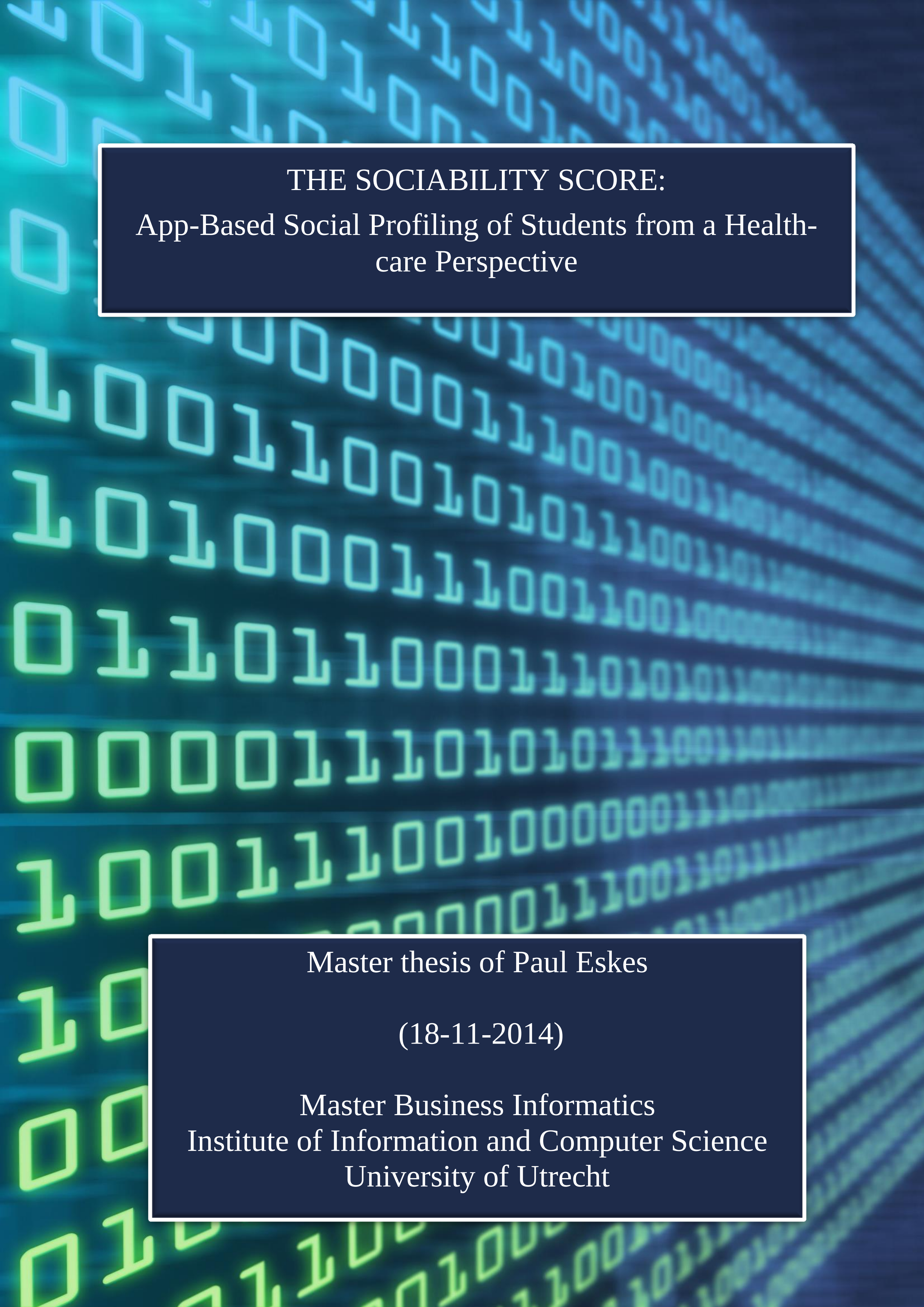

THE SOCIABILITY SCORE:

App-Based Social Profiling of Students from a Health-care Perspective

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(18-11-2014)

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Abstract

As the smartphone becomes an integral part of our lives, its value as a rich data source reaches an increasing potential. Several studies exist that exploit smartphone-derived data to discover relationships between user characteristics and different types of smartphone use. However, none tried to use smartphone data to capture an individual's social behavior into one profile, aimed at providing additional information for the diagnosis of social deficits. This study presents a way of combining different data sources for the creation of sociability profiles using a scoring mechanism that allows for the easy addition and removal of data sources. Finally, this model has been used to create social profiles of ten test subjects, which could function as comparison material for future studies.

