Smartphone Sensors: Predicting smartphone ownership by personality and demographics?

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Abstract

Increased smartphone use throughout the Netherlands provides researchers with new opportunities for (indirect) data collection. Not only are an increasing number of studies being conducted online, smartphones sensors can be a source of data too. For example, smartphones can be used for monitoring mental health (Ben-Zeev, Scherer, Wang, Xie & Campbell, 2015). Smartphone sensor research has advantages like keeping costs low. Another advantage is smartphone research allows for large samples. Data gathering via smartphones only, unfortunately has the possible risk of causing a systematic error in your dataset. A systematic error can emerge because specific groups are under- or overrepresented. For example it could be that women more often own Apple phones. As a result, bias can emerge in studies that are conducted via specific smartphones only. In this study the existing GESIS dataset is used. I investigated whether ownership of a specific type of smartphone can be predicted by personality and demographic variables. Multinomial logistic regression showed no homogenous effects of personality, but did indicate main effects of demographics (income, age and gender). The absence of personality effects might be explained by the measurement of personality with the ultra-short BFI-10. For future research it is good to keep in mind background demographics can distort your sample when gathering data via smartphones only.

Keywords: Smartphones, smartphone sensors, personality, Big Five, demographics, GESIS-panel, multinomial logistic regression.

1. Introduction.

The Netherlands are one of the leading countries concerning internet penetration in individual households. In 2017, 98% of the Dutch households had an internet connection at home. This is clearly above the European average of 87%. Moreover, also in terms of the speed of the broadband connection the Netherlands are in a leading position (CBS, 2018).
In the Netherlands, 89% of the population above age 12 owns a smartphone or similar device with internet connection (CBS, 2018). Using smartphones, and more specifically smartphone sensors for data collection, can be very valuable in various areas of research. For instance it is possible to accurately recognize an individual's physical activity pattern using data obtained from an accelerometer – which is a specific type of sensor (Lu, et al., 2016).

In smartphone research, data is very often obtained from only one brand- or type of smartphone. This is caused by the fact that the application used is only suitable for a specific operating system. For example an application for sensing mood was developed (*Moodscope*), but it was only tested on iPhones (Likamwa, Liu, Lane & Zhong, 2013). Another example is from Dartmouth college, Texas, where students were tracked with their phone during 10 weeks. The phones were used to assess mental health, academic performance and behavioural trends. This was done exclusively done using Android phones (Wang et al., 2014). Another possible difficulty is when research is specifically interested in data collection using a specific sensor. As currently not all smartphones are equipped with the same sensors.

These examples illustrate there are many opportunities for smartphone research, though possible problems should be kept in mind. Research has indicated, that focusing research on a specific operating system, might lead to a systematic error. As a results, findings might lack external validity. For example, iPhone owners are found more likely to be female, younger and increasingly concerned about their smartphone being viewed as a status object (Shaw, Ellis, Kendrick, Ziegler & Wiseman, 2016). The same research found that iPhone users showed lower levels of Honesty-Humility and higher levels of emotionality. Thus, demographic and personality differences can effectively differentiate Android and iPhone users (Shaw et al., 2016). Interestingly, other research focusing on the Big Five personality traits, found minor differences in personality (but they were of small to negligible effect sizes) (Götz, Stieger & Reips., 2017).

In order to understand and explain why people start using information systems, like computers, researchers have used the TAM Model* (Mathieson, 1991). In short, the TAM states that *perceived usefulness (A)* and *perceived ease of use (B)* are most important for computer acceptance behaviours. Extraversion is found to have a significant positive relation to behavioural intentions - although this is fully mediated by TAM beliefs*; *Perceived usefulness, perceived ease of use and behavioural intention* (Svendsen, Johnsen, Almås-Sørensen & Vittersø, 2011).

Previous research has also looked into personality traits and smartphone ownership. A finding is that extraverted individuals are more likely to own a smartphone (Lane & Manner, 2011). Even more interesting, it was found that extraverts with low income, spend a greater portion of their money on status (Landis & Gladstone, 2017). This implicates that, since Apple phones are seen as status objects, their owners might on average be more extraverted. Research focusing on the Big Five trait agreeableness has been done as well. More agreeable individuals place greater importance on using the smartphone to make calls and less importance on texting. A 2011 study by Chittaranjan, Blom and Gatica-Perez shows that several aggregated features obtained from smartphone usage data can be indicators of the Big-Five traits. Moreover, a study from South Korea found that sociodemographics were major predictors of smartphone and smartphone application use (Kim, Briley & Ocepek, 2014). In addition, openness, extraversion, and conscientiousness were associated with increased probability of smartphone ownership (Kim et al., 2014). Concluding, this implies that sociodemographics and personality may predict smartphone innovation. First, using selling data over the years 2013-2017, I will investigate what the top 20 most frequently used smartphones are. Furthermore, I will document what sensors these smartphones have. Following this, the relationship between both demographic and personality characteristics and smartphone ownership will be further investigated. I hypothesize that:

- **H1.** Women are more likely than man to own Apple smartphones;
- **H2.** Younger people are more likely to own newer smartphones;
- **H3.** People with a high income are more likely to own Apple phones;
- **H4.** People with a lower income are more likely to own Cheaper (Android) phones;
- **H5.** More extravert individuals are more likely to own newer smartphones;
- **H6.** More extravert individuals are more likely to own Apple smartphones;

- **H7**. People who score higher on openness are more likely to own new smartphones;
- **H8.** More emotionally unstable people (neurotic) are more likely to own Apple Smartphones;
- **H9**. More emotionally stable people are more likely to own Android smartphones.

