Unobtrusive Personality Recognition for Health Interventions: A Literature Review

Dominik Rüegger[1], Tobias Kowatsch[2], Mirjam Stieger[3], Mathias Allemand[3]
[1]**Center for Digital Health Interventions (CDHI), ETH Zurich;** [2]CDHI, University of St. Gallen; [3]Department of Psychology, University of Zurich

Introduction

We propose exploring the use of automatic, unobtrusive recognition of **personality traits** for adapting health interventions to the patient.

Personality traits are known to be connected to health outcomes, particularly two traits from the widely-used Big Five model, which we focus on here:

- **Conscientiousness** (self-controlled, task- and goal-directed, planful, and rule following). *Predictive of health outcomes. Individuals with low conscientiousness are relatively less likely to follow medical prescriptions.*
- **Neuroticism** (anxiety, worry, anger, and depression). *Alongside conscientiousness, it is predictive of the long-term health of chronic patients. Overall, high levels of neuroticism may contribute more to health costs than common mental disorders.*

Data from usage of smartphones and social media allow prediction of personality traits. We expect that predictions can potentially be used for:

- delivery of **appropriate motivational feedback** to the user, which can help motivate the pursuit of the intervention-specific goals
- **personalization** of the intervention
- **noticing and adapting to** changes in behavior

Method

A **systematic literature review** to find features derived from unobtrusively collected behavioral data that have been most relevant for inferring an individual's conscientiousness and neuroticism traits (exploratory approach).

Challenge:

- Studies report results very differently, difficult to compare

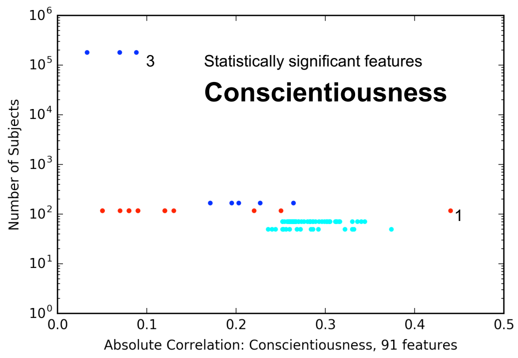
Solution:

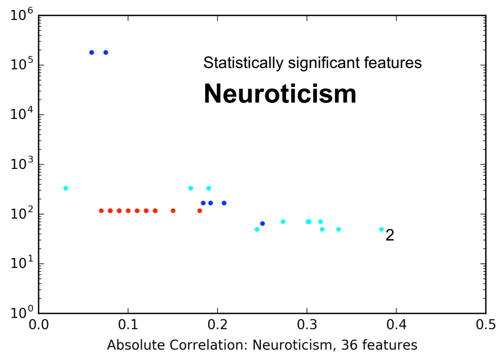
- Across studies we assess relevance of features by values of their correlation with traits
- Within studies (for studies that don't report correlations), consider most relevant as indicated in the study

Results

We found **17 relevant studies**, published from **2011 to 2016**, of which **7 report correlation values** of a total of 117 features. Data sources include social media platform profiles (Facebook, Twitter), and smartphone.

Below are plots showing features with statistically significant correlations.





Example features:

1. Number of times the YouTube app was started (N=117, r=0.44)
2. Use of words relating to religion (e.g. altar, church, mosque, N=50, r=0.38)
3. Number of Facebook likes (N=180'000, r=0.09)

Overall most correlated features (+: positive correlation, -: negative correlation) are:

Conscientiousness
- media consumption (- video) and creation (- photo)
- communication style (- use of negations)
- behavior of social contacts and variety of balancedness of relationships (-)

Neuroticism
- use of words of particular classes (+ religion, + hearing)
- variation in message length across contacts (+)
- communication style (+ use of exclamation marks)

Conclusion & Future Work

It is difficult to determine which features are most relevant overall. Nevertheless, we have been able to provide some suggestions of features which are likely to be relevant.

We plan to collect data in a large field study to validate our approach.