Acknowledgements

In the first place, I would like to express my gratitude to Martien Kas and Jacob Vorstman, my supervisors at the UMC Utrecht, for their enthusiastic encouragement, positive mindset and for providing me with a wealth of information on both scientific research in general and the research domain around my research topic, which aided significantly in the realization of this thesis.

Then, I would like to show my appreciation for my supervisors at the University of Utrecht; Marco Spruit, for having trust in me as an independent researcher and for providing me with useful feedback on my research progress and on my conceptual version of this paper, and Ronald Batenburg, for giving his feedback on the same conceptual version.

Also, I would like to thank all the people that were willing to serve as test subjects for this study, for sharing their time to install the application and filling in the personality test, and for trusting me with their privacy-sensitive data. Those people will remain anonymous throughout the rest of this paper out of respect for their privacy.

Lastly, I would like to thank my friends and classmates for the interesting discussions on the potential of this research, especially those with an information science, psychological or sociological background.

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List of abbreviations

Mathematical abbreviations

1. id: the person id
2. β: the regression coefficient
3. σ: the standardized error or standard deviation
4. r: the standardized coefficient calculated as Pearson's r
5. p: the p-value; significance of predictors
6. n: the sample size
7. r^2: the coefficient of determination

Event abbreviations

1. PE: positioning event
2. PC: proximity count
3. BE: Bluetooth event
4. CI: incoming call
5. CO: outgoing call
6. CM: missed call
7. SI: incoming SMS
8. SO: outgoing SMS
9. AA: application activity
10. WO: Whatsapp outgoing
11. WI: Whatsapp incoming event
12. TP: Twitter personal tweet
13. TR: Twitter re-tweet
14. TI: Twitter direct incoming
15. FI: Facebook incoming message
16. FO: Facebook outgoing message
17. FT: Facebook timeline post
18. HI: Hyves incoming message
19. HO: Hyves outgoing message
20. MI: incoming MMS
21. MO: outgoing MMS

1 Introduction

According to a survey by Ernst and Young, Dutch citizens are dissatisfied about IT-innovation in the health-care sector, which is explained by the fact that healthcare specialists provide human-centered services and are not focused on applying IT-solutions to improve their business processes (Ernst & Young, 2011). This observation also suggests a wealth of opportunities present in this sector for new technologies, of which one large opportunity is exploring the ways smartphones can aid in professional health-care. The larger the role of smartphones becomes in our lives, the more interesting these devices will become for health-care, while the information held by these smartphones could provide objective insights into the owner's lifestyle and psychological wellbeing. Currently, many data mining techniques exist that could extract data from smartphones about the user's smartphone use. But to cope with a large set of extracted data from a large group, a validated, scientific model should be developed to present the extracted data in an organized way to create insight into the user's lifestyle and social behavior. Subsequently, this information can be used in the psychological domain to create distinctive social profiles and thus create valuable insights in a person's level of sociability. Finally, this information can be a valuable addition in a clinical context, while possibly increasing the accuracy of medical diagnoses in the cognitive-behavioral domains and therefore improving the overall efficiency of subsequent treatment.

This study serves as a pilot study to explore the possibilities of smartphone data mining for measuring sociability of an individual, including the creation and validation of a sociability model. Additional studies should investigate the usefulness of such a model in a clinical context, examining the differences in the measured sociability between people with and without social deficits.

1.1 Research trigger

Currently, the department of Translational Neuroscience at the UMC Utrecht in cooperation with the department of Psychiatry and a third party software developer develop a smartphone application with the aim to create additional digital assistance for the observation of social behavior and, potentially for the diagnosis of patients with (possible) social deficits. Current methods are mainly based on self-reports, obtained either through questionnaires, real life conversations or through phone-based interviews. The two largest disadvantages of these currently used methods are the restricted amount of information these sessions deliver and the questionable reliability of the information given the inherent subjective quality of the data. As literature states, self-reported statements can only be interpreted when handled with great care, as people may change the truth consciously or unconsciously to get a desired outcome or because they have a wrong impression of their own situation (Straka et al., 1997)(De Reuver et al., 2012).

The smartphone as an objective instrument eliminates both of these disadvantages that are connected with the current diagnosing method, while a smartphone can collect information both extensively and objectively. Therefore it is interesting to examine the role smartphones can play in current diagnosing methods for social deficits. Many studies show the possibilities of smartphones as a data source for all types of social purposes like user profiling, user tracing, activity recognition etcetera. But little research has been done utilizing these possibilities to fit health-care purposes, and more specifically in the psychological health-care domain. To discover the potential of smartphones for clinical purposes, additional research is required that may uncover the possibilities of smartphone data in the diagnosis and treatment of people with possible social deficits.