***TAM** - The Technology Acceptance Model (Background provided later).

2. Hypothesized Theoretical Model.

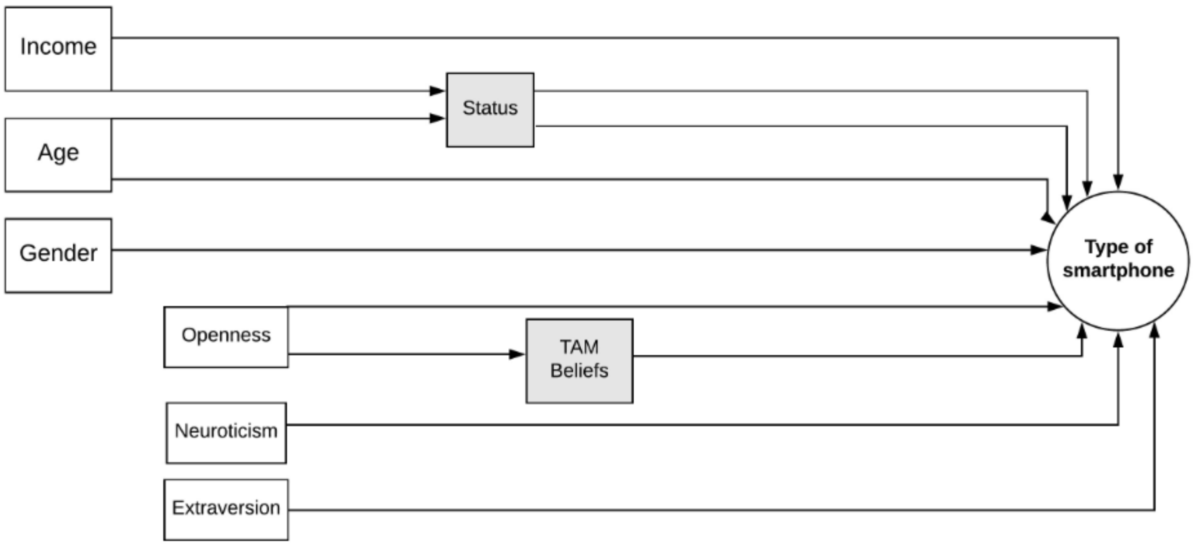

Figure 1. Path diagram showing theoretical relations between personality constructs (Big 5), Demographic variables and smartphone groups. Effects of income and age are hypothesized to be both direct, and indirect via *status*. Gender is hypothesized to only have a direct effect. The effect of Openness is hypothesized to be both direct and indirect via *TAM beliefs*. The effects of Extraversion and Neuroticism are believed to be only direct. Conscientiousness and Agreeableness have no hypothesized effect on smartphone group.

3. Background.

3.1 Smartphone sensors. Inside smartphones, various different sensors are available, (http://fieldguie.gizmodo.com). The **accelerometer** handles axis-based motion sensing, and measures acceleration. It is one of the phones most important sensors. The **gyroscope** helps the accelerometer understand which way your phone is orientated. The gyroscope can also be found in aircrafts, to determine altitude and position. The **magnetometer** measures magnetic fields and thus tell which way is north, these sensors can also be found in metal detectors. **Global Position System (GPS)**, units inside phones, and connects with a satellite to determine which part of the planet you are standing on. The **barometer** measures air pressure. A barometer is useful for detecting weather changes or the altitude you are at. The **proximity sensor** combines infrared LED and light detector to work out when you have the phone to your ear. Furthermore the **ambient light sensor** takes a measure of the light in the room and adjusts the screen's brightness accordingly. In addition, some phones have a **pedometer** which is used to count the number of steps the user has taken. It is more accurate and power efficient than using the accelerometer for this purpose. The **heart rate sensor** can also be found in some phones. To place an extra layer of security, some smartphones are equipped with a **fingerprint sensor.** The newest smartphones are even equipped with **face ID (identification) sensors**.

Sensors are very helpful sources of data collection. Unfortunately, not every smartphone has all sensors. In general, the newer the smartphone is, the more sensors it has.

Many different usage implications for smartphone sensors exist. For example, smartphones can be harnessed as instruments for unobtrusive monitoring of several behavioural indicators of mental health (Ben-Zeev, Scherer, Wang, Xie & Campbell, 2015). Also, smartphone sensors can be used for activity recognition (Su, Tong & Ji, 2014). Moreover, researchers have used smartphones to develop a fall detection system, which can be used for the elderly (Tsinganos & Skodras, 2017). From the field of social sciences, scientists are looking into the possibility of using smartphones for large-scale behavioural change interventions. Examples are monitoring emotions and perform interferences (Lathia et al., 2013).

Whether or not people decide to use new technology -like the newest smartphone- can be partly explained using the Technology Acceptance Model (TAM).

3.2 The Technology Acceptance Model (TAM). Introduced by Davis (1986), is an adaptation of the Theory of Reasoned Action. It is specifically tailored for modelling user acceptance of information systems (Davis, Bogazzi & Warshaw, 1989). TAM proposes that two beliefs, **perceived usefulness (A)** and **perceived ease-of-use (B***)*, are of primary relevance for computer acceptance behaviours. A key aspect of TAM is the relationship between the Attitude Toward Using (A+B) and the Behavioural Intention to Use (BI). The TAM implies that people form intentions to perform behaviours toward which they have positive affect (Davis, Bogazzi & Warshaw). Finally, in the TAM, the **BI** is directly related to **Actual System Use**. In addition, emotional stability is significantly related to behaviour intention. More, openness is significantly and positively related to perceived ease of use (Svendsen, Johnsen, Almås-Sørensen & Vittersø, 2011). An example of a useful application of the TAM is the introduction of healthcare information systems. It was found that information, service and system quality influence **user's intention** through both **perceived usefulness (A)** and **perceived ease-of-use (B)** (Pai & Huang, 2011). To explain why people use new technologies, not only the TAM plays a role, but personality seems of vital importance as well.

3.3 The Big Five. One often used instrument for describing personality, are the Big Five personality characteristics. These five dimensions represent personality at the broadest level of abstraction. Each dimension summarizes a large number of distinct, more specific personality characteristics (John & Srivastava, 1999). The factors are typically labelled:

I. **Extraversion** (talkative, assertive, energetic)
II. **Agreeableness** (good-natured, cooperative, trustful)
III. **Conscientiousness** (orderly, responsible, dependable)
IV. **Neuroticism** (busy, neurotic, easily upset)
V. **Openness** (intellectual, imaginative, independent-minded).

Among researchers, it is commonly agreed that these factors are more or less stable over time. Research by Cobb-Clark and Schurer from 2011 for example demonstrates the traits are stable for working-age adults over a four-year-period. The Big Five are furthermore found to correlate with many important life outcomes, like academic achievement, psychopathology and overall mental health. In a 2011 study, the Big Five characteristics together were found to explain 14% of the variance is GPA (Komarraju, Karau, Schmeck & Avdic, 2011).

Using data from the LISS-panel, personality traits were further found to be related to both mental health and psychopathology. Emotional stability was found to be the main correlate of psychopathology (Lamers, Westerhof, Kovács & Bohlmeijer, 2012). A 2010 Meta-analysis further substantiates this finding, suggesting that neuroticism was the strongest correlate of common mental disorders like anxiety, depressive- and substance use disorders (Kotov, Gamez, Schmidt & Watson, 2010). In addition, a comparison from 55 cultures shows that across most nations, women report higher levels of neuroticism, extraversion, agreeableness and conscientiousness than men. Suggesting differences in personality between males and females (Schmitt, Voracek, Realo & Allik, 2008).