References

1. Chittaranjan, G., J. Blom and D. Gatica-Perez (2011) Mining large-scale smartphone data for personality studies, *Personal and Ubiquitous Computing* 17 (3), 433-450.
2. Golbeck, J., C. Robles and K. Turner (2011b) Predicting personality with social media, in: *Proceedings of the CHI '11 Extended Abstracts on Human Factors in Computing Systems*, Vancouver, BC, Canada, 253-262.
3. Xu, R., R. M. Frey, E. Fleisch and A. Ilic (2016) Understanding the impact of personality traits on mobile app adoption – Insights from a large-scale field study, *Computers in Human Behavior* 62, 244-256.

UNOBTRUSIVE RECOGNITION OF PERSONALITY TRAITS WITH HEALTH IMPACT: A LITERATURE REVIEW WITH A FOCUS ON CONSCIENTIOUSNESS AND NEUROTICISM

Extended Abstract

Rüegger, Dominik, ETH Zurich, Zurich, Switzerland, drueegger@ethz.ch

Kowatsch, Tobias, Institute of Technology Management, University of St. Gallen, St. Gallen, Switzerland, tobias.kowatsch@unisg.ch

Stieger, Mirjam, University of Zurich, Zurich, Switzerland, m.stieger@psychologie.uzh.ch

Allemand, Mathias, University of Zurich, Zurich, Switzerland, m.allemand@psychologie.uzh.ch

Abstract

Non communicable diseases (NCDs) impose the greatest burden on global health. Any technology that helps making treatment more effective or efficient can potentially benefit humanity at a grand scale. Health information technology (HIT) has been identified as offering such potential, and indeed, existing HIT-based interventions are targeting NCD-related specific diseases such as diabetes, asthma, or mental illness. Rather generic determinants impacting health outcomes are the personality traits conscientiousness and neuroticism. We argue in this article that HIT-based interventions can benefit from an unobtrusive recognition of conscientiousness and neuroticism, both for tailoring interventions and for the adaptation of these traits. We conducted a systematic literature review to identify relevant behavioral features representing conscientiousness and neuroticism. Overall, 17 out of 262 articles have been found to be relevant for this purpose. We found that for conscientiousness, features relating to media consumption (video) and creation (photo) were highly relevant, as well as features related to communication style (use of negations), and features relating to the behavior of social contacts and variety of balancedness of relationships. For neuroticism, we found that features relating to the use of words of certain classes (religion, hearing) were particularly relevant, as well as variation in message length across contacts, and communication style (use of exclamation marks). This work concludes with an outlook on future research.

Keywords: Non communicable diseases, Personality recognition, Conscientiousness, Neuroticism, Intervention.

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). Therefore, any technology that helps making treatment more effective or efficient can potentially benefit humanity at a grand scale. Health information technology (HIT) has been identified as offering such potential (Agarwal et al., 2010; Fichman et al., 2011; Martin et al., 2010).

One of the determinants impacting health outcomes related to NCDs are personality traits, particularly conscientiousness and neuroticism, two personality traits from the widely-used Big Five model (John et al., 2008). Conscientiousness reflects the propensity to be self-controlled, task- and goal-directed, planful, and rule following. Neuroticism contrasts even-temperedness with the experience of anxiety, worry, anger, and depression. Conscientiousness and neuroticism have been shown to be linked to health outcomes: Individuals with low conscientiousness are relatively less likely to follow medical prescriptions, which has been shown for some chronically ill people 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). Neuroticism is another significant predictor of health outcomes (Lahey, 2009). Alongside conscientiousness, it is predictive of the long-term health 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 (Mroczek, 2014). Both for conscientiousness (Magidson et al., 2014) and neuroticism, first steps have been explored. 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).

With recent advances in information and communication technology, it becomes more and more feasible to automatically and unobtrusively draw conclusions about users' personality traits, because a variety of relevant behavioral data can efficiently be collected and analyzed. For example, the smartphone is used by more than a billion people and almost always kept on the person and can record information such as movement patterns, location, sounds, phone calls, or mobile applications installed (Miller, 2012; Xu et al., 2016). This data has been found to allow inferences about the personality of smartphone users (Chittaranjan et al., 2011; Xu et al., 2016). A similar number of people regularly use Facebook, Twitter and other social media platforms, maintaining personal profiles, connecting with others, and creating streams of messages, which likewise are indicators of personality (e.g. Golbeck et al., 2011b).