1.2 Research questions

To uncover the potential of the smartphone as a measurement instrument for the psychological healthcare domain, the following research question has been formulated:

1. *How can a social profile of an individual be created for psychological healthcare purposes based on smartphone usage and smartphone-registered behavior?*

The first step in answering the main question is to identify and define the different factors that can be considered as the building blocks of a social exploration profile. In the context of this research, all of these factors are built upon smartphone-retrieved data, including smartphone -activity data and data retrieved from smartphone sensors, which directly or indirectly describe an aspect of a user's sociability. It should be taken into consideration that some of these factors may be explained by certain user characteristics and demographics and are no direct consequence of a person's sociability.

1.1 What factors can be defined that determine a healthcare-related sociability profile?

Based on the categorization of the smartphone data and the factors defined in the previous research question, the next step is to discover the possible contribution each of the categories can deliver for the final social exploration profile. The next three questions are each based on one of these smartphone data categories.

1.2 How can mobile social media use contribute to the creation of a sociability profile?

1.3 How can smartphone communication data contribute to the creation of a sociability profile?

1.4 How can GPS location in combination with social environment density contribute to the creation of a sociability profile?

1.3 Relevance

This research has relevance for multiple target groups when looked at from different perspectives. First, the scientific world gains a unique insight into the possibilities of smartphone data for social studies, more specifically, using information about an individual's smartphone use as an additional source for describing the sociability of an individual.

From a business perspective, a description about an individual's sociability levels can function as an additional source for physicians during the process of diagnosis, which ideally can gain hospitals an increased effectiveness and efficiency of several treatments in the psychological domain, reducing treatment times, waiting lists and overall treatment costs.

Finally, from a social point of view, patients benefit equal to the hospitals as it is also in their best interest to have a reduced treatment time and a reduced chance of illness exacerbation.

1.4 Structure

The structure of this article is as follows; first a theoretical background will be provided for this topic in the form of a systematic literature review; exploring the current best practices in the field of smartphone mining and sociability. Then, both the research and data mining method will be described in the research approach chapter to provide structure to the research process. Next, the collected smartphone data will be analyzed to assess both the validity and reliability of the different data sources, and to create conclusions about each of the data sources' usability for the eventual sociability profile. Chapter 5 then will combine the information from the previous chapters to present the first version of the sociability model, which will be tested subsequently by applying the model in a test group of 10 individuals of which the results will be presented in the results chapter. To end this paper, the conclusion and discussion chapters will evaluate the results and describe the way future research can elaborate on this subject.

1.5 Privacy and legislation issues

We will make a distinction in privacy issues with respect to this research and the future deployment of the application when it is used as an addition for diagnosing social deficits.

While personal data is automatically collected by the smartphone application the Dutch Data Protection Act (in Dutch: ‘Wet Bescherming Persoonsgegevens’) could be considered as applicable (art. 2, clause 1, WBP). This act describes several privacy issues concerning the recording and using of personal data. First, the act mentions the urge for careful processing of the data (art. 6, WBP), which is realized through the anonymization of research subjects and the encryption of data like phone numbers, MAC-addresses and types of activities. The anonymization and encryption make interpretation impossible by malicious individuals that succeed in capturing data chunks.

Secondly, the act states that the data should be protected against loss and any type of unjustifiable processing (Art. 13, WBP).

The data collected by this application will be stored on a hospital server at the UMC Utrecht with restricted access and will receive similar protection when compared to Dutch patient records, which should be sufficient to protect the data against loss or unjustifiable processing.

Then, the law also states that the processing of personal data can only occur with justifiable intentions (Art. 7& art. 9 clause 1, WBP). One form of justifiable intentions that is applicable for this research is scientific intentions, which on the long run will transform into health-care purposes when the application will be used as an addition for the diagnostic process of several social deficits. Both purposes can be argued as justifiable and are therefore not violating the Dutch Data Protection Act.

An additional article of the WBP states that in the case the collected data is considered health-care information, the information can only be processed by health-care professionals (Art. 21, clause 1a, WBP). At the current stage, the data for this research cannot be considered health-care data, because this study only stores information about healthy persons’ sociability. However, when the application will be released as an addition for the diagnosis of social deficits, the data collected can be considered as health-care information and should therefore be processed by health-care related professional only.

Finally, the research subjects in this study will have to give explicit permission to the researchers to process their information and can quit the study prematurely at any given moment. This corresponds with article 8 of the Dutch Data Protection Act stating that process of personal data may occur under with explicit permission, which will give the researchers enough freedom to perform this study (Art. 8, WBP).

