriad of positive outcomes including positive health outcomes (Bogg and Roberts, 2004). Previous research could show that conscientiousness even appears to be a predictor of longevity (Friedman et al., 1995). Various unhealthy habits and behaviors including smoking, improper diet, and lack of exercise are negatively correlated to conscientiousness (Bogg and Roberts, 2004; Hampson et al., 2000). Furthermore, people with lower levels in conscientiousness are less likely to follow medical prescriptions, which could be shown for chronically ill people in particular (Christensen and Smith, 1995; O'Cleirigh et al., 2007). Not following medical prescriptions might lead to a greater risk for complications among patients and might lastly even increase the financial burden placed on society and themselves (Sokol et al., 2005).

The personality trait of neuroticism (negative emotionality) represents individual differences in the frequency and intensity of negative affect (Clark and Watson, 2008). Neuroticism includes the three key facets of anxiety, depression and emotional volatility. The facet of anxiety represents one’s level of stress and worries, for example how often someone feels stressed, anxious, afraid or tense. Depression as a facet of neuroticism includes the feeling of sadness, level of self-confidence and optimism. Someone’s level of temperament and the ability to control emotions adequately is represented in the third facet called emotional volatility (Soto and John, 2016). The relation between neuroticism, health and longevity is more complex since some studies support an association between neuroticism and increased risk of actual disease, whereas others show links with illness behavior only (Smith and Spiro III, 2002). Neuroticism, including vulnerability and rumination, seems to contribute to disease by shaping reactions to illness. For example, a study by (Brickman et al., 1996) could show that neuroticism seems to be predictive of the long-term health of chronic patients. Another study could show that neuroticism might also be related to somatic complaints (Rosmalen et al., 2007). Cuijpers et al. (2010) found that the economic costs of neuroticism are enormous and even exceed those of common mental disorders and those of somatic disorders. Finally, it is well-known that stress, a facet of anxiety, is linked to both the causes and consequences of NCDs and thus plays a significant role in the health condition of individuals (Harrison and Cooper, 2011; Kozora et al., 2009).

Against this background and consistent with recent findings indicating that conscientiousness (Magidson et al., 2014) and neuroticism (Armstrong and Rimes, 2016; Barlow et al., 2013) can be changed by appropriate interventions (Allemand and Flückiger, 2017; Mroczek, 2014), we now outline how personality traits can be sensed unobtrusively with the long-term goal to design personality change DHIs.

2.3 Automatic Personality Recognition

A very common way to assess personality traits according to the Big Five framework is to use a self-assessment questionnaire, in particular the Big-Five-Inventory (BFI) (John and Srivastava, 1999). However, filling out such an inventory with more than 40 items takes time and puts a relatively large burden on an individual. Moreover, when applied once, it does not allow to measure dynamic changes over time of the personality traits. Therefore, it is desirable that DHIs recognize personality traits and changes in these traits in a ubiquitous and unobtrusive fashion over the course of several weeks or months. Computationally determining personality traits from behavioral data of individuals has been termed Automatic Personality Recognition (APR) (Vinciarelli and Mohammadi, 2014). A suitable and commonly used method for APR is to use machine learning (ML) algorithms, which can learn to perform this task by generalizing from examples (Chittaranjan et al., 2011; Xu et al., 2016). In the context of APR, ML algorithms would learn to map a representation of behavioral data to a representation of personality. Critically, both representations need to be chosen and the choices are not straightforward. As we will discuss later in this paper, different APR approaches use different representations. The representation of behavioral data corresponds to the set of input variables for the ML algorithm. These input variables are termed “features” in the ML literature, and correspond to our digital markers. Domingos (2012) makes two noteworthy observations: (1) The choice of digital markers is easily the most important factor for whether a ML project succeeds or fails; (2) If the markers are numerous, independent from each other and each correlate well with the output variable, then learning is easy. Marker selection is the process of selecting a subset of best markers within a given set in order to improve prediction performance and advance understanding of the data (Guyon and Elisseeff, 2003). It may also reduce data collection efforts and privacy concerns, if it can remove the dependency on privacy-critical data (e.g., GPS data streams).

In an attempt to address our research question, we will now outline the details about our systematic literature review in order to find digital markers that are related to conscientiousness and neuroticism.