However and to the best of our knowledge, research into the design of HIT-based interventions has so far neglected personality traits and a way to adapt them for improving health outcomes (Abraham and Michie, 2008; Alkhaldi et al., 2016; Kraft et al., 2009; Michie et al., 2013; Morrison et al., 2012). HIT-based interventions for personality adaptation could therefore benefit from unobtrusive recognition of personality traits: it would allow for the continuous monitoring of an individual's behavior and dynamic adjustment of the intervention itself. It may also enable the delivery of appropriate motivational feedback to the user, which can help motivate the pursuit of the intervention-specific goals (Fishbach et al., 2010). Furthermore, it may allow for the personalization of the intervention (Brinkman and Fine, 2005; Moon, 2002; Morrison et al., 2012; Tkalcic et al., 2009). Finally, and most important, techniques to measure and adjust personality traits would be not limited to specific HIT-based interventions for people with a particular NCD such as asthma, diabetes or depression only, but can be universally applied to almost all behavioral health interventions.

As a first step towards HIT-based interventions that consider health-related personality change, we investigated the recognition of conscientiousness and neuroticism from behavioral data, i.e. two relevant health-related personality traits. We formulated our research question as follows:

> *What features derived from unobtrusively collected behavioral data have been most relevant for inferring an individual's personality related to conscientiousness and neuroticism?*

We answered the research question by applying a systematic literature review. To the best of our knowledge, this research is both (1) the first review of literature on personality recognition that focuses on health-related features from behavioral data, and (2) the first to use a systematic search process.

2 Background: Automatic Personality Recognition & Machine Learning

Today, it is still a challenge for computers to make sense of an individual's needs and characteristics in order to adapt accordingly. Personality traits can represent a solution. They constitute a conceptually rather simple framework for representing individual characteristics of users. They are also helpful for predicting a wide range of behavior and emotions (Ozer and Benet-Martinez, 2006). Asking the user to fill in a personality questionnaire may however represent a prohibitively large burden on the user. Therefore, it is desirable that computers can unobtrusively recognize the personality traits of the user. Computationally determining self-assessed personality of individuals from data has been termed *Automatic Personality Recognition (APR)* (Vinciarelli and Mohammadi, 2014). By self-assessed personality we mean the representation of personality obtained by self-assessment questionnaires such as the BFI (John and Srivastava, 1999).

A suitable and commonly used method for solving 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. The representation of behavioral data corresponds to the set of input variables (features) for the ML algorithm. Domingos (2012) makes two noteworthy observations: (1) The choice of features is easily the most important factor for whether a ML project succeeds or fails; (2) If the features are numerous, independent from each other and each correlate well with the output variable, then learning is easy. In this research, we therefore focused on finding relevant features related to conscientiousness and neuroticism within the set of features used in existing research.

3 Method

We conducted a systematic literature review based on guidelines (Okoli and Schabram, 2010; Webster and Watson, 2002). We defined a search strategy and search query that gave us a total of 262 potentially relevant articles. A manual filtering reduced this to 17 relevant articles.

Our search strategy included top IS journals, i.e. the Senior Scholar's Basket of Journals of the Association for Information Systems (AIS). 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 conferences and journals of the Computer Science community, and therefore we also included the ACM Digital Library and IEEE Explore to the list of relevant databases.

We chose our method for analysis to fit the research question and the articles obtained in the search process. In our research question, we ask for the *most* relevant features. More precisely, we are interested in finding the features that have been most relevant not within, but *across* the different studies. We therefore created a list of features which had the greatest correlation with either conscientiousness or neuroticism across all articles. However, due to limitations in the kind and level of detail of reported results, this only covered 7 of the relevant articles. For the remaining articles, we instead noted the features that they have found relatively most useful within their particular study.