2 Theoretical background/systematic literature review

The following section will provide a full overview of the approach and the results of the systematic literature review. The main purposes of the literature study is to create context understanding of the research problem, to get an insight in state of the art smartphone mining methods and possible data visualizations and to discover reference material for comparing the eventual results of this study.

2.1 Method

To create a theoretical background, a systematic literature review has been executed following the guidelines by the PRISMA statement (Moher et al., 2009). This method prescribes a systematic method to identify, select, and critically appraise relevant research, and to collect and analyze data from the studies that are included in the review.

In some cases, topic elaboration was required, where additional papers were added by identifying relevant articles from the reference lists of articles found during the systematic literature review. This method is also referred to as 'snowballing' and is recommended for discovering articles that are uneasily found with typical database searches (Kitchenham et al., 2009)(Jalali and Wohlin, 2012).

2.2 Databases

The systematic literature is restricted to the search engine Google Scholar. A few initial searches where done using MedlinePlus, PubMed, IEEE Xplore, ScienceDirect and Google Scholar to determine their effectiveness. PubMed and MedlinePlus did not hold interesting results for the search queries, while IEEE XPlore and ScienceDirect both showed papers that were also present in the results from Google Scholar, making Google Scholar as a broad search engine the most elaborate and efficient option.

2.3 Keyword selection

After the business understanding phase, which included preliminary interviews with domain experts, a list of keywords was composed in which the keywords were divided over the categories 'general research characteristics', 'social deficits', 'confounding factors', 'data mining', 'GPS tracking', 'social media' and 'smartphone use'. These categories where labeled from X and A to F respectively and subsequently combined to create queries according to the following formula:

[Cat. X] + (([Cat. B] || ([Cat. D] || [Cat. E] || [Cat. F] || NULL) + ([Cat. A] || [Cat. C]))

The formula is aimed at observing social profiling from both a business and a data mining perspective and additionally at discovering to what extent existing literature has bridged the gap between data mining and health-care based social profiling. The formula can be explained as follows; category X represents keywords that describe the general goal of this research (i.e. social profiling). These keywords are combined with a perceived confounding factor, a smartphone-related data mining source or an empty string. As a final addition, either a data mining term or health-care related term is added to put the search into context of either the business or data understanding phase.

A full list of keywords and their respective categorization can be found in Appendix A. Overall, this formula delivered 576 unique search queries which in total yield about 13.000.000 results.

2.4 Paper selection criteria

The first step towards the paper selection included the filtering of all papers that exceeded the boundary of being among the first hundred results, while the first initial searches showed the relevance of papers beyond this boundary to be too low. We assume that for further searchers this same irrelevance holds for papers being on page eleven and further.

The next selection phase included the selection by title, where the papers were selected that appeared relevant enough in the context of smartphone data mining social studies. Also all papers where filtered on publication status and language, where papers that weren't published or not being written in either English or Dutch were excluded.

The papers then were divided, based on the contents of the papers, into the following categories: smartphone mining and social context, smartphone movement mining, smartphone physical activity mining, smartphone use and personality, smartphone use and social deficits, general smartphone mining, social media and personality, social media usage and social media, internet and social deficits.

Eventually, due to irrelevance, the following topics were excluded: research solely observing physical smartphone activity using the accelerometer, research focusing extensively on social deficits and all types of social network visualization methods. For further reference, a summary of the paper selection phase is visualized in figure 1.