4. Method.

4.1 Sample and Participants. The sample was drawn from the existing GESIS Panel dataset. The reference population of the GESIS Panel is the German-speaking population aged between 18 and 70 years, permanently residing in Germany (Bosnjak et al., 2017). The GESIS panel is a probability-based mixed-mode panel infrastructure operated by GESIS. The GESIS panel started in 2013. The sample, consisted of N=1602 participants, of which 956 (59,7%) were female, and 646 (40,3%) male. The age ranged from 22 to 74. Participants of the GESIS panel receive an unconditional incentive of €5 for each self-administered wave they participate in.

Moment in Study	**Sample Size** *1 wave*	**Total Sample Size** *For 6 waves*	**Percentage of total Sample**
Participants complete GESIS-Panel	3797	22.782	100%
Participants online (versus offline)	2346	14.076	61,79%
Participants using a smartphone (versus other devices)		2.422	10,63%
Wave 1	391		
Wave 2	382		
Wave 3	406		
Wave 4	405		
Wave 5	418		
Wave 6	420		
Participants after data cleaning		1.602	7,03%

Figure 2. Size of the sample throughout the study

4.2 Procedure. Data collection is done in two self-administrative survey methods, namely 1) Online, through web-based surveys and 2) Off-line through paper-and-pencil surveys sent via postal mail (Bosnjak et al., 2017). Each two months, there is a new wave of data collection. This means there are six wave of data collection each year. In this study data from six waves, wave

DA to wave *DF*, all from 2016, are used. The online surveys can be completed on either a desktop computer, laptop, tablet or smartphone.

4.3 Materials. The Big Five items used were measured in wave *DD* (ranging from august 2016 till october 2016) by the ultra-short BFI-10. The BFI-10 assesses the five dimensions, using ten items and has an average duration of one minute (Rammstedt et al,., 2012, 2013). Research indicated that the breadth of the constructs are assessed as well, given the shortness of the measures for each construct (Rammstedt et al., 2012, 2013; Rammstedt & John 2007). Answers could be given on a 5-point Likert scale, ranging from *Trifft überhaupt nicht zu* (not correct at all) to *Trifft voll und ganz zu* (completely right).

The demographic variables were furthermore collected using multiple choice options, they were taken from data wave *DF* (ranging from december 2016 till february 2017). For gender, there were option *'Mannlich'* (male) and '*Weiblich'* (female). Income was both measured using household income and individual income. For individual income there were 15 answer categories, ranging from less than 300€ to more than 5000€ each month. For household income, 9 answer categories were provided, ranging from less than 900€ to more than 6000€ a month. Age was collected by asking the year of birth.

4.4 The User Agent String. Moreover, survey data were collected which can be used to trace back the device respondents have used (Callegaro, 2010). Used in this study, is the *User Agent String*, which provides information about the device the participant has used. This data was also obtained from wave *DF*. More specifically, a *user agent string*, is a text variable that can be captured when connecting to a website (Callegaro, 2010). If analysed properly, it can tell if the user was using a PC or a mobile device, and more precisely what specific device was used.
In this study, only participants who filled in the questionnaire using their smartphone are included.

4.5 Dependent variable: Smartphone sensors. Secondly, the smartphones were clustered based upon their sensors (See Appendix). This was done by first investigating what the most frequently used smartphones over the last five years were, using selling data found via Wikipedia.

Next, around twenty of the most popular smartphones were chosen, and analysed in further depth in terms of sensors. This was done using technical websites and manufacturers information. These provide information about whether a smartphone has a certain sensor or not. (www.apple.com; https://gadgets.ndtv.com). This resulted in an overview of the smartphones and what sensors they possess, and what sensors they do not possess (See *Appendix, table 1)* .

Next, smartphones were categorized based on how many and what specific sensors they have. For example, all phones who lacked a barometer, pedometer, heart rate sensor and fingerprint sensor, but equipped were with all other frequently used sensors were grouped together, forming the group *Older Apple Phones.* Doing this, seven different smartphone groups evolved. This resulted in a distinction in terms of sensors between Apple- and Android phones, between older and newer smartphones, and between high- and low budget smartphones (For details see *Appendix, table 2*).

Smartphone group	**What differentiates group?**
Apple 5 and older	No barometer, fingerprint sensor and HR-sensor
Apple 6 and newer	No HR-sensor, but have a barometer
Samsung S-Series	Have a hall sensor, a barometer and a HR-sensor
Samsung A/M-Series	Have no gyroscope, barometer, pedometer, HR-sensor or fingerprint sensor
Huawei Lite	Have no gyroscope, barometer, magnetometer, fingerprint sensor or HR-sensor
Huawei New	Have no barometer, HR-sensor or fingerprint sensor
Rest	All phones left over

Figure 3. Short summary of the smartphone groups.

4.6 Data reduction and restructuring. Before the analysis could be conducted, the data needed to be reduced and restructured. The smartphone groups, as explained in the previous section, were coded using *R.* This way, each participant was connected to a smartphone group. Since data were gathered six times each year - each participant was placed in a group six times, resulting in six different variables. This could be either six times the same group (when the participant had used the same device to fill in the questionnaire), or different groups (if the participant had used various devices in the different waves of data collection), or no group at all (NA), when the participant didn't use a smartphone for filling in the questionnaire.

To facilitate the analysis, the dataset was first reshaped. Specifically, to convert the wide dataset into a long dataset. This was done using SPSS statistics. Advantage of this procedure is when a multinomial logistic regression is appropriate, the analysis only has to be conducted once.

Furthermore, data from participants that did not belong to a smartphone group (NA), was removed. This way the dataset became more manageable. Only data from participants that did belong to a smartphone group were included in the analyses.

More data screening included removing strange values of the variables that were included in the analysis (Big Five items, age, income, gender). Missing- and high leverage values were removed, so that only true scores remained.

Finally, the Big Five factor model was tested (see 4.7). Afterwards some questions had to be reversed because they were inversely coded in the original dataset. After this, the Big Five constructs were computed by adding up the items belonging to the scale and dividing them by two.

4.7 Measurement model. A principal component analysis with Oblimin rotation* was performed on the Big Five items. Five factors were extracted based on the Eigenvalue >1 criterion, the obtained factors were saved as *Bartlett.* The factors cumulatively explained 67,8% of variance. The alpha values for all constructs of the Big Five were not very reliable. (Figure 2).

Construct	**Cronbach's Alpha**	**Evaluation** (Using George & Mallery, 2003)
Extraversion	.589	Poor
Openness	.410	Unacceptable
Agreeableness	.170	Very poor
Conscientiousness	.385	Unacceptable
Neuroticism	.414	Unacceptable

Figure 4. Big Five constructs and reliability analysis.

***EFA** (Exploratory Factor Analysis) with Oblimin rotation and Eigenvalue >1 criterion gave almost similar outcomes – also five factors were extracted. A total of 68,23% explained variance.