4 Results

We considered only features that had an absolute correlation value with either conscientiousness or neuroticism of at least 0.2. This corresponds to something between a small (0.1) and a medium (0.3) effect size, according to Cohen (1992).

It turns out that many features derived from content (classes of words and other text characteristics), have been revealed as good for predicting both conscientiousness and neuroticism, at least on Facebook and Twitter (Adalı and Golbeck, 2014; Golbeck et al., 2011b), with absolute correlations up to 0.38. Furthermore, features based on who messages whom and in which patterns (Adalı and Golbeck, 2014) also showed up numerously (up to 0.34 absolute correlation). In contrast, smartphone studies (Chittaranjan et al., 2011) contributed only a single feature ("YouTube" use), however it is the highest correlation overall (0.44), highly predictive of low conscientiousness. Having contacts that write very long messages is associated with low conscientiousness on Twitter (Adalı and Golbeck, 2014). The same holds for the use of negation words (e.g. no, not, never) in one's tweets, or having a variety of balancedness of communication across different contacts.

For neuroticism, the use of words related to religion or hearing are most (and positively) correlated (Golbeck et al., 2011a), as are deviations from a person's average message length across her contacts (Adalı and Golbeck, 2014). A special case is the use of exclamation marks (Golbeck et al., 2011a), as this is associated both with high conscientiousness as with high neuroticism: Most other features that correlate with both traits do so with opposite signs, i.e. have a positive correlation with one and a negative one with the other.

5 Discussion

With respect to our research question, we've been able to compile a list of existing research studies that investigate APR, which allowed us to consider the features that were used, and their relevance with respect to predicting conscientiousness and neuroticism. Our list of most relevant features is a first step towards improving the state of the art in personality recognition and building HIT-based interventions that consider personality change and automatically take into account the personality traits of the user, without obtrusively requiring additional manual input.

From this list and from the features that are mentioned as particularly predictive without indicating the correlation, we found that for conscientiousness, features relating to media consumption (video) and creation (photo) were highly relevant, as well as features related to communication style (use of negations), and features relating to the behavior of social contacts and variety of balancedness of relationships. For neuroticism, we found that features relating to the use of words of particular classes (religion, hearing) were particularly relevant, as well as variation in message length across contacts, and communication style (use of exclamation marks).

It is noteworthy that in our list of most correlated features, there is only one feature from a smartphone-based study that reports correlations (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 correlations concerning their entire population: They found different and higher correlations when considering male and female subjects separately. This is something that all future studies should consider: If a reliable indication of gender is available, it may boost prediction performance.

We point out that our approach has the following limitations with respect to the across-studies analysis: First, it does not consider *independence* of features. Unfortunately, this is not possible as mutual correlations are not reported in the articles, and furthermore we could only speculate about how features from different studies would be correlated if used in a single study. Second, it does not consider the *interdependence* of features. As described in Guyon and Elisseeff (2003), a set of features that are each individually uncorrelated with the target variable, may be extremely useful for prediction through their combined use. Finally, it does not consider the size of the populations within which the correlations were found. Correlations found within smaller populations have a larger margin of error (Niven and Deutsch, 2012).

6 Future Work

As a next step in our research, we are going to design and evaluate a HIT-based intervention that detects the degree of conscientiousness and neuroticism and aims to support individuals affected by noncommunicable diseases and willing to adapt their personality with the overall goal to improve their health and well-being. In particular, we will use the insights from this literature review to implement a smartphone-based digital health intervention for recognizing these personality traits, tracking them over time and providing tailored personality-change interventions, accordingly.

References

Abraham, C. and S. Michie (2008) A Taxonomy of Behavior Change Techniques Used in Interventions, *Health Psychology* 27 (3), 379-387.

Adalı, S. and J. Golbeck (2014) Predicting personality with social behavior: a comparative study, *Social Network Analysis and Mining* 4 (1), 1-20.

Agarwal, R., G. Gao, C. DesRoches and A. K. Jha (2010) Research commentary-The digital transformation of healthcare: current status and the road ahead, *Information Systems Research* 21 (4), 796-809.