3 Finding Relevant Digital Markers

3.1 Selection Criteria and Search Process

In an effort to make the search process as transparent as possible we followed the guidelines for systematic literature reviews (Okoli and Schabram, 2010; vom Brocke et al., 2009; Webster and Watson, 2002). We started with an exploratory literature search using Google Scholar. This led to an initial list of relevant publications, including a survey paper (Vinciarelli and Mohammadi, 2014) from which the search query was defined. From this initial list we developed the following search query:

Title (OR)		**Abstract** (OR)
personality, conscientiousness, neuroticism, "emotional stability"	AND	predict*, classif*, recogni*, determin*, "personality analysis", "personality detection"

We set the relevant time range for the search query from January 2006 to May 2017, as a preliminary search of papers related to the topic almost exclusively yielded papers from the last 7 years, and none published before 2008. We also developed the following selection criteria of relevance, according to our focus on unobtrusive ARP for conscientiousness and neuroticism:

Criterion 1: Inclusion of studies where personality data was collected unobtrusively from individuals' interaction with information technology, i.e. studies with explicit test tasks were ignored.

Criterion 2: Inclusion of studies that performed APR to predict personality traits and predict at least either conscientiousness or neuroticism.

Criterion 3: Inclusion of studies that adopted the widely used Big Five framework to represent personality related to conscientiousness and neuroticism, as ground truth and for comparability reasons.

Criterion 4: Inclusion of studies that investigate personality-related data from smartphones or strongly frequented social platforms, i.e. with at least 100 million monthly active individuals. We used a recent report by We Are Social Singapore (2016) to determine social online platforms of that size. Specifically, we included Facebook, Twitter, and the Chinese social network "Weibo", but excluded articles discussing personality prediction on personal blogs, the Chinese social network "RenRen" or with a special focus on subgroups, such as photo sharing and online gaming platforms.

Our search strategy included top IS journals, i.e. the Senior Scholar's Basket of Journals of the Association for Information Systems. We also considered the journals Computers in Human Behavior, and Social Network Analysis and Mining, as these journals appeared during our exploratory search to be relevant outlets. Finally, the exploratory search also revealed that most relevant research was published in computer science outlets, and therefore we also included the ACM Digital Library and IEEE Explore to the list of relevant databases. Table 1 gives an overview of the journals and conferences, databases, number of hits, i.e. papers that matched the search query, and papers included for further analysis, i.e. papers that matched the selection criteria. Moreover, we added one paper that appeared to be highly relevant from our preliminary search and one paper that was cited in review paper.

3.2 Analysis

To judge the relevance of a digital marker for the prediction of conscientiousness or neuroticism, we observed four approaches from the list of selected articles as outlined in Table 2. These are:

(1) **Correlation approach**: Nine articles report statistically significant correlations between personality traits and digital markers. Of these, eight provide the values of the correlations.

(2) **Digital marker selection approach**: Six articles report results of marker selection ML algorithms.

(3) **Digital marker importance measurement approach**: One article reports a list of most important markers, which are selected by an ML algorithm.

(4) **Regression approach**: one article reports regression coefficients.

As we were interested in digital markers related to conscientiousness or neuroticism that are most relevant not only within but also across the studies, we used the following two methods for our analysis:

Across-study analysis: As already outlined above, with highly correlated digital markers, learning is easy. Therefore, we created a list of the most highly correlated markers, see Subsection 4.1.

Within-study analysis: For the remaining articles, we discuss the digital markers that they have found particularly useful, see Subsection 4.2.

#	Journal / Conference	Database	Hits	Included
1	European Journal of Information Systems*	Palgrave Macmillan	0	0
2	Information Systems Journal*	EBSCOhost	1	0
3	Information Systems Research*	Informs	1	0
4	Journal of AIS*	AIS eLibrary	0	0
5	Journal of Information Technology*	Palgrave Macmillan	0	0
6	Journal of MIS*	EBSCOhost	0	0
7	Journal of Strategic Information Systems*	ScienceDirect	0	0
8	MIS Quarterly*	AIS eLibrary	1	0
9	Computers in Human Behavior	ScienceDirect	63	1
10	Social Network Analysis and Mining	Springer Link	2	2
11	(all journals and conferences)	ACM Digital Library	98	9
12	(all journals and conferences)	IEEE Explore	178	7
13	Included from explorative search process: De Montjoye et al. (2013)		–	1
14	Included from review articles: Bhardwaj et al. (2016)		–	1
		Total	**344**	**21**

Table 1. List of journals, conferences and databases.