5. Results.

5.1 Analysis. The assumptions for conducting a multilinear logistic regression were not violated. The only side note is that the Big Five items had moderate to high correlations. This is not ideal since they are predictor variables; but this could be expected from a theoretical viewpoint.

A Multinomial Logistic Regression was performed using SPSS statistics. The model only looked at main effects. The reference category was '*Apple 6 and newer'*.

5.2 Outcomes. A Multinomial Logistic Regression was performed to model the relationship between the predictors and the smartphone sensor category. A .05 criterion of statistical significance was employed for all tests. Addition of the predictor to a model that contained only the intercept significantly improved the fit between model and data, X^2 (42, N=1602) = 290.09, Nagelkerke R^2 =.173, p <.001. Significant unique contributions were made by age, income (both personal and household), gender and neuroticism. Both extraversion and openness did not make a significant contribution to the model. For details, see Table 7. Results tables with other reference categories (iPhone 5 and older, Samsung S-series) can be found in the appendix.

Apple versus Android. More analyses were done, comparing specifically Apple to Android (by creating a new variable). Looking into this table, it is clear that Samsung (Android) owners have a significant lower household income. This is in line with the fourth hypothesis, stating that people with a low income are more likely to own cheaper (Android) phones. Although, on the contrary, no effect of personal income was found. Further, a significant effect of gender is found. In accordance with the first hypothesis, women significantly more often own Apple phones than males do.

Brand			**95% CI For Odds Ratio**		
Reference category = Apple		***b (SE)***	**Lower**	**Odds ratio**	**Upper**
Samsung	Intercept	68.91 (12.85)***			
	Gender	-.72 (.16)***	.70	.49	1.31
	Extraversion	.12 (.08)	.96	1.13	1.32
	Neuroticism	.16 (.09)	.94	1.17	1.35
	Openness	.03 (.08)	.79	1.03	1.08
	Age	-.03 (.01)***	.96	.97	.99
	Income (personal)	-.01 (.03)	.93	.99	1.04
	Income (household)	-.12 (.05)**	.80	.89	.95

Note. R^2= .086 (Cox and Snell), .097 (Nagelkerke). Model X^2 (21) = 143.9889, p <.001. * p < .05, ** p < .01, *** P < .001.

Figure 5. Outcomes of the Multinomial Logistic regression, with Apple as reference category.

Old versus New. Another Multinomial Logistic Regression was done, this time comparing **Old** (consisting of the Apple 5, Hauwei Lite and Samsung A/M range) to **New** (consisting of Apple 6, Hauwei new and Samsung-S). A significant effect of age can be observed; although it is the other way around than hypothesized. Older people more often own newer smartphones than younger people do. Second, a significant effect of gender is found. Indicating that females more often own a newer smartphone than males do.

Age of phone			**95% CI For Odds Ratio**		
Reference category = Old		***b (SE)***	**Lower**	**Odds ratio**	**Upper**
New	Intercept	-74.999 (12.69)***			
	Gender	.50 (.16)**	1.21	1.65	2.26
	Extraversion	-.07 (.08)	.79	.93	1.09
	Neuroticism	-.21 (.09)*	.67	.81	.97
	Openness	.004 (.08)	.86	1.00	1.18
	Age	.04 (.006)***	1.03	1.04	1.05
	Income (personal)	.02 (.03)	.97	1.02	1.08
	Income (household)	.07 (.04)	.98	1.07	1.17

Note. R^2= .058 (Cox and Snell), .066 (Nagelkerke). Model X^2 (14) = 95.609, p <.001. * p < .05, ** p < .01, *** P < .001.

Figure 6. Outcomes of Multinomial Logistic regression, with Old phones as reference category.

Individual Smartphone Groups. When looking at Figure 7 in detail, some interesting results can be found. For example, women significantly more often own a iPhone 6 or newer, over either a Huawei (Lite or New) or a Samsung Phone (S-series and A/M-series). Moreover, the **odds ratio**, indicating how the risk of the outcome falling in the comparison group compared to the risk of the outcome falling in the referent group changes with the variable in question, is low in these cases, ranging from to .001 to .52. This indicates quite a strong effect of gender, therefore providing support for hypothesis 1 (women are more likely than man to own Apple phones). A similar pattern can be found when using iPhone 5 as a reference category, thus providing more proof for hypothesis 1.

Secondly, some effects of age can be observed, although they do not show an homogenous character. Samsung A/M users are significantly younger than iPhone 6 users, whereas iPhone 6 users are significantly younger than Samsung-S users. These findings do not clearly support hypothesis 2 (Younger people are more likely to own newer smartphones).

Third, an effect of household income is observed. With a lower household income, people significantly more often own a Samsung-S, or Samsung A/M than an iPhone 6, thus supporting hypothesis 3 (people with a high income are more likely to own Apple phones). A similar pattern can be observed when comparing iPhone 5 to Samsung S-series. Although, it is not observed when the iPhone 5 was compared to the Samsung A/M-series.

Hypotheses 5 and 6, concerning extraversion, are both rejected. No main effect of extraversion exist, and it is also not found when looking into further detail.

When looking into openness, some intriguing effect is observed. Huawei Lite users are found to be significantly less open than users of Samsung-S, Samsung A/M, iPhone 5 and iPhone 6, with a odds ratio's ranging from .253 to .279, indicating quite a strong effect. Though, it should be kept in mind that the confidence intervals are relatively large caused by the small size of the Huawei groups. This is not fully in accordance with hypothesis 7, stating that more open people are more likely to own newer smartphones. Still, it is more likely to own either an Apple of Samsung phone than a Huawei Lite, when scoring high in openness.

Lastly, when looking at the results with the Samsung S-series as a reference group (See Appendix), some more things can be observed. For example, iPhone 5 users are found to be significantly more neurotic than users of the Samsung-S series, with an odds ratio of 1.37. Thus, confirming hypothesis 8, stating that more neurotic people are more likely to own Apple phones. Although, this effect was not significant when comparing Samsung-S to iPhone 6 or newer. Interestingly, when using Samsung A/M as a reference category, no significant effect of neuroticism was found when comparing to iPhone 5. An effect was observed when comparing to iPhone 6 (p=.016), although this effect pointed in a different direction. Samsung A/M users seemed more neurotic than iPhone 6 users. These findings are not in favour of hypothesis 9, stating that more emotionally stable people are more likely to own Android phones.