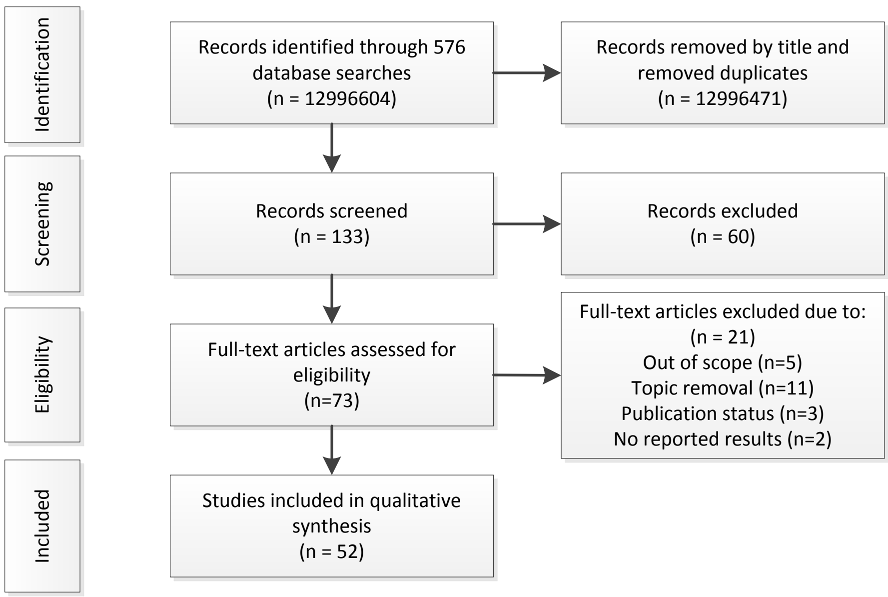

Figure 1. Systematic literature review – paper selection

2.5 Content analysis

The following section will present the findings of the systematic literature review per category. Four chapters are created, each dedicated to a certain category described in the ‘Paper selection criteria’-section, recalling; smartphone use, social smartphone mining, social media usage and smartphone localization and movement patterns.

2.6 Smartphone use

Many factors can be identified that might influence a person’s general smartphone use. Several studies have tried to capture several of these factors, and we categorized these papers into the following sections; user demographics, smartphone application usage, smartphone use motivations, user-context, personality and an overlapping section dedicated to the ‘theory of real behavior’.

2.6.1 User demographics and smartphone use

The first study provides insights into how students prefer to consume information on their mobile devices, ranging from broad categories to coursework-specific areas of interest (Bowen & Pistilli, 2012). A survey was held among 1566 students, answering 32 questions categorized in three sections: demographic information, general mobile application usage, and educational mobile application usage. The most relevant results are the following; the level of smartphone experience is positively correlated with the length of smartphone ownership, WiFi connectivity has a significant influence on the user’s smartphone activities and students prefer native apps for most mobile activities. Also, 70% of the students indicated that applications are both faster and easier in use than mobile browsers.

The next study by Uys et al., aimed at getting descriptive results about the frequency and intensity of smartphone application usage, specifically social networking applications. A survey was held among 57 students from the University of Western Cape, who had to rate their levels of social network application usage and other applications. Also, they had to fill in an estimation of both SMS and Call use. This descriptive study came to the conclusion that university students spend an average of five hours per day on their smartphones interacting with others via social network sites, and remain online for about 16 hours per day. Phone calls where considered to take 60 minutes of a student’s day and SMS messaging took 20 minutes; in contrast to the 4h45 minutes spend on face-to-face interactions (Uys et al., 2012).

Also, differences in socio-economic status (SES) appear to influence smartphone use (Rahmati et al., 2012). In their study, Rahmati et al. conducted a longitudinal study monitoring 34 iPhone 3Gs users divided over three groups; a group low on SES, one high on SES and one control group low on SES that confirmed the influence of SES on smartphone use. One of the results indicates that people low on SES spend more money on applications in total. According to the authors, this can be explained when separating the expenses per installed application. People low on SES spend less money per application, but install more applications in total, which cumulatively makes them the biggest payers.

Li et al. examined the relationship between smartphone use and the user demographics age and occupation. For smartphone use, they distinguish three social behavior purposes smartphone data offers; temporal interaction, spatial interaction and movement patterns (Li et al., 2012). Temporal interaction can be reflected by the call/SMS log data, spatial interaction by the Bluetooth data, and GPS (outdoor movement tracker) in combination with WLAN (indoor movement tracker) could simulate complete movement patterns. These three types of social behavior are compared in the context of users at different ages (one age group ranging from 22 to 33 and one group from 33 to 44) and distinct occupations (students and full-time employees) for different time periods (workday daytime, workday night, holiday daytime, holiday night). The work was part of the “Mobile Data Challenge” that made data available which was collected from 38 Nokia users over a year. Results indicated that interrelationships exist between all three elements and people between 22 and 33, but not for those elements and older people between 33 and 44. Furthermore, significant differences for the different populations were found in social interaction features and activity patterns. As an example, type of day (workday/holiday) has a different influence on call behavior for both age groups; where both the amount of phone calls increase for holiday nights as compared to workday nights, phone calls also increase during holiday daytime for students in contrast to middle-agers, who do not report a significant change compared to workday nights.

As one of the few, the authors of the paper mention the psychological relevance for health care purposes, stating that personal results could aid in detecting stress and facilitate increasingly tailored health care services.

2.6.2 Smartphone application usage

In their study, Xu et al. use a definition for smartphone app usage that revolves around the app being used rather than the smartphone owner using different types of apps They monitored usage per smartphone application by using an anonymized data set retrieved from a tier-1 cellular network provider in the U.S., containing flow-level information about IP flows carried in PDP Context tunnels (Xu et al., 2013). This basically means that all data traffic sent to and from mobile phones is collected and stored in their private database, which eventually contained data from over 600.000 unique subscribers. Finally, the researchers used four main metrics to evaluate every smartphone app: traffic volume, network access time, number of unique subscribers, and then attempted to discover the impact of location, time, user, and app interest accordingly. Results indicated that several similarities exist across applications in terms of co-occurrence, diurnal usage patterns and categorical usage. For instance, the researchers found that several apps frequently appear simultaneously for the same subscriber. This can be explained by either a user is more likely to use the second application if he is also using the first, or the installation of similar applications reflects a user's special type of interest.