4 Results

The list of relevant articles is provided in Table 2. It includes the results from the systematic search and the article of De Montjoye et al. (2013) that we identified being relevant during our explorative search process. We excluded three meta-review articles (Lambiotte and Kosinski, 2014; Pianesi, 2013; Vinciarelli and Mohammadi, 2014) that describe studies which either are covered already in other articles we reviewed or that do not match our criteria of relevance. However, we found one review article (Carvalho and Pianowski, 2017), from which we included one relevant article (Bhardwaj et al., 2016). The table also lists the performance metrics that the articles used to evaluate their prediction model. If several predictive models were described, we list the outcome that was best overall. We use the following notation to describe the ML tasks: 2-Class represents a binary classification task, i.e. a personality trait has one of two values (high vs. low), while 3-Class represents a multi-class classification task with three values (high vs. middle vs. low) for either conscientiousness or neuroticism. It must be noted that some articles use evaluation metrics that depend on the scale and actual range of the input values, such as the Mean Absolute Error (MAE) or the Root Mean Square Error (RMSE). Two of those, i.e. the articles of Quercia et al. (2011) and Adalı and Golbeck (2014) do not provide any details about the actual distribution of the input values, making it difficult to interpret the error values.

#	Reference	Data Source, Analysis Approach & Sample Size			Evaluation Metric	C	High C	Low C	N	High N	Low N
1	Adalı and Golbeck (2014)	Twitter	CA, DS	60	MAE	0.14	–	–	0.19	–	–
2	Bachrach et al. (2012)	Facebook	CA	180000	R-squared	0.17	–	–	0.26	–	–
3	Bai et al. (2013)	Weibo	RA	444	MAE	0.14	–	–	0.13	–	–
4	Bhardwaj et al. (2016)	Facebook, LinkedIn	CA, DS	31	MAE (0 to 100)	2.61	–	–	3.58	–	–
5	Celli et al. (2014)	Facebook	–	112	2-Class Accuracy	0.75	–	–	0.61	–	–
6	(Chapsky, 2011)	Facebook	DS	615	R-squared	0.19	–	–	0.35	–	–
7	Chittaranjan et al. (2011)	Smartphone	CA	117	2-Class F-Measure	0.78	–	–	0.75	–	–
8	De Montjoye et al. (2013)	Smartphone	CAS	69	3-Class Accuracy	0.51	–	–	0.54	–	–
9	Gao et al. (2013)	Weibo	–	1766	Correlation	0.41	–	–	0.32	–	–
10	Ghavami et al. (2015)	Facebook	CA	65	Accuracy	0.59	–	–	0.48	–	–
11	Golbeck et al. (2011a)	Twitter	CA, DS	50	MAE on (0 to 1)	0.14	–	–	0.18	–	–
12	Golbeck et al. (2011b)	Facebook	CA	167	MAE on (0 to 1)	0.10	–	–	0.11	–	–
13	Mukta et al. (2016)	Facebook	–	663	2-Class AUC	0.70 59	–	–	0.68 60	–	–
14	Nie et al. (2014)	Weibo	DS	1792	MAE (0 to 5)	0.43	–	–	–	–	–
15	Pratama and Sarno (2015)	Twitter	–	250	2-Class Accuracy	0.63	–	–	0.58	–	–
16	Quercia et al. (2011)	Twitter	CA	335	RMSE (1 to 5)	0.76	–	–	0.85	–	–
17	Staiano et al. (2012)	Smartphone	–	53	2-Class Accuracy	0.77	–	–	0.74	–	–
18	Thilakaratne et al. (2016)	Facebook	DS	1000	2-Class Accuracy	0.65	–	–	0.64	–	–
19	Wald et al. (2012)	Facebook	–	537	Accuracy of Top / Bottom 10%	–	0.42	0.40	–	0.35	0.40
20	Wei et al. (2017)	Weibo	–	1804	2-Class Accuracy; for High / Low: Precision	0.70	0.73	0.68	0.58	0.70	0.60
21	Xu et al. (2016)	Smartphone	DI	2043	3-Class F-Measure	–	0.39	0.42	–	0.29	0.34

Table 2. List of relevant articles and evaluation results. Note: CA = Correlation approach; CAS = Significance of correlation coefficient is reported; DS = digital marker selection approach; DI: Digital marker importance measurement approach; RA: regression approach; – = none or only examples; MAE = Mean Absolute Error; RMSE = Root Mean Square Error; C = Conscientiousness; N= Neuroticism.