Sensorcategory			**95% CI For Odds Ratio**		
Reference category: Apple 6		***b (SE)***	**Lower**	**Odds ratio**	**Upper**
Apple 5 and older	Intercept	8.60 (17.82)			
	Gender	-0.35 (.22)	.663	.97	1.47
	Extraversion	-.05 (.11)	.77	.95	1.17
	Neuroticism	.19 (.06)	.95	1.21	1.54
	Openness	-.06 (.11)	.76	.94	1.16
	Age	-.005 (.009)	.98	.995	1.01
	Income (personal)	.00 (.04)	.93	1.00	1.08
	Income (household)	-.009 (.06)	.88	.991	1.12
Huawei Lite	Intercept	413.2 (114.29)			
	Gender	-6.89 (1.98)***	0.00	.001	.05
	Extraversion	.43 (.52)	.55	1.54	4.26
	Neuroticism	-1.24 (.64)	.08	.29	1.01
	Openness	-1.34 (.57)*	.09	.262	.80
	Age	-.22 (.06)***	.72	.81	.90
	Income (personal)	.28 (.17)	.95	1.33	1.86
	Income (household)	1.71 (.55)**	1.88	5.55	16.39
Huawei New	Intercept	93.59 (33.06)**			
	Gender	-1.93 (.58)**	.05	.15	.45
	Extraversion	.31 (.26)	.83	1.37	2.27
	Neuroticism	.37 (.27)	.85	1.45	2.46
	Openness	-.42 (.24)	.41	.66	1.06
	Age	-.05 (.02)**	.92	.95	.99
	Income (personal)	.25 (.09)**	1.08	1.28	1.52
	Income (household)	-.63 (.14)***	.41	.53	.70
Samsung A/M	Intercept	96.09 (13.51)***			
	Gender	-.65 (.17)***	.37	.523	.73
	Extraversion	.12 (.09)	.95	1.12	1.33
	Neuroticism	.24 (.10)*	1.05	1.27	1.54
	Openness	.03 (.09)	.87	1.03	1.23
	Age	-.05 (.01)***	.94	.95	.97
	Income (personal)	-.03 (.03)	.92	.97	1.03
	Income (household)	-.10 (.05)*	.82	.90	.99
Samsung S	Intercept	-48.45 (21.31)*			
	Gender	-.99 (.24)***	.23	.373	.60
	Extraversion	.13 (.24)	.90	1.14	1.43
	Neuroticism	-.13 (.14)	.67	.88	1.16
	Openness	.02 (.12)	.81	1.02	1.29
	Age	.02 (.01)*	1.00	1.03	1.05
	Income (personal)	.097 (.04)*	1.01	1.10	1.20
	Income (household)	-.20 (.07)**	.72	.82	.93
Rest	Intercept	66.02 (13.76)***			
	Gender	.07 (.17)	.77	1.07	1.50
	Extraversion	.18 (.09)*	1.01	1.20	1.42
	Neuroticism	.09 (.10)	.90	1.09	1.33
	Openness	-.07 (.09)	.78	.93	1.11
	Age	-.03 (.007)***	.96	.97	.98
	Income (personal)	-.05 (.03)	.90	.95	1.01
	Income (household)	-.16 (.05)**	.78	.86	.94

Note. R^2= .078 (Cox and Snell), .081 (Nagelkerke). Model X^2 (42) = 156.939, p <.001.
* p < .05, ** p < .01, *** P < .001.

Figure 7. Outcomes of Multinomial Logistic Regression with iPhone 6 and newer as reference category.

6. Discussion.

The increased use of smartphones and smartphone sensors as a means of data collection in various areas of research is a clear trend. Smartphones are widespread among the population, and data gathering can be done efficiently is terms of both time and costs. However, there is the possible risk of systematic distortion in data. This is the case when the people who use different types or brands smartphones, differ significantly is terms of for example, demographics.

The results presented in this paper suggest that this can be the case for demographics, but not for personality. It was found that iPhone owners are more likely to be female, thereby substantiating the findings of Shaw et al. (2016). Shaw et al., found that iPhone owners are more likely to be female, younger and more concerned with status. The finding that iPhone owners are younger on average was replicated in this study, status was not explicitly taken into account.

Moreover, there is a main effect of age, although this effect is not homogenous and even seems to be opposite of what was hypothesized. Older people significantly more often own newer smartphones than younger people. Further, this result is not in line with the findings of Kim, Briley & Ocopek (2014), who found that younger, wealthier and more educated individuals tend to use smartphones a lot more than older people.

Furthermore, a higher household income has a significant positive effect on owning an iPhone, probably caused by the fact that iPhones (Apple) in general are more expensive than other smartphones are. Interestingly, these effects where not found when looking at personal income. Even more conspicuous is that this effect was even the other way around in some cases. A possible explanation of this phenomenon is that household income could have a larger influence on the type of smartphone you buy than personal income has, though this is only speculative.

No clear effects of personality were found in this study, thus providing support in favour of the research done by Gotz, Stieger & Reips (2017). They only found minor differences in personality too, and they were of small to negligible effect size.

The personality questionnaire, shortened and based on only 10 items, resulted to be not very reliable in the specific sample that was used in this study.

Whereas Rammstedt & John (2007) overall concluded that the scale is sufficient in terms of reliability and validity, taking into account the shortness. They also point out that, although the scale is acceptable, there is a substantial loss compared to the full scale. They only recommend using the scale when time is *really limited*. Further, their sample was made up of students for the large majority – which may have caused some lack of external validity. They also pointed that the least homogenous scales *openness* and *agreeableness* were least well represented in the BFI-10. A 2012 study by Credé and Harms further critically looked into the widespread use of shortened measures of Big Five personality traits, like the BFI-10. Although they understand the practical advantages, they point out a few reasons for caution:

1. Firstly, they explain that by using a (very) short scale, the **random measurement error** is larger. With more items, the measurement error is minimized, because the error is random and thus cancels each other out with several items. Evidently, more questions thus lead to improved **criterion validity**. Second, short scales are likely to be characterized by a substantial content deficiency, because not all facets of a construct are represented. Consequence is that the construct is underrepresented, and that substantial breadth in **predictive validity** is lost. Together, this might lead to the increased risk of a **type II error.** For example, declaring the influence of personality as non-substantial, when this is in fact not the case.
2. Moreover, there is also the risk of an increased **type I error**, thus finding an effect, when in reality there is none. Reason behind this is that short scales account for significantly less variance. As a consequence, the **incremental variance** explained by a variable is likely to be artificially inflated.

In spite of my efforts to conduct the present research in the best way possible, both theoretically and methodologically, this study has its shortcomings.

Firstly, in terms of theory, there was relatively scarce literature on the specific subject of both smartphone ownership, personality and smartphone sensors.

Second, the literature used on *TAM* did not talk about smartphone ownership or smartphone use, but only about technology acceptance in general. It is therefore only theoretically hypothesized that this can be applied to smartphone acceptance and usage as well. What is more, is that no specific literature about *status, personality* and smartphone ownership was studied, and again, these relationships are only theoretically hypothesized. All in all, this made it difficult to come up with explicit and good quality hypotheses.

