

---

**HOGREFE PUBLISHING - AUTHOR QUERY FORM**

---

Journal Code: JID	Article DOI: 10.1027/1614-0001/a000139
Article Number: a000139	First Author: Christian Montag
Article Title: Correlating Personality and Actual Phone Usage	Corresponding Author: Christian Montag

**AUTHOR QUERIES – TO BE ANSWERED BY THE CORRESPONDING AUTHOR**

Dear Author,

During the preparation of your manuscript for typesetting, the queries listed below have arisen. Please answer these queries by marking the required corrections at the appropriate point in the text.

**Electronic file usage**

Sometimes we are unable to process the electronic file of your article and/or artwork. If this is the case, we have proceeded by:

☐ Scanning (parts of) your article      ☐ Rekeying (parts of) your article

**Precopyedited Manuscript**

☐ While processing the precopyedited manuscript some oversights were noted. These have been listed below.

**Queries and/or remarks**

Location in article	Query/remark	Response
Q1	The reference “Takao et al. (2009)” is cited in the text but not listed in the References. Please provide full reference details.	
Q2	Please provide significance of single asterisk in Table 4–6 and Table A2.	
Q3	Please provide English article-title for reference “Borkenau and Ostendorf (1991)”.	
Q4	Please provide publisher location for reference “Costa and McCrae (1992)”.	

CE: Deepa  
Thanks for your assistance.

# Correlating Personality and Actual Phone Usage

## Evidence From Psychoinformatics

Christian Montag,<sup>1,2</sup> Konrad Błaskiewicz,<sup>3</sup> Bernd Lachmann,<sup>1</sup> Ionut Andone,<sup>3</sup>  
Rayna Sariyska,<sup>2</sup> Boris Trendafilov,<sup>3</sup> Martin Reuter,<sup>1,2</sup>  
and Alexander Markowetz<sup>3</sup>

<sup>1</sup>Department of Psychology, University of Bonn, Germany, <sup>2</sup>Center for Economics and Neuroscience, University of Bonn, Germany, <sup>3</sup>Department of Informatics, University of Bonn, Germany

**Abstract.** In the present study we link self-report-data on personality to behavior recorded on the mobile phone. This new approach from *Psychoinformatics* collects data from humans in everyday life. It demonstrates the fruitful collaboration between psychology and computer science, combining Big Data with psychological variables. Given the large number of variables, which can be tracked on a smartphone, the present study focuses on the traditional features of mobile phones – namely incoming and outgoing calls and SMS. We observed  $N = 49$  participants with respect to the telephone/SMS usage via our custom developed mobile phone app for 5 weeks. Extraversion was positively associated with nearly all related telephone call variables. In particular, Extraverts directly reach out to their social network via voice calls.

**Keywords:** personality, actual mobile phone use, psychoinformatics, Big Data, extraversion

Nowadays, smartphones represent one of the major communication channels. The devices can be carried easily on the body and provide the user with a large number of functions including telephone, text messages, app usage, and mobile Internet. New statistics for the year 2013 suggest that about 40% of the German population use a smartphone, numbers rising. Relevant figures for this and other countries are regularly provided by Google (<http://www.thinkwithgoogle.com/mobileplanet/de/>). Given the enormous distribution of smartphones in modern society, a better understanding of mobile phone behavior is of great importance to get deeper insights into human communication patterns. In the following the words “smartphone” and “mobile phone” are used interchangeably, although smartphones are actually more sophisticated, containing a broader functionality than older mobile phones.

Until now, a small number of studies tried to link personality traits to smartphone usage. Most of these studies in the field solely relied on self-report data both on the side of the personality assessment and on the side of the smartphone behavior. It is apparent that more objective data like statistics on the actual use of smartphones are of higher quality than self-report data that are often biased by factors like social desirability or self-deception.