4.1 Between-Study Analysis: Digital Markers with Highest Correlations

With respect to our between-study analysis, the list of digital markers is shown in Table 3. We report only digital markers related to conscientiousness or neuroticism that show a correlation coefficient of at least 0.2. This reflects a small (0.1) to medium (0.3) effect (Cohen, 1992). Correlation coefficients that are larger or equal to 0.2 and statistically significant ($p < .05$) are formatted in bold text.

It turns out that many digital markers derived from content, i.e. classes of words and other text characteristics, are relevant predictors of both conscientiousness and neuroticism, at least on LinkedIn, Facebook and Twitter (Adalı and Golbeck, 2014; Bhardwaj et al., 2016; Golbeck et al., 2011b). Furthermore, digital markers based on the meta data of tweets, i.e. information about the sender, receiver, time of tweet, number of characters and communication patterns), also represent viable predictors particularly for conscientiousness (Adalı and Golbeck, 2014).

In contrast to various relevant digital markers derived from these social media platforms, digital markers from smartphones are sparse. In fact, only one digital marker, i.e. the usage frequency of the YouTube app has a significant relationship with conscientiousness above our effect size threshold of 0.2 (Chittaranjan et al., 2011).

The largest correlations are reported in Bhardwaj et al. (2016), however these correlations are based on rather a small sample size (N=31) and thus, these correlation coefficients have a larger error margin. The number of positive and negative words used on LinkedIn are reported as highly correlated with neuroticism, whereas the length of the profile, number of skills and number of photos on Facebook show a particularly high correlation with conscientiousness. Another digital marker that is negatively correlated with conscientiousness of an individual is having contacts that write very long messages on Twitter. The same holds for the use of negation words such as no, not or never, in tweets, or having a variety of balancedness of communication across different contacts.

For neuroticism, the use of words related to religion or hearing show a high positive relationship (Golbeck et al., 2011a), as are deviations from an individual's average message length across his or her contacts (Adalı and Golbeck, 2014). A special case is the use of exclamation marks, as this has a positive relationship with both conscientiousness and neuroticism (Golbeck et al., 2011a). Most other markers that correlate with both personality traits do so with opposite signs, i.e. have a positive correlation with either one and a negative one with the other. That is, the identified digital markers have the potential to differentiate between conscientiousness and neuroticism.

Source	Category	Digital Marker	Description [# Reference from Table 2]	C	N
Smartphone	**App use**	NoYTU	Number of times the YouTube app was used [7]	**-0.44**	–
LinkedIn	**LIWC**	NoPW	Number of positive words [4]	**-0.44**	**0.90**
		NoNW	Number of negative words [4]	**-0.34**	**0.83**
	Content	LoP	Length of profile [4]	**0.75**	-0.30
	Counts	NoS	Number of skills [4]	**0.70**	**-0.60**
		NoC	Number of connections [4]	**0.61**	-0.12
Facebook	**LIWC**	Social Processes	e.g. mate, talk, they [12]	**0.26**	–
		Seeing Words	e.g. view, saw, seen [12]	**-0.23**	–
		Ingestion Words	e.g. dish, eat, pizza [12]	–	**0.21**
		Human Words	e.g. baby, man [12]	**0.20**	–
	Counts	NoP	Number of photos [4]	**0.83**	-0.35
		NoF	Number of friends [4]	**0.40**	-0.32
	Comments	CLP	A Node's PageRank in CommentLikeGraph [10]	–	**-0.25**