Alkhaldi, G., F. L. Hamilton, R. Lau, R. Webster, S. Michie and E. Murray (2016) The Effectiveness of Prompts to Promote Engagement With Digital Interventions: A Systematic Review, *Journal of Medical Internet Research* 18 (1), e6.

Armstrong, L. and K. A. Rimes (2016) Mindfulness-Based Cognitive Therapy for Neuroticism (Stress Vulnerability): A Pilot Randomized Study, *Behavior Therapy* 47 (3), 287-298.

Barlow, D. H., S. Sauer-Zavala, J. R. Carl, J. R. Bullis and K. K. Ellard (2013) The Nature, Diagnosis, and Treatment of Neuroticism: Back to the Future, *Clinical Psychological Science*.

Brickman, A. L., S. E. Yount, N. T. Blaney, S. T. Rothberg and A. K. De-Nour (1996) Personality Traits and Long-Term Health: Status The Influence of Neuroticism and Conscientiousness on Renal Deterioration in Type-1 Diabetes, *Psychosomatics* 37 (5), 459-468.

Brinkman, W.-P. and N. Fine (Year) Towards customized emotional design: an explorative study of user personality and user interface skin preferences, Proceedings of the 2005 annual conference on European association of cognitive ergonomics, University of Athens, 2005, 107-114.

Chittaranjan, G., J. Blom and D. Gatica-Perez (2011) Mining large-scale smartphone data for personality studies, *Personal and Ubiquitous Computing* 17 (3), 433-450.

Christensen, A. J. and T. W. Smith (1995) Personality and patient adherence: correlates of the five-factor model in renal dialysis, *Journal of behavioral medicine* 18 (3), 305-313.

Cohen, J. (1992) A power primer, *Psychological bulletin* 112 (1), 155.

Cuijpers, P., F. Smit, B. W. Penninx, R. de Graaf, M. ten Have and A. T. Beekman (2010) Economic costs of neuroticism: a population-based study, *Archives of General Psychiatry* 67 (10), 1086-1093.

Domingos, P. (2012) A few useful things to know about machine learning, *Communications of the ACM* 55 (10), 78-87.

Fichman, R. G., R. Kohli and R. Krishnan (2011) Editorial overview-the role of information systems in healthcare: Current research and future trends, *Information Systems Research* 22 (3), 419-428.

Fishbach, A., T. Eyal and S. R. Finkelstein (2010) How positive and negative feedback motivate goal pursuit, *Social and Personality Psychology Compass* 4 (8), 517-530.

Golbeck, J., C. Robles, M. Edmondson and K. Turner (Year) Predicting Personality from Twitter, Privacy, Security, Risk and Trust (PASSAT) and 2011 IEEE Third Inernational Conference on Social Computing (SocialCom), 2011 IEEE Third International Conference on, 2011a, 149-156.

Golbeck, J., C. Robles and K. Turner (2011b) Predicting personality with social media, in: *Proceedings of the CHI '11 Extended Abstracts on Human Factors in Computing Systems*, Vancouver, BC, Canada, 253-262.

Guyon, I. and A. Elisseeff (2003) An introduction to variable and feature selection, *The Journal of Machine Learning Research* 3, 1157-1182.

John, O. P., L. P. Naumann and C. J. Soto (2008) Paradigm shift to the integrative big five trait taxonomy, *Handbook of personality: Theory and research* 3, 114-158.

John, O. P. and S. Srivastava (1999) The Big Five trait taxonomy: History, measurement, and theoretical perspectives, *Handbook of personality: Theory and research* 2 (1999), 102-138.

Kraft, P., F. Drozd and E. Olsen (2009) ePsychology: Designing Theory-Based Health Promotion Interventions, *Communications of the Association for Information Systems* 24 (1, Paper 24), 399-426.

Krug, E. G. (2016) Trends in diabetes: sounding the alarm, *The Lancet* 387 (10027), 1485-1486.

Lahey, B. B. (2009) Public health significance of neuroticism, *American Psychologist* 64 (4), 241.