From a psychological perspective the Five Factor Model of Personality represents the dominant model in the mobile

phone studies to date. It has been derived from a lexical approach and describes human personality with the five dimensions *Openness to Experience*, *Conscientiousness*, *Agreeableness*, *Extraversion*, and *Neuroticism* (McCrae & John, 1992). In the context of telecommunication, Lane and Manner (2011) reported a positive association between being extraverted and owning a smartphone. Moreover, this self-report study revealed that extraverts stated a higher importance of using text messages. The personality dimension Extraversion describes humans who are sociable, communicative, and outgoing, which fits perfectly to these results. An earlier self-report study by Butt and Phillips (2008) linked Extraversion to longer telephone use (in detail: calling someone). Moreover, the authors linked individual differences in four of the five personality dimensions with the exception of Openness to the variable “time spent on text message use.” In detail, Neuroticism and Extraversion were positively associated with this variable, Conscientiousness and Agreeableness inversely correlated. Another study by Takao et al. (2009) emphasized excessive mobile phone use, and linked the female gender along with higher scores on self-monitoring and stronger need for social approval to mobile phone addiction. Billieux, Van der Linden, and Rochat (2008) provided additional evidence for a link between impulsivity and mobile phone addiction. The importance to study mobile phone addiction

is reflected by the rising numbers of questionnaires used for diagnostics in this field: several self-report inventories have been published in the recent years (e.g., Bianchi & Phillips, 2005; Billieux et al., 2008). However, self-report inventories are problematic in terms of social desirability – especially when dealing with stigmatizing phenotypes such as addiction. Therefore, it has been put forward by Markowetz, Błaskiewicz, Montag, Switala, and Schläpfer (2014) that recording mobile phone behavior directly on the technical devices might represent an important step to study human behavior in real life without relying on self-report both in the domains of personality and addiction. The fusion of computer science and psychology gives rise to a new emerging research field called *Psychoinformatics* (Markowetz et al., in press; Yarkoni, 2012).

The here described new approach using directly recorded mobile phone behavior for research has been recently used by Chittaranjan, Blom, and Gatica-Perez (2013). To our knowledge this group demonstrated for the first time how direct data from the mobile phone correlates with individual differences in personality measured via a traditional self-report inventory. Chittaranjan et al. (2013) used a very brief self-report inventory called TIPI (Gosling, Rentfrow, & Swann, 2003) to measure the Five Factor Model of Personality. Among a large number of significant correlations between smartphone variables and personality the authors were able to observe positive associations between Extraversion and telephone use, as well as between emotional stability and word length of written SMS. Although the study by Chittaranjan et al. (2013) is of large importance, because it reports for the first time associations between personality and a large number of smartphone variables, it becomes clear, that most of the reported associations are rather small (most significant correlations are around  $r = .10$ ). In addition, given the enormous number of variables tested most of the associations would not hold for multiple testing in this study. Therefore, we follow in the present study a different approach. First of all, we included a more classic personality inventory called NEO-FFI (NEO-Five-Factor Inventory) with excellent psychometric properties (Costa & McCrae, 1992) instead of the very brief TIPI measure. Second, on the side of the directly recorded smartphone variables we concentrated on a rather small number of variables reflecting the use of classic features – namely telephone use (speaking to someone) and short text message functions. A more narrow focus helps to circumvent the need to strongly control for multiple testing. Moreover, it is apparent that most of the dependent variables in the Chittaranjan study are highly correlated.

Given first results from the literature, we were able to set up a directed hypothesis: As earlier studies indicated in particular a link between Extraversion and mobile phone behavior, we hypothesized that high Extraversion scores should be associated with stronger use of the telephone in terms of in- and outgoing calls, length of telephone calls, and the number of different persons directly contacted reflecting a larger social network. Moreover, this link is to be expected, because telephoning perhaps represents

the most direct form of social interaction among the large available features on a smartphone (with the exception of video calls). Although voice calls clearly are no face-to-face interaction, persons talking on the phone are able to hear their voices and derive emotional content and other information from this channel (e.g., Scherer, 2003). Thereby this way of communication might be particular chosen by extraverts, because they are known to be characterized by higher self-esteem (e.g., Bagley & Evan-Wong, 1975; Cheng & Furnham, 2003; Uziel, 2007) facilitating this direct form of communication.