Also usage of several applications appears to be time dependent, which is called diurnal usage patterns. For instance, news applications are much more frequently used in the early morning in contrast to sport applications, which are mostly being used during the evening. Furthermore, mobility of the user appears to be of influence on the use of social networking and gaming applications, while those are especially being used when the user is on the move.

2.6.3 Smartphone use motivations

Park et al. looked into factors affecting smartphone use in the context of the technology acceptance model or TAM-model (Park et al., 2013). These factors include motivations for social inclusion and instrumental use of smartphones as well as innovativeness, behavioral activation system (BAS), locus of control (LOC) and perceived relationship control which were also examined in their relationship with perceived usefulness (PU and perceived ease of use (PEAU The data collection was based on a survey held among 852 smartphone users from South Korea within the age range of 17 to 49.

Findings confirm the basic principles of the technology acceptance model in the context of a smartphone, indicating that the smartphone usage can be described by the same factors that contribute to the usage of other types of technologies. Additionally, the authors found a relationship between PU and PEAU, which suggest that even if people perceive their smartphone as easy to use, they only use the technology when they perceive it as useful. The authors also found that smartphone dependency among users increases as PU and PEAU are perceived as higher. This means that users become dependent on the technology once they perceive it as easy to use and useful. It also shows that smartphones are already a successful technology and positioned as an indispensable communication medium for many users.

2.6.4 User-context and smartphone use

Do, Blom and Gatica-Perez used data collected from 77 Nokia N95 users to discover application usage patterns and analyzed this usage in the context of the variables semantic places and physical proximity (Do, Blom & Gatica-Perez, 2011). Data was collected over a time period of 9 months, where usage patterns were derived from the smartphone's log files, and the contextual data was recovered from the sensors GPS, GSM, WiFi, Bluetooth and the accelerometer. To make comparison possible, locations were grouped into categories (semantic places) including Home, Work, Friend-Home and Other. As a result, the authors concluded that phone usage depends significantly on both location and social context. We will discuss the most important result for semantic places and physical proximity as well as a combination of both.

Location categories

The first location related findings include that people who spend more time at the friend's home also use phone calls and the web browser more often. Also, there appears to be a strong correlation between people who use the calendar application often and the amount of time spent on other locations than home. Furthermore, people who spend more time at transportation related locations tend to use the web browser and multimedia applications for a longer period of time, which could be explained as typical ways to kill time. Finally, duration of clock and camera usage increases when spending time at transportation related locations, which could be explained by the general interest in travel times, respectively the sight of newly visited places.

Bluetooth density

In the context of Bluetooth density, a significant increase was observed in the frequency of application use when the density was higher for SMS, phone calls and internet browser usage, in contrast to use of the clock application which appeared to be significantly lower in higher Bluetooth density places. For checking email, people are more likely to check when in places that are either very high or very low on Bluetooth density places, which could resemble the situations of either being alone or being at school or work-related places.

Combination of location and Bluetooth density

By combining the location category, Bluetooth density and smartphone use, the authors came to conclusions that explain some findings in more detail. For instance, phone call and SMS usage increases when being outdoors in combination with being surrounded by many Bluetooth signals. This could be explained by the need to meet up with people, where communication is required to locate. Also, being outdoors in combination with a low Bluetooth density positively influences the usage of multimedia apps, the camera and navigation maps.

As a point of discussion, the authors indicate the fact that the Nokia N95 used during the study could be considered as outdated, making the relevance of the conclusions depended on the generalizability of the smartphone. Also, the authors stated that the population sample is not generalizable to the general population, while the sample contains an overrepresentation of people of the male gender and between the age of 20 to 30 and results are not differentiated per gender or age group.

2.6.5 Personality and smartphone use

A frequently used model for measuring personality is the Five-Factor Model, also referred to as the Big-Five (Goldberg, 1990). This model is based on the theory that individuals can be categorized based on their scores for five distinctive bipolar factors: extraversion, agreeableness, conscientiousness, neuroticism and openness to experience (McCrae & John, 1992). In turn, these factors can be broken down into more specific personality traits. For example, individuals that score high on openness to experience have the tendency to be creative, original and curious while the low scoring individuals tend to be more pragmatic, conventional and have a low diversity in interests (Costa & McCrae, 1992).