Methodologically, there are also some weak points. First of all, many people did not use a smartphone, but instead another device or an offline mode to fill in the questionnaire. This made it impossible to include them in the study. This resulted in a smaller sample size. This poses questions about the external validity of the study. Moreover, missing data or *I don't know* answers were removed from the dataset - thereby maybe causing measurement error because it is unknown if the missing data is *missing completely at random* (MCAR) or even *missing at random* (MAR) (Vink, G. (2017, december). Inference and Missing Data [html]. Obtained via http://blackboard.com).

On the level of the variables used, some remarks can be made as well. First, because the smartphones were categorized in groups, inevitably a *rest* category emerged. This group was very heterogeneous and thus no significant deductions can be made from this group. Moreover, the sensors that are looked into are the most used ones in smartphones; but the selection is certainly not exhaustive. Many more sensors exist that are not investigated in this study. Also, the *smartphone groups* that are formed from the selection of sensors, have a certain degree of arbitrariness. There can be discussion about if this is the best and/or only classification possible.

Second, the choice of studying the specific background demographic variables (income, age and gender) is somewhat random, mostly because these are frequently used in social sciences in general. Plus, both the variables *household income* and *personal income* were treated as continuous variables, while this is in fact not completely true. The highest answer category for both variables lacked an upper limit. This means the variable can strictly not be treated as a continuous variable, as they were in the analysis. More generally, the drawback of using an existing dataset is the fact that you have to work with the data you have. The specific questions and/or answer categories used can be different from the ideal you would've used when you would have done the data collection yourself.

In terms of representativeness of the sample and therefore of the generalizability of the results, is that the GESIS panel is a large and generally representative sample of the German population. What is unknown, if the findings can be generalized to other countries, both in- and outside of Europe.

In further research, it would be useful to look into the same subject, but preferably using a longer Big Five questionnaire. Also, using smartphones as the main method of data collection and therefore having a larger group of participants that can be classified into a smartphone group can largely improve the quality, in terms of external validity, of this type of study.

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8. Appendix.

8.1 Results table – Samsung S-range as reference

Sensorcategory			**95% CI For Odds Ratio**		
Reference category: Samsung S		***b (SE)***	**Lower**	**Odds ratio**	**Upper**
Apple 5 and older	Intercept	57.05 (23.07)*			
	Gender	.95 (.27)***	1.54	2.59	4.37
	Extraversion	-.18 (.13)	.65	.83	1.08
	Neuroticism	.32 (.15)*	1.02	1.37	1.85
	Openness	-.09 (.13)	.71	.92	1.19
	Age	-.03 (.01)*	.95	.97	.99
	Income (personal)	-.097 (.05)*	.83	.91	.99
	Income (household)	.19 (.07)**	1.05	1.21	1.40
Apple 6 and newer	Intercept	48.45 (21.31)*			
	Gender	.99 (.24)	1.67	2.68	.432
	Extraversion	-.13 (.12)	.70	.88	1.11
	Neuroticism	.13 (.14)	.87	1.14	1.49
	Openness	-.02 (.12)	.78	.98	1.24
	Age	-.02 (.01)	.96	.98	.997
	Income (personal)	-.19 (.04)	.84	.91	.99
	Income (household)	.20 (.07)	1.08	1.23	1.40
Huawei Lite	Intercept	416.67 (115.26)***			
	Gender	-5.90 (1.98)**	0.00	.003	.13
	Extraversion	.30 (.53)	.48	1.35	3.79
	Neuroticism	-1.11 (.64)	.09	.33	1.16
	Openness	-1.36 (.58)*	.08	.26	.79
	Age	-.24 (.06)***	.70	.79	.88
	Income (personal)	.19 (.18)	.85	1.21	1.70
	Income (household)	1.92 (.55)**	2.29	6.80	20.15
Huawei New	Intercept	142.04 (35.91)***			
	Gender	-.94 (.60)	.12	.39	1.26
	Extraversion	.19 (.27)	.71	1.20	2.03
	Neuroticism	.50 (.28)	.94	1.64	2.86
	Openness	-.44 (.25)	.40	.65	1.06
	Age	-.07 (.02)***	.90	.93	.96
	Income (personal)	.15 (.09)	.93	1.16	1.39
	Income (household)	-.43 (.14)**	.50	.65	.86
Samsung A/M Series	Intercept	144.53 (19.91)***			
	Gender	.34 (.23)	.89	1.40	2.22
	Extraversion	-.01 (.11)	.80	.99	1.23
	Neuroticism	.36 (.13)**	1.11	1.44	1.86
	Openness	.01 (.11)	.81	1.01	1.26
	Age	-.07 (.01)***	.91	.93	.95
	Income (personal)	-.13 (.04)**	.82	.88	.95
	Income (household)	.10 (.06)	.98	1.11	1.25
Rest	Intercept	114.47 (20.11)***			
	Gender	1.06 (.23)***	1.83	2.88	4.54
	Extraversion	.05 (.11)	.84	1.05	1.32
	Neuroticism	.21 (.13)	.95	1.24	1.60
	Openness	-.09 (.11)	.73	.913	1.14
	Age	-.06 (.01)***	.93	.94	.96
	Income (personal)	-.14 (.04)***	.80	.87	.94
	Income (household)	.05 (.06)	.93	1.05	1.19

Note. R^2= .078 (Cox and Snell), .081 (Nagelkerke). Model X^2 (42) = 156.939, p <.001. * p < .05, ** p < .01, *** P < .001.