Magidson, J. F., B. W. Roberts, A. Collado-Rodriguez and C. W. Lejuez (2014) Theory-driven intervention for changing personality: expectancy value theory, behavioral activation, and conscientiousness, *Dev Psychol* 50 (5), 1442-1450.

Martin, L. R., K. B. Haskard-Zolnierek and M. R. DiMatteo (2010) Health behavior change and treatment adherence: Evidence-based guidelines for improving healthcare, Oxford University Press, USA.

McCrae, R. and P. Costa (1996) Toward a New Generation of Personality Theories: Theoretical Contexts for the Five-Factor Model.[In] Wiggins JS (Ed.): The Five-Factor Model of Personality: Theoretical Perspectives, *Guilford, New York*.

Michie, S., M. Richardson, M. Johnston, C. Abraham, J. Francis, W. Hardeman, M. P. Eccles, J. Cane and C. E. Wood (2013) The Behavior Change Technique Taxonomy (v1) of 93 Hierarchically Clustered Techniques: Building an International Consensus for the Reporting of Behavior Change Interventions, *Annals of Behavioral Medicine* 46 (1), 81-95.

Miller, G. (2012) The smartphone psychology manifesto, *Perspectives on Psychological Science* 7 (3), 221-237.

Moon, Y. (2002) Personalization and personality: Some effects of customizing message style based on consumer personality, *Journal of Consumer Psychology*.

Morrison, L. G., L. Yardley, J. Powell and S. Michie (2012) What Design Features Are Used in Effective e-Health Interventions? A Review Using Techniques from Critical Interpretive Synthesis, *Telemedicine and e-Health* 18 (2), 137-144.

Mroczek, D. K. (2014) Personality Plasticity, Healthy Aging, and Interventions, *Developmental psychology* 50 (5), 1470-1474.

Niven, E. B. and C. V. Deutsch (2012) Calculating a robust correlation coefficient and quantifying its uncertainty, *Computers & Geosciences* 40, 1-9.

O'Cleirigh, C., G. Ironson, A. Weiss and P. T. Costa, Jr. (2007) Conscientiousness predicts disease progression (CD4 number and viral load) in people living with HIV, *Health Psychol* 26 (4), 473-480.

Okoli, C. and K. Schabram (2010) A guide to conducting a systematic literature review of information systems research, *Sprouts Work. Pap. Inf. Syst* 10, 26.

Ozer, D. J. and V. Benet-Martinez (2006) Personality and the prediction of consequential outcomes, *Annu. Rev. Psychol.* 57, 401-421.

Rosmalen, J. G., J. Neeleman, R. O. Gans and P. de Jonge (2007) The association between neuroticism and self-reported common somatic symptoms in a population cohort, *J Psychosom Res* 62 (3), 305-311.

Sokol, M. C., K. A. McGuigan, R. R. Verbrugge and R. S. Epstein (2005) Impact of medication adherence on hospitalization risk and healthcare cost, *Med Care* 43 (6), 521-530.

Tkalcic, M., J. Tasic and A. Košir (2009) Emotive and personality parameters in multimedia recommender systems, *ACII 2009 Affective Computing and Intelligent Interaction*, 33.

Vinciarelli, A. and G. Mohammadi (2014) A survey of personality computing, *Affective Computing, IEEE Transactions on* 5 (3), 273-291.

Webster, J. and R. T. Watson (2002) Analyzing the past to prepare for the future: Writing a, *MIS quarterly* 26 (2), 13-23.

WHO (2011) Global Health and Aging, Genéve, Switzerland: World Health Organization.

WHO (2015) Report of the First Dialogue Convened by the World Health Organization Global Coordination Mechanism on Noncommunicable Diseases. Geneva, Switzerland: World Health Organization Global Coordination Mechanism on Noncommunicable Diseases., in: Proceedings of, W. H. O. (ed.).

Xu, R., R. M. Frey, E. Fleisch and A. Ilic (2016) Understanding the impact of personality traits on mobile app adoption – Insights from a large-scale field study, *Computers in Human Behavior* 62, 244-256.