As the literature on the remaining personality dimensions is rather heterogeneous and scarcer we refrained from putting forward a directed hypothesis here and therefore applied procedures for multiple testing for these exploratory tests.

## Material and Methods

### Participants

$N = 49$  students (28 male/21 females) from the University of Bonn/Germany participated in the present study. Initially five more participants were recruited. These five participants had to be excluded from the analyses, because the recording software failed to track their behavior. Mean age of the participants was 24.00 years ( $SD = 4.14$ ). Inclusion criterion for the present study was a smartphone running on the operating system Android 4 or higher. The participants visited the experimenters of the present study to have the app “Menthall” (see below) installed. In this context, we also administered the personality questionnaire measuring the Five Factor Model of Personality. This NEO-FFI questionnaire contains 60 items, measuring the personality dimensions *Openness to Experience*, *Conscientiousness*, *Agreeableness*, *Extraversion*, and *Neuroticism* (Costa & McCrae, 1992). In detail, we employed the German version by Borkenau & Ostendorf (1991). The questionnaire is five point Likert scaled, ranging from strongly disagree to strongly agree (1–5). After 5 weeks of mobile phone recording participants visited the experimenters for a second time to get the application deinstalled. All participants gave written consent in advance of participation. The study was approved by the psychological ethics committee at the University of Bonn, Germany.

### The Application (app) Called Menthall

The developed application for the smartphones in the present study is able to track basically every interaction with a smartphone. The present form of the installed application was not visible for the participants of the study. Although a large number of variables can be tracked via the app on the smartphone, we focused on a small number of variables being of interest in the context of our hypothesis to largely circumvent the need for multiple testing. For the present

Table 1. Call-related variables extracted from the smartphones (all means per day)

Variable name	Internal consistency <sup>+</sup>	Variable information
Call in count	.92	Number of incoming calls
Call out count	.88	Number of outgoing calls
Call total count	.91	Total number of calls
Call in participants	.87	Number of unique calling participants
Call out participants	.89	Number of unique called participants
Call participants count	.90	Number of unique interacted participants
Call in duration*	.81	Incoming call duration in minutes
Call out duration	.83	Outgoing call duration in minutes
Call total duration	.85	Total call duration in minutes
Call miss count*	.94	Number of missed calls

Notes. Variables marked with an “\*” deviate from normal distribution. <sup>+</sup>Internal consistencies have been computed by inserting the mean-day variables/each week into the analyses (four means for each variable as the study was conducted for 4 weeks).

Table 2. SMS-related variables extracted from the smartphones (all means per day)

Variable name	Internal consistency <sup>+</sup>	Variable information
SMS in count*	.84	Number of incoming SMS
SMS out count*	.80	Number of outgoing SMS
SMS total count*	.82	Total number of SMS
SMS in participants	.79	Number of unique texted participants
SMS out participants	.58	Number of unique senders of SMS
SMS participants count	.64	Number of unique participants interacted with via SMS
SMS in length (in letters)*	.85	Length of incoming SMS in letters
SMS out length (in letters)*	.54	Length of outgoing SMS in letters

Notes. Variables marked with an “\*” deviate from normal distribution. <sup>+</sup>Internal consistencies have been computed by inserting the mean-day variables/each week into the analyses (four means for each variable as the study was conducted for 4 weeks).

study we extracted data for the following variables presented in Tables 1 and 2.

### Technical Aspects of Mental and Data Cleaning

The installed app monitors almost the entire range of phone interaction. For the context of this paper most importantly, it records meta-data about phone calls and SMS. For calls, it stores data tuples of the format (anonymized number, start-time, end-time, in/out). For outgoing SMS, it records (anonymized number, length in characters, time-sent), and for incoming SMS (anonymized number, length in characters, time-received, and time-read). Phone numbers of third parties are anonymized, using a cryptographic hash function on the phone (SHA-512<sup>1</sup>). This method ensures that the original phone number cannot be reverse-engineered. At the same time, it allows to monitor how many *separate* contacts a participant interacts with.