Several studies examine the relation between smartphone usage and personality traits, examining different dependencies. First, some studies state their presumptions on the relationship between personality and smartphone use as a conclusion from their research. For instance, Butt and Phillips propose that phone usage could reflect an individual's personality (Butt & Phillips, 2008). The same presumption can be derived from the research by Wolfradt and Doll, who found that personality traits influence the motives of media use, which possibly leads to different usage patterns (Wolfradt & Doll, 2001). Four studies were retrieved that actually examined the role of personality traits in smartphone use, using different research methods and focusing on different aspects of smartphone use.

The first study dates from 2008, where 200 university students had to fill in a questionnaire, reporting the average time they spend on calling, texting and instant messaging (Ehrenberg et al., 2008). Additionally, they had to answer questions related to technology addiction tendencies, which included giving self-reflecting scores for statements about salience, loss of control and withdrawal. In conclusion, the students had to complete a self-esteem test, assessing the students' attitudes towards themselves, and a personality test based on the Big Five personality traits.

Overall, the results showed that personality and self-esteem were weak predictors of smartphone use among youngsters, with disagreeableness as the most consistent predictor (Ehrenberg et al., 2008). They found that disagreeable students, who can be characterized by their skepticism about other people's motives and lower empathy levels, used their smartphones to a larger extent for calling than agreeable students. This finding could be explained by the preference of disagreeable individuals for communicating via technology rather than face-to-face, which could be triggered by lower levels of social skill or a more pragmatic approach of life. Also, although supported by little evidence, an increased SMS use is reported for extraverted individuals and individuals high on neuroticism.

On the other hand, this same research found personality as a stronger predictor for addiction tendencies, where mainly neurotic people have the most potential to develop mobile addictive tendencies.

The main limitations of this research are the self-reporting aspect of the data collection, which generates subjective data only, and the overrepresentation of female participants in the test group (146 females out of 200 participants).

The second study by Lane and Manner used a similar research approach, but they changed the method by Ehrenberg et al. by increasing the sample size (312 participants, from which 233 had a smartphone), by obtaining a more equal gender distribution (60% female, 40% male) and by increasing the age range (18-77 years) (Lane & Manner, 2011). Similar to the previous study, Lane and Manner found that extraverts report an increased use of the SMS function. In contrast to the study by Ehrenberg et al however, this study found that more agreeable people show a higher interest in making phone calls, where Ehrenberg found the opposite. Furthermore, Lane and Manner also found agreeable people to place less importance on sending SMS messages. The results on agreeableness are here explained as; people high in agreeableness tend to have higher levels of interpersonal skills, which create the preference for calling over text messaging. Additionally, the study found some significant differences for both genders' smartphone use, for which was reported that females are less likely to own a smartphone, but show more interest in sending SMS messages than male users. The largest limitation of this study is again that it is based on self-reported smartphone use, and therefore not providing an objective insight into a user's real smartphone use profile. The final two papers retrieved both use similar research methods based on collecting objective data from a smartphone's log files (Chittaranjan, Blom & Gatica-Perez, 2011)(Chittaranjan, Blom & Gatica-Perez, 2013). In 2011, a test group of 83 participants (53 males/28 females/2 unknown) between the age of 19 and 63 years old was monitored during 8 months, where all participants had acquired a Nokia N95 with pre-installed observational software (Chittaranjan, Blom & Gatica-Perez, 2011). The results indicated that application usage, call and SMS logs all appeared to contain several significant relationships to the Big Five personality traits. Office apps were more used by conscientious, neurotic and low-openness individuals. Also, mail applications were used more frequently by conscientious and neurotic people. Conscientious people on the other hand show less interest in media apps, like audio, video and music applications. SMS applications were frequently used by disagreeable, conscientious participants who scored low on openness. Surprisingly, introverts are less likely to use internet applications on the smartphone. Extraverts and agreeable people are more likely to receive more calls, also the diversity of contacts and duration of calls, both average and total, was higher for extraverts. Furthermore, individuals that score high on openness missed an incoming call less often. When looking at SMS logs, the only evidence was found for a relationship between the high number of messages in the inbox and an individual's low score on neuroticism or openness. The opposite of the latter also was confirmed; individuals that score high on openness were less likely to send an SMS.

As the authors indicate in their follow-up study, making a distinction in gender can lead to stronger correlations, whilst differences in personality utterances exist across genders (Chittaranjan, Blom & Gatica-Perez, 2013)(Lane & Manner, 2011). Therefore a second study is conducted under the same circumstances, only with a larger test group. Additionally, a machine learning framework based on a prediction model is constructed that delivers some promising results towards predicting personality traits based on smartphone use per gender. The most noteworthy findings will be mentioned here.