8.2 Results table – Apple 5 and older as reference

Sensorcategory			**95% CI For Odds Ratio**		
Reference category: Apple 5 and older		***b (SE)***	**Lower**	**Odds ratio**	**Upper**
Apple 6 and newer	Intercept	-8.45 (17.92)			
	Gender	.35 (.22)	.71	1.12	1.70
	Extraversion	.06 (.11)	.86	1.07	1.32
	Neuroticism	-.19 (.13)	.86	1.17	1.59
	Openness	.06 (.11)	.86	1.07	1.33
	Age	.005 (.009)	.99	1.00	1.02
	Income (personal)	.00 (.04)	.93	1.00	1.08
	Income (household)	.009 (.06)	.90	1.01	1.14
Huawei Lite	Intercept	305.35 (89.62)**			
	Gender	-.5.00 (1.47)**	.00	.01	.12
	Extraversion	.55 (.54)	.60	1.73	4.95
	Neuroticism	.197 (.83)	.42	1.22	6.13
	Openness	-.85 (.49)	.16	.43	1.13
	Age	-.16 (.05)***	.78	.85	.93
	Income (personal)	.41 (.19)*	1.04	1.50	2.18
	Income (household)	1.02 (.39)**	1.30	2.76	5.88
Huawei New	Intercept	85.89 (33.49)*			
	Gender	-2.01 (.58)**	.04	.13	.42
	Extraversion	.46 (.26)	.96	1.59	2.65
	Neuroticism	-.72 (.33)*	.25	.49	.94
	Openness	-.33 (.25)	.44	.72	1.16
	Age	-.04 (.02)*	.93	.96	.99
	Income (personal)	.25 (.09)**	1.07	1.28	1.54
	Income (household)	-.63 (.15)***	.40	.53	.71
Samsung A/M	Intercept	87.58 (16.11)***			
	Gender	-.63 (.20)**	.36	.53	.79
	Extraversion	.16 (.10)	.96	1.17	1.44
	Neuroticism	.01 (.15)	.76	1.01	1.34
	Openness	.09 (.10)	.90	1.10	1.34
	Age	-.04 (.01)***	.94	.96	.97
	Income (personal)	-.03 (.04)	.90	.97	1.04
	Income (household)	-.09 (.06)	.82	.91	1.02
Samsung S	Intercept	-52.06 (23.07)*			
	Gender	-.86 (.26)**	.25	.42	.71
	Extraversion	.26 (.13)*	1.00	1.30	1.69
	Neuroticism	-.10 (.19)	.63	.90	1.30
	Openness	.07 (.13)	.83	1.08	1.39
	Age	.03 (.01)*	1.00	1.03	1.05
	Income (personal)	.099 (.05)*	1.01	1.10	1.21
	Income (household)	-.19 (.07)**	.72	.83	.95
Rest	Intercept	58.70 (16.33)***			
	Gender	.13(.20)	.77	1.14	1.68
	Extraversion	.27 (.11)*	1.07	1.31	1.61
	Neuroticism	-.11 (.15)	.68	.90	1.20
	Openness	-.007 (.11)	.81	.99	1.22
	Age	-.03 (.01)***	.96	.97	.99
	Income (personal)	-.05 (.04)	.89	.96	1.02
	Income (household)	-.14 (.06)*	.78	.87	.97

Note. R^2= .166 (Cox and Snell), .173 (Nagelkerke). Model X^2 (42) = 290.09, p <.001. * p < .05, ** p < .01, *** P < .001

8.3 Smartphones studied and their sensors.

Smart-phone	**Release date**	**Accelero-meter**	**Gyroscope**	**Magneto-meter / Compass**	**GPS**	**Barometer**	**Proximity sensor**	**Ambient light sensor**	**Pedo meter**	**Heart rate sensor**	**Fingerprint sensor**
Samsung Galaxy S4	April 2013	Yes	Yes	Yes	Yes	Yes	Yes				
Extra		Gesture sensor, face recognition, voice recognition									
Samsung Galaxy S5	April 2014	Yes	Yes	Yes	Yes	Yes	Yes	Yes		Yes	Yes
Extra		Hall sensor, gesture sensors									
Samsung Galaxy S6	April 2015	Yes	Yes	Yes	Yes	Yes	Yes	Yes		Yes	Yes
Extra		Thermometer									
Samsung Galaxy S7	March 2016	Yes	Yes	Yes	Yes	Yes	Yes	Yes		Yes	Yes
Extra		Hall sensor									
Samsung Galaxy S8 & S8+	April 2017	Yes	Yes	Yes	Yes	Yes	Yes	Yes		Yes	Yes
Extra		Iris sensor, pressure sensor , hall sensor									
iPhone 4s	October 2011	Yes	Yes	Yes	Yes		Yes	Yes			
iPhone 5	September 2012	Yes	Yes	Yes	Yes		Yes	Yes			
iPhone 5s	September 2013	Yes	Yes	Yes	Yes		Yes	Yes			Yes

iPhone 6s	September 2015	Yes	Yes	Yes	Yes	Yes	Yes	Yes			Yes
Extra		Pressure sensitive display									
iPhone 7	September 2016	Yes	Yes	Yes	Yes	Yes	Yes	Yes			Yes
iPhone 8	September 2017	Yes	Yes	Yes	Yes	Yes	Yes	Yes			Yes
Extra		Three-axis gyro									
iPhone X	November 2017	Yes	Yes	Yes	Yes	Yes	Yes	Yes			
Extra		Face ID, three-axis gyro									
Samsung Galaxy S III	May 2012	Yes	Yes	Yes	Yes	Yes	Yes	Yes			
Samsung Galaxy note 3	September 2013	Yes	Yes	Yes	Yes	Yes	Yes	Yes			
Samsung note 8	August 2017	Yes	Yes	Yes	Yes	Yes	Yes	Yes		Yes	Yes
Extra		Iris sensor, pressure sensor, hall sensor									
HTC One (M8)	March 2014	Yes	Yes	Yes	Yes	Yes	Yes	Yes			
Redmi 3S prime	August 2016	Yes	Yes	Yes	Yes		Yes	Yes			
Huawei Mate 10	October 2017	Yes	Yes	Yes	Yes	Yes	Yes	Yes			
Huawei P10	February 2017	Yes	Yes	Yes	Yes		Yes	Yes			

Huawei P10 lite	February 2017	Yes			Yes						
Huawei Mate 9	November 2016	Yes	Yes	Yes	Yes		Yes	Yes			
Extra		G-sensor, Hall sensor, IR									
Huawei P9	April 2016	Yes	Yes	Yes	Yes		Yes	Yes			
Huawei P9 lite	April 2016	Yes			Yes		Yes	Yes			
Huawei Mate 8	November 2015	Yes	Yes		Yes		Yes	Yes			
Huawei P8	April 2015	Yes	Yes	Yes	Yes		Yes	Yes			
Huawei P8 lite	April 2015	Yes			Yes		Yes	Yes			
Samsung A3	November 2014	Yes		Yes	Yes		Yes	Yes			
Samsung A5	November 2014	Yes		Yes	Yes		Yes	Yes			
Samsung A7	January 2015	Yes		Yes	Yes		Yes	Yes			