During the 5 weeks lasting study, the user is not reminded of the app’s existence (for an exception see

footnote 2 later on). In particular, data are stored temporarily on the phone (in an encrypted database) and automatically sent to the server via UMTS/3G or WiFi. The user thus does not actively have to engage in the data upload. On the same note, the app does not display an icon in the home menu. It is only visible in “settings”/“apps,” a menu point rarely visited by any user. In practice, the app thus remains invisible to the user.<sup>2</sup> On the server side, the raw data tuples are aggregated into indicators, such as the total number of calls per day, or the number of separate interactions with contacts.

### Statistical Analyses

We did not analyze data recorded in the first week after installation of the application, in order to diminish the potential influence on the quality of data by participants’ rumination on being observed. For the remaining 4 weeks of recorded mobile phone behavior we produced means per day with respect to the above-described variables

<sup>1</sup> Secure Hash Algorithm using 512 bit blocks.

<sup>2</sup> The app asked the users three times a day for their mood. This was the only exception to being invisible. As mood is not the topic of the present research article, this is not further mentioned in the present study.

**Table 3.** Means and standard deviations of the personality dimensions for each day

Personality dimension	Mean/standard deviation
Neuroticism	2.72/0.68
Extraversion	3.45/0.53
Openness to experience	3.54/0.64
Conscientiousness	3.64/0.51
Agreeableness	3.61/0.67

(Table 1 and 2). Although several of the mobile phone variables were not normally distributed, we report Pearson correlations in the Result section. For the not normally distributed variables we additionally report the Spearman correlations ( $\rho_s$ ) in brackets for the main analyses (Table 6). The variables deviating from normal distribution are marked with an asterisk in Tables 1 and 2. For the personality dimension Extraversion directed hypotheses were set up. Here, no corrections for multiple testing were applied. For the remaining variables we adjusted the values to  $p = .01$  (dividing  $p < .05$  by the five personality dimensions). All reported results stem from two-sided tests. Finally, a stepwise multiple regression model was conducted to carve out the most important predictors for personality from the mobile phone recordings. Although one might propose to predict telephone variables from the personality scores, this would result in numerous models (as we have a large number of mobile phone variables and a small number of personality variables), which are not of help to illuminate which of the intercorrelated phone variables are of most interest for personality-phone usage research. Furthermore, this study represents a correlational study. Therefore no causality in either direction could be derived from the following statistical analyses (in terms of certain personality traits leading to a certain phone usage, or phone usage being responsible to personality traits). Nevertheless, it is very unlikely that mobile phone usage changes personality traits.

## Results

### Age, Gender, and Smartphone Variables

MANOVA revealed that four out of 10 call variables were significantly influenced by gender ( $p$ -values ranging between .03 and .04; for exact statistics see Appendix). As we set up no hypotheses, these results would not hold for multiple testing. Of note, all variables dealing with short text messages (SMS) were strongly influenced by gender with females showing higher scores. All  $p$ -values of the conducted MANOVA were smaller  $p \leq .01$ , therefore showing a clear gender trend (again for exact statistics see Appendix). Although this was not hypothesized, the clear result pattern together with the strong significance of the conducted tests made it necessary to include gender

as a control variable in the analyses of the SMS-related variables.

With respect to age, two out of ten call variables showed significantly positive associations (call in count:  $r = .30$ ,  $p = .04$  and call in participants:  $r = .31$ ,  $p = .03$ ). Furthermore, significant negative correlations could be observed between age and “SMS out count” ( $\rho = -.41$ ,  $p = .003$ )/“SMS in count” ( $\rho = -.28$ ,  $p < .05$  ( $= .048$ ))/“SMS out length” ( $\rho = -.33$ ,  $p = .02$ )/“SMS total count” ( $\rho = -.34$ ,  $p = .02$ ) and SMS out participants ( $p = -.30$ ,  $p = .04$ ). Because of the rather small  $p$ - $\rho$  values and multiple testing issues we did not control for age in the following correlational analyses. Nevertheless, we included age as a variable in the final stepwise multiple regression analysis.