Source	Category	Digital Marker	Description [# Reference from Table 2]	C	N
Facebook & Twitter	Counts	log(TIME)	Log of TIME Magazine's Influence Index (Silver, 2010), based on the number of Twitter followers and Facebook contacts [16]	0.18	**-0.20**
Twitter	LIWC	Exclamation Marks	"!"[11]	**0.26**	**0.32**
		Sadness	e.g. crying, grief, sad [11]	**-0.25**	**0.23**
		Feeling	e.g. feels, touch [11]	**-0.24**	**0.24**
		"You"	e.g. you, your [11]	**0.25**	**-0.21**
		Religion	e.g. altar, church, mosque [11]	–	**0.38**
		Negations	e.g. no, not, never [11]	**-0.37**	–
		Hearing	e.g. listen, hearing [11]	–	**0.34**
		Death	e.g. bury, coffin, kill [11]	**-0.33**	–
		Work	e.g. job, majors, xerox [11]	**0.33**	–
		Colons	":"[11]	**0.32**	–
	Content	STD-Len	STD of mean text length [1]	**-0.21**	**0.32**
		FF-Len	FF of mean text length [1]	**-0.32**	–
		FF-STD-Hash	FF of STD of mean number of hashtags in a tweet [1]	**-0.27**	–
		FF-URL	FF of Mean number URLs in a tweet [1]	**-0.26**	–
		LpT	Links per tweet [11]	**0.26**	–
	Counts	FF-Fav	FF of the number of messages favorited [1]	**-0.23**	**0.30**
		STD-Fo	STD of the number of followers [1]	–	**0.30**
		NoD	Number of days Twitter is used [16]	–	**-0.27**
	Tweets	KL-RespH	KL of Balance/reciprocity of response time A==>B; B==>A [1]	**-0.34**	–
		KL-PMsg	KL of Mean #messages A==>B [1]	**-0.30**	–
		KL-ConvTau	KL of Mean tau (time between messages) in conversations [1]	**-0.26**	–
		KL-PriH	KL of Mean priority reciprocity [1]	**-0.25**	–
		Pri	Mean priority (number of messages of A that are replied to before others) [1]	**-0.28**	–
		STD-Worth	STD of Mean worthiness of A (proportion of messages of A that are propagated by A's contacts) [1]	**-0.26**	–
		ConvTau	Mean tau (time between messages) in conversations [1]	**-0.25**	–
		BalP	Mean balance/reciprocity of msgs A==>B; B==>A [1]	**-0.30**	–
		DelH	Mean delay reciprocity [1]	**-0.28**	–
		FF-STD-Worth	FF of STD of Mean worthiness of A (proportion of messages of A that are propagated by A's contacts) [1]	**-0.28**	**0.25**
		FF-KL-ConvTau	FF of KL of Mean tau (time between messages) in conversations [1]	**-0.34**	–

Table 3. *Correlation coefficients of digital markers with either conscientiousness (C) or neuroticism (N). Note: LIWC = Linguistic Inquiry and Word Count (Pennebaker et al., 2001) is a program for extracting digital markers from text. Because of space constraints we do not list all digital markers of Adalı and Golbeck (2014) and Golbeck et al. (2011a), they can be looked up in their articles*

4.2 Within-Study Analysis

In this section we present the digital markers that have been found to be relevant for predicting conscientiousness and neuroticism, but for which no correlation coefficients have been reported.

Xu et al. (2016) used data from the history of mobile app installations and updates on Android to predict personality traits. This data can be accessed by any Android smartphone app. Their digital markers are based on temporal patterns and the categories of Android apps. They used the Random Forest algorithm for prediction (Breiman, 2001). This algorithm provides a ranking of digital marker importance, based on which they report the most important digital markers. For neuroticism, the installation of apps in the categories *Shopping* and *Puzzle Game*, and the entropy across the categories of the installed apps were most important, along with temporal markers, in particular, the number of distinct app install days, the first quartile of an individual's interval between installations, and the maximum number of apps installed per month. For conscientiousness, apps in the categories *Video*, *Lifestyle*, *Photography*, *Game*, *Trivia Game*, *Social* and *Music* were most relevant, besides the third quartile of app install intervals and the number of months with updates. Xu et al. also looked at the directions of some associations and found that neuroticism was positively associated with the adoption of photo and personalization apps. By contrast, conscientiousness was negatively associated with the adoption of music apps, video apps, photo apps and personalization apps.

Staiano et al. (2012) used data acquired from Android smartphones. They focused on network-based digital markers and did not report on the association between individual markers and personality traits. However, they found that centrality measures from call data, i.e. from the network of who is calling whom, are particularly predictive for neuroticism. Centrality measures are also useful for predicting conscientiousness, particularly when combining data from Bluetooth with call data.

De Montjoye et al. (2013) used call, text, and location data from smartphones. They indicated which of their digital markers were significantly correlated with personality traits. However, they did not report the correlation values. With this information, it is difficult to derive any conclusion about which markers are most relevant, as many markers are significantly correlated and there is no obvious pattern.