8.4 Smartphone sensor groups

Group	Description	Phones	Sensors	What differentiates group?
A	Samsung S-range	Galaxy S5, Galaxy S6, Galaxy S7, Galaxy S8, Note 8	Accelerometer, gyroscope, Magnetometer, GPS, Barometer, Proximity sensor, Ambient light sensor, HR-sensor, fingerprint sensor, hall sensor.	Only one with Hall sensor Have Barometer Have HR-sensor
B	Samsung A/M range	Galaxy A3, Galaxy A5, Galaxy A7	Accelerometer, Magnetometer, GPS, proximity sensor, Ambient Light Sensor.	Have no Gyroscope Have no Barometer No Pedometer, HR-sensor or fingerprint sensor
C	Apple 5s and older	iPhone 4s, 5, 5s	Accelerometer, gyroscope, magnetometer, GPS, proximity sensor, ambient light sensor.	No Barometer No fingerprint sensor No HR-Sensor
D	Apple 6 and newer	iPhone 6s, iPhone 7, iPhone 8, iPhone X	Accelerometer, gyroscope, magnetometer, GPS, barometer, proximity sensor, ambient light sensor, fingerprint sensor (except X).	No HR-sensor Have barometer
E	Huawei Lite	Huawei P9 lite, Huawei P8 lite	Accelerometer, GPS, Proximity sensor, Ambient light sensor.	No Gyroscope No Barometer No Magnetometer No fingerprint sensors No HR-sensor
F	Huawei New	Huawei P8, Huawei P9, Huawei P10, Huawei Mate 9	Accelerometer, Gyroscope, Magnetometer, GPS, Proximity sensor, Ambient light sensor.	No Barometer No HR-sensor No fingerprint sensors
Rest	Rest category	All other phones	-	-

8.5 Syntax

```
NOMREG sensorcategories (BASE='Apple 5 and older' ORDER=ASCENDING) BY Male_Female
WITH
    Extraversion Openness dfzh038c dfzh055b dfzh056c Neuroticism
  /CRITERIA CIN(95) DELTA(0) MXITER(100) MXSTEP(5) CHKSEP(20) LCONVERGE(0)
PCONVERGE(0.000001)
    SINGULAR(0.00000001)
  /MODEL
  /STEPWISE=PIN(.05) POUT(0.1) MINEFFECT(0) RULE(SINGLE) ENTRYMETHOD(LR)
REMOVALMETHOD(LR)
  /INTERCEPT=INCLUDE
  /PRINT=CELLPROB CLASSTABLE FIT PARAMETER SUMMARY LRT CPS STEP MFI.
```

```
NOMREG sensorcategories (BASE='Apple 6 and newer' ORDER=ASCENDING) BY Male_Female
WITH
    Extraversion Openness dfzh038c dfzh055b dfzh056c Neuroticism
  /CRITERIA CIN(95) DELTA(0) MXITER(100) MXSTEP(5) CHKSEP(20) LCONVERGE(0)
PCONVERGE(0.000001)
    SINGULAR(0.00000001)
  /MODEL
  /STEPWISE=PIN(.05) POUT(0.1) MINEFFECT(0) RULE(SINGLE) ENTRYMETHOD(LR)
REMOVALMETHOD(LR)
  /INTERCEPT=INCLUDE
  /PRINT=CELLPROB CLASSTABLE FIT PARAMETER SUMMARY LRT CPS STEP MFI.
```

```
NOMREG sensorcategories (BASE='Samsung A/M-series' ORDER=ASCENDING) BY Male_Female
WITH
    Extraversion Openness dfzh038c dfzh055b dfzh056c Neuroticism
  /CRITERIA CIN(95) DELTA(0) MXITER(100) MXSTEP(5) CHKSEP(20) LCONVERGE(0)
PCONVERGE(0.000001)
    SINGULAR(0.00000001)
  /MODEL
  /STEPWISE=PIN(.05) POUT(0.1) MINEFFECT(0) RULE(SINGLE) ENTRYMETHOD(LR)
REMOVALMETHOD(LR)
  /INTERCEPT=INCLUDE
  /PRINT=CELLPROB CLASSTABLE FIT PARAMETER SUMMARY LRT CPS STEP MFI.
```

```
NOMREG Apple_Samsung_Huawei (BASE='Apple' ORDER=ASCENDING) BY Male_Female WITH
Extraversion
    Openness dfzh038c dfzh055b dfzh056c Neuroticism
  /CRITERIA CIN(95) DELTA(0) MXITER(100) MXSTEP(5) CHKSEP(20) LCONVERGE(0)
PCONVERGE(0.000001)
    SINGULAR(0.00000001)
  /MODEL
  /STEPWISE=PIN(.05) POUT(0.1) MINEFFECT(0) RULE(SINGLE) ENTRYMETHOD(LR)
REMOVALMETHOD(LR)
  /INTERCEPT=INCLUDE
  /PRINT=CELLPROB CLASSTABLE FIT PARAMETER SUMMARY LRT CPS STEP MFI.


NOMREG Old_New (BASE=LAST ORDER=ASCENDING) BY Male_Female WITH Extraversion
Openness dfzh038c
    dfzh055b dfzh056c Neuroticism
  /CRITERIA CIN(95) DELTA(0) MXITER(100) MXSTEP(5) CHKSEP(20) LCONVERGE(0)
PCONVERGE(0.000001)
    SINGULAR(0.00000001)
  /MODEL
  /STEPWISE=PIN(.05) POUT(0.1) MINEFFECT(0) RULE(SINGLE) ENTRYMETHOD(LR)
REMOVALMETHOD(LR)
  /INTERCEPT=INCLUDE
  /PRINT=CELLPROB CLASSTABLE FIT PARAMETER SUMMARY LRT CPS STEP MFI.


NOMREG sensorcategories (BASE='Apple 6 and newer' ORDER=ASCENDING) WITH Extra_inverted
ddze006a
    neuro_inverted ddze009a Open_inverted ddze010a
  /CRITERIA CIN(95) DELTA(0) MXITER(100) MXSTEP(5) CHKSEP(20) LCONVERGE(0)
PCONVERGE(0.000001)
    SINGULAR(0.00000001)
  /MODEL
  /STEPWISE=PIN(.05) POUT(0.1) MINEFFECT(0) RULE(SINGLE) ENTRYMETHOD(LR)
REMOVALMETHOD(LR)
  /INTERCEPT=INCLUDE
  /PRINT=CELLPROB CLASSTABLE FIT PARAMETER SUMMARY LRT CPS STEP MF
```

8.6 Big Five Questionnaire (BFI-10)

Construct: **Extraversion**

1. 1. Ich bin eher zuruckhaltend, reserviert (inverted)
2. 6. Ich gehe mich heraus, bin gesellig.

Construct: **Openness**

5. Ich have nur wenig kunstlerisches Intresse (inverted)

10. Ich have eine Aktive Vorstellungskraft, bin fantasievoll.

Construct: **Agreeableness**

3. Ich schenke anderen leicht Vertrauwen, glaube an das Gutei m Menschen.

7. Ich neige dazu, andere zu kritisieren (inverted)

Construct: **Conscientiousness**

4. Ich bin bequem, neige zur Faultheit (inverted).

8. Ich erledige Aufgaven grundlich

Construct: **Neuroticism**

5. Ich bin entspannt, lasse mich durch Stress nicht aus der Ruhe bringen (inverted)
6. Ich werde leicht nervos und unsich