### Age, Gender, and Personality

Age did not correlate with any of the personality dimensions. The personality dimensions Openness to Experience and Neuroticism were significantly influenced by gender with females showing higher scores on both dimensions (Openness:  $F_{(1, 47)} = 4.90$ ,  $p = .03$ ,  $\eta^2 = .09$ ; Neuroticism:  $F_{(1, 47)} = 5.06$ ,  $p = .03$ ,  $\eta^2 = .10$ ). These results do not hold a Bonferroni adjustment ( $p < .05$  divided by five tests for five personality dimensions resulting in a  $p = .01$ ). As a consequence gender did not play a role for personality in the present analyses. Means and standard deviations of the personality dimensions are presented in Table 3.

### Personality and the Smartphone Variables


Table 4 presents the means and standard deviations of the call variables. Similarly, Table 5 presents the means and standard deviations of the SMS variables.

Table 6 shows the significant correlations between the call variables and personality. Here, a large number of positive correlations could be observed between these variables and Extraversion. No other significant associations (besides two correlations reported in Table 6 for Conscientiousness not holding for multiple testing) could be observed between the smartphone call variables and

**Table 4.** Means and standard deviations of the call variables for each day

Call variables	Mean/standard deviation
Call in count	1.07/1.03
Call out count	2.29/1.67
Call total count	3.34/2.46
Call in participants	0.74/0.52
Call out participants	1.42/0.92
Call participants count	1.80/1.05
Call in duration (in min)*	3.96/4.53
Call out duration (in min)	5.06/5.17
Call total duration (in min)	9.02/8.09
Call miss count*	0.71/1.02


Table 5. Means and standard deviations of the SMS variables for each day

SMS variables	Mean/standard deviation
SMS in count*	3.92/4.09
SMS out count*	2.90/3.99
SMS total count*	6.81/7.91
SMS in participants 	1.23/0.73
SMS out participants	0.88/0.73
SMS participants count	1.43/0.88
SMS in length (in letters)*	294.45/278.92
SMS out length (in letters)*	230.19/306.98

personality. Besides one weak negative significant association between SMS in length and Conscientiousness ( $\rho = -.29$ ,  $p = .045$ ), no other personality-SMS related correlations could be observed.

Based on the correlational data a stepwise multiple regression model was set up to predict personality from the mobile phone data. The issue of the chosen dependent variable in this model has been already discussed in the Statistical Analyses section. In short, it is very unlikely that mobile phone usage changes personality traits. Therefore, it would be logical to predict mobile phone variables from personality traits and not the other way round. Given that the present study is not able (a) to derive causality from the data and (b) numerous stepwise multiple regression models would be needed (due to the large number of the to be predicted phone variables), we tried to predict Extraversion by entering the significant variables from Table 6, along with age and gender in one block. Moreover, in the

Table 6. Significant correlations between personality dimensions (mainly Extraversion appeared) and call-related variables. For reasons of clarity the remaining two nonsignificant correlations (after multiple testing) are also reported. All reported results stem from two-sided tests

Phone variables	Extraversion
Call in count	$r = .21$ , $p = .136$
Call out count	$r = .45$ , $p = .001$
Call total count	$r = .36$ , $p = .012$
Call in participants	$r = .34$ , $p = .018$
Call out participants	$r = .43$ , $p = .002$
Call participants count	$r = .41$ , $p = .003$
Call in duration*	$r = .26$ , $p = .077$ ( $\rho = .36$ , $p = .011$ )
Call out duration 	$r = .33$ , $p = .020$
Call total duration	$r = .36$ , $p = .012$
Call miss count*	$r = .35$ , $p = .013$ ( $\rho = .46$ , $p = .001$ )
	Conscientiousness
Call out duration	$r = .29$ , $p = .044$
Call total duration	$r = .29$ , $p = .047$

light of the societal debate on what we can learn from mobile phone data, the present use of Extraversion as the to- be-predicted variable in our model could be justified. One model appeared ( $F_{(1, 48)} = 11.58$ ,  $p = .001$ ) with the variable “call out count” ( $\beta = .45$ ;  $T = 3.40$ ,  $p = .001$ ) explaining 20% of the variance in Extraversion. Intercorrelations of the call and SMS variables are presented in the Appendix.