Celli et al. (2014) recognized personality traits from an individual's Facebook profile picture. Utilizing Scale-Invariant Feature Transform (SIFT) markers (Lowe, 2004), they predicted conscientiousness and neuroticism with similar performance as other studies. By manual inspection they concluded that individuals with lower degrees of neuroticism tend to have pictures where they are smiling and are together with other people. By contrast, neurotics tend to use an image without any close-up faces or even no person at all. They suggested that conscientiousness might be associated with the direction of eye gaze. It should however be noted that their model for prediction of conscientiousness is based on a very small dataset and thus requires further investigation.

Chapsky (2011) used Facebook profile data, which they enriched with additional meta data, such as statistics about the population of cities. Conscientiousness was most associated with a low location latitude and female sex. Neuroticism was most associated with younger female individuals. This is consistent with known gender differences in average levels of neuroticism (Lynn and Martin, 1997).

Thilakaratne et al. (2016) used the knowledge base DBpedia (Mendes et al., 2011) to enrich Facebook status updates with the categories of semantic concepts that are mentioned therein. Through digital marker selection techniques, they found that digital markers related to nature, perceptual skills, confidence and developing skills, writing, songs, pianists, artists, television stations and movies were predictive with respect to conscientiousness. By contrast, neuroticism was related to sadness, negativity and anger, illnesses, medicines, comedy movies, song writers, populated places, comic strips, and television programs.

Mukta et al. (2016) used APR to find groups of people on Facebook that interact with each other and share similar personality traits. They found that for conscientiousness and neuroticism, prediction based on topic models yields better results than an approach based on LIWC markers.

In addition to reporting correlations on predicting personality traits from Twitter data, Adalı and Golbeck (2014) found that their digital markers of communication patterns, which do not consider the textual content (i.e. specific words), allows equally good prediction as digital markers based on specific words. They concluded that it is important to capture the kinds of relationships that a person has with others. For conscientiousness, they found that these relationships are characterized by a lack of distinctive behavioral patterns, i.e. these individuals behave like other individuals on average. Neuroticism was associated with behavior that highly varies across communication partners.

Four studies predicted personality traits from the Weibo microblogging service, which is widely used in China with about 222 million monthly active users in January 2016 (We Are Social Singapore, 2016): First, Nie et al. (2014) used digital marker selection to determine the best subset of markers. They found that more conscientious individuals have a more complete profile, more mutual followers, and shorter screen names. Individuals with a high degree of neuroticism, by contrast, seem to prefer to post new status messages after midnight or in the early morning, and they also publish more status updates. Second, Gao et al. (2013) used digital markers based on status statistics, sentence-based markers, word-based markers, character-based markers, LIWC markers and Chinese-specific word categorizations based on Pinyin lexicons. They found that conscientious individuals tended to use more exclamation marks, and that more neurotic people used more words about religion and art. Third, Bai et al. (2013) used a set of 29 digital markers based on profile attributes and numbers of connections and status updates. They found that, on the one hand, conscientious individuals have many mutual followers, a large number of friends but less followers overall. These individuals tend to have also shorter user names and publish less posts. On the other hand, individuals with high neuroticism tend to publish more status updates. Fourth, Wei et al. (2017) used heterogeneous information from the Weibo service. They derived their digital markers from language use, avatars, emoticon use, and response patterns. They found some correlations between language use and conscientiousness and neuroticism. For example, conscientious individuals tend to use formal words like *era* and *society*, while neurotic individuals tend to use theatrical emoticons that exaggerate their feelings. Overall, they concluded that combining different sources of information and, especially, considering an individual's reaction to other people's behavior improves the performance of social media-based APR.

Finally, Wald et al. (2012) used demographic and text-based digital markers from Facebook while Pratama and Sarno (2015) employed text data from Twitter, but both groups did not report anything about which digital markers are associated with either conscientiousness or neuroticism.

5 Discussion and Limitations

With respect to our research question, we conducted a systematic literature review with the objective to identify a list of digital markers that were used in APR with a particular focus on personality traits with health impact, namely conscientiousness and neuroticism. The identified digital markers as outlined in Section 4 are relevant predictors of these personality traits and thus, are recommended to inform the design of DHIs that automatically take into account the personality traits of individuals without obtrusively requiring additional manual input. The current work builds therefore also the foundation with respect to our overall research goal, i.e. to build and evaluate personality change DHIs that help individuals to increase their conscientiousness trait and to reduce their neuroticism trait if applicable. In the following paragraphs, we will discuss and summarize our results and outline the limitations of the current literature review.