## Internal Consistencies of the Recorded Mobile Phone Variables

In addition to the above mentioned analyses, we also computed mean-day-variables for the mobile phone data for each of the 4 weeks of the study. As can be seen from Table 1 the internal consistencies for the call variables are very good to excellent. Table 2 shows that the internal consistencies of the SMS related variables range from low (.54) to very good (.84). Taken together, in particular the call-related variables seem to be characterized by very good reliabilities. As “call out count” appeared as the most important predictor from the smartphone for Extraversion, we also investigated the robustness of the association across the 4 weeks. Here, the highest correlation was observed in week 2:  $r = .49$ ,  $p < .001$  and the lowest correlation in week 4:  $r = .25$ ,  $p = .09$ . These numbers illustrate the importance to record the actual mobile phone behavior for several weeks to achieve robust results.

## Discussion

The present study investigated recorded smartphone behavior in the context of personality variables. As hypothesized, we observe a positive association between Extraversion and nearly all telephone call relevant variables including number of calls conducted per day, unique persons called, and missed calls. Only two out of ten correlations missed significance, which might be related to the rather small sample size. Interestingly, a completely different pattern could be observed for the SMS related variables. Here, none of the variables were significantly associated with personality, underlining the social aspect of personality being linked to direct communication but not “indirect” communication channels such as texting. As mentioned in the Result section, it is not possible to derive causality from the data with respect to the direction of the association between Extraversion and the call variables, although it is much more plausible that personality influences phone usage compared to the opposite explanation. However, due to economic reasons (in terms of a significant smaller number of models) and in light of the debate what information can be derived from the analyses of mobile phone data, a stepwise regression model was set up with Extraversion to be predicted by the mobile phone variables. This model showed that one call variable alone predicted Extraversion – namely the total number of outgoing calls. This single variable explains

20% of the variance in Extraversion and demonstrates that it is possible to use smartphone variables as diagnostic tools to predict personality traits. Again, it is very likely though that the present empirical data support the notion that Extraverts use their smartphone to directly contact their social networks in form of telephone calls.

In general, the present research endeavor demonstrates that it will be possible to get insights into psychological variables such as personality by studying human-machine-interaction patterns. Of note, similar approaches have been also used to predict personality from Facebook use (Ortigosa, Carro, & Quiroga, 2014) and micro-blogging behavior (Li, Li, Hao, Guan, & Zhu, 2014). Although data derived from *Psychoinformatics* can be used for good in several important settings such as the health care system (Markowetz et al., 2014), the collection and analysis of smartphone or other computer-related human-machine interaction data always bears the risk of misuse. Data privacy and protection of the individual's rights represents a new challenge to be solved by society.

The present findings fit well with the literature, because several other Extraversion-mobile phone associations had been observed in the self-report literature before (e.g., Extraversion has been reported to be associated with ownership of smartphones, Lane & Manner, 2011; and longer smartphone use, Butt & Phillips, 2008). Of importance, in comparison to the study by Chittaranjan et al. (2013), who also recorded actual smartphone behavior, the present findings are more consistent and the observed correlations larger, which could be explained by the use of a much more reliable inventory in the present study (the brief TIPI vs. the NEO-FFI inventory). To illustrate this: The highest association in the present study between "daily number of outgoing calls" and Extraversion was  $r = .45$ , in the Chittaranjan study the highest reported association for Extraversion/call-variables was between "unique contacts in call logs" and Extraversion with  $r = .15$  (both for the total sample under investigation). Summarizing, Extraversion plays the most prominent role when investigating communication call behavior in humans.

The present study has several limitations: In the last years, one of the most prominent communication tools on the smartphones represents instant messaging via applications such as WhatsApp or the use of social networks such as Facebook. In future studies, we will focus more on the use of these new communication channels including the analyses of the actual communication in form of text-mining. In addition to this critique the present study is rather small with respect to the sample size. Future studies need to investigate larger samples and apply pattern classification approaches. At the moment, for a study such as the present with participants coming two times in our laboratory, the sample size appears adequate. A future public release of the Menthal app in the Google Android Store will make it easier to collect large sample sizes to predict psychological variables.

## Conclusions

Concluding, the present study indicates how psychology and computer science can collaborate in the field of *Psychoinformatics*, using Big Data to tackle research questions in the social sciences.

## Acknowledgments

The study was funded by a grant awarded to CM by the DFG (MO-2363/2-1).

## References

- Bagley, C., & Evan-Wong, L. (1975). Neuroticism and extraversion in responses to Coopersmith's Self-Esteem Inventory. *Psychological Reports*, 36, 253–254.
- Bianchi, A., & Phillips, J. G. (2005). Psychological predictors of problem mobile phone use. *CyberPsychology & Behavior*, 8, 39–51.
- Billieux, J., Van der Linden, M., & Rochat, L. (2008). The role of impulsivity in actual and problematic use of the mobile phone. *Applied Cognitive Psychology*, 22, 1195–1210.
- Borkenau, P., & Ostendorf, F. (1991). Ein Fragebogen zur Erfassung fünf robuster Persönlichkeitsfaktoren. *Diagnostica*, 37, 29–41.
- Butt, S., & Phillips, J. G. (2008). Personality and self reported mobile phone use. *Computers in Human Behavior*, 24, 346–360.
- Cheng, H., & Furnham, A. (2003). Personality, self-esteem, and demographic predictions of happiness and depression. *Personality and Individual Differences*, 34, 921–942.
- Chittaranjan, G., Blom, J., & Gatica-Perez, D. (2013). Mining large-scale smartphone data for personality studies. *Personal and Ubiquitous Computing*, 17, 433–450.
- Costa, P. T., & McCrae, R. R. (1992). *Revised NEO Personality Inventory (NEO PI-R) and NEO Five-Factor Inventory (NEO FFI): Professional Manual*. Psychological Assessment Resources.
- Gosling, S. D., Rentfrow, P. J., & Swann, W. B. Jr. (2003). A very brief measure of the Big-Five personality domains. *Journal of Research in personality*, 37, 504–528.
- Lane, W., & Manner, C. (2011). The impact of personality traits on smartphone ownership and use. *International Journal of Business and Social Science*, 2, 22–28.
- Li, L., Li, A., Hao, B., Guan, Z., & Zhu, T. (2014). Predicting active users' personality based on micro-blogging behaviors. *PloS one*, 9, e84997.
- Markowetz, A., Błaszczewicz, K., Montag, C., Switala, C., & Schläpfer, T. (2014). Psycho-Informatics: Big data shaping modern psychometrics. *Medical Hypotheses*, 82, 405–411.
- McCrae, R. R., & John, O. P. (1992). An introduction to the five factor model and its applications. *Journal of Personality*, 60, 175–215.
- Ortigosa, A., Carro, R. M., & Quiroga, J. I. (2014). Predicting user personality by mining social interactions in Facebook. *Journal of Computer and System Sciences*, 80, 57–71.
- Scherer, K. R. (2003). Vocal communication of emotion: A review of research paradigms. *Speech Communication*, 40, 227–256.



- Uziel, L. (2007). Individual differences in the social facilitation effect: A review and meta-analysis. *Journal of Research in Personality*, 41, 579–601.
- Yarkoni, T. (2012). Psychoinformatics new horizons at the interface of the psychological and computing sciences. *Current Directions in Psychological Science*, 21, 391–397.

**Date of acceptance:** May 7, 2014  
**Published online:** XXX

Christian Montag

Department of Psychology  
 University of Bonn  
 Kaiser-Karl-Ring 9  
 53111 Bonn  
 Germany  
 Tel. +49 228 73-4309  
 Fax +49 228 73-62331  
 E-mail christian.montag@uni-bonn-diff.de

490  
 488  
 491  
 492  
 493  
 494  
 495  
 496  
 497  
 498  
 499  
 500

## Appendix

The results of the MANOVA investigating the influence of gender on both the call and SMS-related variables are presented in Table A1 and Table A2. Intercorrelations of the call and SMS variables are presented in Table A3 and Table A4.