First, for conscientiousness, digital markers related to media consumption (e.g. watching video clips) and the creation of media (e.g. taking photos) were highly relevant. Moreover, digital markers related to a particular communication style (e.g. the use of negations), the behavior of social contacts and the variety of balancedness of relationships should be taken into account as digital markers of conscientiousness, too. It should be, however, noted that the direction of correlations with these digital markers may differ depending on the data sources or categories. For example, the number of photos on Facebook was positively associated with conscientiousness (Bhardwaj et al., 2016), whereas installation of photo apps on Android phones was negatively associated with conscientiousness (Xu et al., 2016).

For neuroticism, we conclude that digital markers which are related to the use of words of particular classes such as religion, hearing, positive or negative words, were particularly relevant. Furthermore, variation in message length across contacts and the communication style, especially the use of exclamation marks, reflect digital markers of neuroticism.

It is also noteworthy that in our list of relevant digital markers, there is only one marker from a smartphone-based study that reports corresponding correlation coefficients (Chittaranjan et al., 2011). The absolute values of the correlations that they found are, in fact, rarely above 0.1. This is, however, only true for correlation coefficients concerning their entire population. They found different and higher correlations when considering male and female subjects separately. Consistent with prior research on personality traits (Toda et al., 2016), it is therefore recommended to explicitly consider demographic characteristics in studies that investigate digital markers of personality traits. If a reliable indication of gender is available, it may significantly boost prediction performance.

In addition, it is recommended to combine digital markers from several sources and categories as it has been done in a recent approach to detect complex psychological states in couples with the help of multimodal wearable technology (Timmons et al., 2017; Toda et al., 2016). Another complementary data source could be the driving style of individuals based on car data (Dahlena et al., 2012; Taubman et al., 2012).

Finally, we outline the limitations of the current work. First, our between-study analysis does not consider *independence* of the digital markers. Unfortunately, this is not possible as mutual correlations are not reported in the articles. That is, we could only speculate about how the digital markers from different studies would be correlated if used in a single study. Second, the between-study analysis also does not consider the *interdependence* of digital markers. As described in Guyon and Elisseeff (2003), a set of digital markers that are each individually uncorrelated with the target variable, i.e. in our case self-reported conscientiousness or neuroticism, may be extremely useful for personality prediction through their combined use. And finally, the between-study analysis does not consider the size of the populations. That is, correlations found in smaller populations have per se a larger margin of error (Niven and Deutsch, 2012).

6 Summary and Future Work

Two personality traits, namely conscientiousness and neuroticism, have been neglected so far in the design process of DHIs although there is evidence on their impact on health outcomes. Conscientiousness is related to therapy adherence and neuroticism impacts long-term health. Being able to unobtrusively sense these personality traits via digital markers from various data sources and then to increase conscientiousness and / or to reduce neuroticism depending on an individual's needs, may be an important active and generic ingredient for various DHIs, so called personality change DHIs. Because unprecedented and as a very first step towards the design of this novel class of DHIs, we have conducted a literature review to identify digital markers that can be measured unobtrusively and are related to conscientiousness and neuroticism.

As a next step in our work, we will use the results of this systematic literature review, i.e. the list of relevant digital markers for conscientiousness and neuroticism to derive concrete design requirements for a personality change intervention. That is, we plan to cross-validate and assess recent assumptions and empirical evidence on personality change interventions (Allemand and Flückiger, 2017; Armstrong and Rimes, 2016; Barlow et al., 2013; Magidson et al., 2014; Mroczek, 2014) with the help of our digital markers in a prospective randomized controlled trial with healthy participants. The personality change intervention will be implemented on the open source behavioral intervention platform MobileCoach (Filler et al., 2015; Haug et al., 2017; Kowatsch et al., 2017a; Kowatsch et al., 2017b). Elements of the intervention include psychoeducation in the form of video and text, goal-setting, behavioral experiments, reminders, feedback, self-reflection exercises, and continuous tracking of conscientiousness and neuroticism using the digital markers (Allemand and Flückiger, 2017; Magidson et al., 2014). Thereafter and if successfully validated, we will use these elements as building blocks for DHIs targeting various non communicable diseases and chronic patients with the overall goal to improve their health and well-being.

Acknowledgements

We would like to thank the anonymous reviewers and Benjamin Ryder for their valuable feedback that helped us to improve the paper. The work is part-funded by the Swiss National Science Foundation (http://p3.snf.ch/Project-162724).

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