*Table A1.* Influence of gender on the call-related variables

Call variables	<i>F</i> -values, <i>p</i> -values
Call in count	$F_{(1, 47)} = 2.89, p = .10$
Call out count	$F_{(1, 47)} = 4.53, p = .04$
Call total count	$F_{(1, 47)} = 4.46, p = .04$
Call in participants	$F_{(1, 47)} = 3.70, p = .06$
Call out participants	$F_{(1, 47)} = 4.71, p = .04$
Call participants count	$F_{(1, 47)} = 5.19, p = .03$
Call in duration (in min)	$F_{(1, 47)} = 0.39, p = .54$
Call out duration (in min)	$F_{(1, 47)} = 0.01, p = .95$
Call total duration (in min)	$F_{(1, 47)} = 0.10, p = .76$
Call miss count	$F_{(1, 47)} = 0.59, p = .45$

*Note.* In ST1 all significant results are linked to higher call values in males compared to females.

*Table A2.* Influence of gender on the SMS-related variables

SMS variables	<i>F</i> -values, <i>p</i> -values
SMS in count*	$F_{(1, 47)} = 8.95, p = .004$
SMS out count*	$F_{(1, 47)} = 7.19, p = .01$
SMS total count*	$F_{(1, 47)} = 8.47, p = .005$
SMS in participants	$F_{(1, 47)} = 8.54, p = .005$
SMS out participants	$F_{(1, 47)} = 11.47, p = .001$
SMS participants count	$F_{(1, 47)} = 8.56, p = .005$
SMS in length (in letters)*	$F_{(1, 47)} = 8.44, p = .006$
SMS out length (in letters)*	$F_{(1, 47)} = 11.98, p = .001$

*Note.* In ST2 all significant results are linked to higher SMS values in females compared to males.

Q2

*Table A3.* Intercorrelations of the call variables

	Call in count	Call in duration	Call in participants	Call miss count	Call out count	Call out duration	Call out participants	Call participants count	Call total count
Call in count	1								
Call in duration	.85**(.78**)	1							
Call in participants	.94**	.76**(.79**)	1						
Call miss count	.77**(.59**)	.77**(.52**)	.66**(.60**)	1					
Call out count	.66**	.47**(.46**)	.75**	.65**(.65**)	1				
Call out duration	.29*	.39**(.46**)	.30*	.37**(.49**)	.43**	1			
Call out participants	.60**	.41**(.53**)	.74**	.52**(.62**)	.96**	.37**	1		
Call participants count	.71**	.51**(.62**)	.84**	.56**(.62**)	.94**	.36*	.98**	1	
Call total count	.85**	.68**(.62**)	.88**	.77**(.67**)	.96**	.42**	.90**	.92**	1
Call total duration	.66**	.81**(.78**)	.62**	.67**(.56**)	.54**	.86**	.47**	.52**	.65**

*Notes.*  $N = 49$ . \* $p < .05$ ; \*\* $p < .01$ .



Table A4. Intercorrelations of the SMS variables

	SMS in count	SMS in length	SMS in participants	SMS out counts	SMS out length	SMS out participants	SMS participants count
SMS in count	1						
SMS in length	.95**(.96**)	1					
SMS in participants	.73**(.85**)	.78**(.87**)	1				
SMS out counts	.91**(.87**)	.79**(.76**)	.58**(.71**)	1			
SMS out length	.88**(.88**)	.85**(.84**)	.68**(.81**)	.88**(.92**)	1		
SMS out participants	.76**(.84**)	.75**(.79**)	.87**	.73**(.88**)	.83**(.92**)	1	
SMS participants count	.67**(.85**)	.72**(.87**)	.97**	.55**(.75**)	.69**(.84**)	.91**	1
SMS total count	.98**(.98**)	.89**(.91**)	.67**(.83**)	.98**(.94**)	.90**(.93**)	.76**(.89**)	.62**(.84**)

Notes.  $N = 49$ . \* $p < .05$ ; \*\* $p < .01$ .

uncorrected proof  
- not for distribution