Similar to their previous study, it has been found that extraverts receive more calls and spend more time on them, where outgoing calls appeared not to be predictive for any of the personality traits. Gender specifically, agreeable women receive more incoming calls, while agreeable men have a higher diversity in interlocutors. Conscientiousness for both sexes is associated with a higher Mail app usage, a lower YouTube usage and is also an indicator of a lower diversity in interlocutors. Furthermore, low scores on neuroticism appear to be predictors of a higher rate of incoming SMS messages. Finally, a high openness among women correlates with an increased usage of media like audio, video and music applications.

Arguably, the major limitation of these final two studies is the use of the Nokia N95 phone, which could already be considered as an old-fashioned handset. Modern devices for instance are exclusively built with a touchscreen interface and are running on operating systems like Android or iOS. These differences in technology could hinder future comparison of results in newly conducted studies.

2.6.6 Theory of real behavior

The last study by Maheshwaree et al. overlaps with all the previous sections of this chapter in the sense that it presents a model, referred to as "theory of real behavior" which is designed to predict mobile service usage (Maheshwaree et al., 2009). This model specifies a list of factors influencing smartphone behavior, which can be divided over the following categories: consumer attributes, user-context, service characteristics, intentions, and technology enablers. For each of the categories, relationships are found between the factor and actual service usage.

Consumer attributes or user characteristics, are shown to have a predominant impact on smartphone use, relatively, which includes age, occupation, gender, smartphone use experience, intentions to use a smartphone (e.g. Female users are nearly twice more likely to use SMS service than males). Contextual variables like time of the day and roaming status appear to have a substantial effect on the usage of smartphone services, while for instance odds of using the web browser or the voice-search almost halved when not at home. Regarding service characteristics, it has also been revealed that people with access to a WiFi-connection are 1,5 times more likely to use a smartphone web browser. Also, the type of access network technology (i.e. technology enablers like WLAN or WCDMA) has an effect on the session duration when using data services.

2.7 Social media usage

We restricted the literature study for social media usage to research studies that examine usage of the social medium Facebook. Initially, searches for Twitter research were included, but no relevant results were found. Also, since results for Facebook on smartphones were scarce, the scope has been broadened to platform independent usage. Therefore, this section is fully dedicated to factors influencing Facebook usage for both pc and smartphone, complemented by a section that states the most important differences between the platforms. According to the literature, social media usage is influenced by many different factors, which we will categorize into the following two sections: user demographics and personality characteristics.

2.7.1 User demographics

Hargittai showed during several studies among undergraduate students that the use of Facebook varies according to a user's gender, cultural background, parental educational background and the race and ethnicity homogeneity of his social network (Hargittai, 2008; Hargittai & Hsieh, 2010a; Hargittai & Hsieh, 2010b). First, she showed that women are more likely to use Facebook than men, which was confirmed in a similar study by (Bozkir, Mazman & Sezer, 2010), who found that gender influences usage time for 68%. Hargittai also found differences among several cultures, concluding for instance that Hispanic students were much less likely to use Facebook than Caucasians. Other studies complement cultural differences by presenting a difference in Facebook usage among different countries like US, UK, Italy, Germany and Greece. As an example, Vasalou, Joinson and Courvoisier concluded that French users visit Facebook less frequently and are less interested in status updates than US users (Vasalou, Joinson and Courvoisier, 2010).

Educational background also influenced Facebook use; former research shows that Facebook is frequently used as a medium for educational communication purposes, making scholars and students in general more participative in discussions on social media (Bozkir, Mazman & Sezer, 2010).

Then, Vasalou, Joinson and Courvoisier suggest that users with cultural homogeneous social network show more distinctive behavioral patterns than users with diverse social networks, while their study showed cultural differences in Facebook use and previous research found that minorities had increasingly diverse social networks in Facebook (Lewis et al., 2008).

Additionally, age has proven to be of influence on the access frequency (Bozkir, Mazman & Sezer, 2010)

To summarize, these studies showed that females, scholars/students and ethnic minorities use Facebook to a higher extent when compared to their respective opposites and differences exist in Facebook behavior patterns for different cultures.

2.7.2 Social media and personality

For social media in general, evidence has been found for several of the Big Five personality factors to have a direct influence on the way we socially interact and the way we maintain our social network. For example, a positive correlation has been discovered between extraversion and the size of an individual's social network and the amount of social interactions the individual is engaged in (Aspendorpf & Wilpers, 1998). In the context of Facebook and Twitter, similar research has been conducted, where several correlations have been found between the Big Five traits and differences in usage. The most relevant findings will be presented below.

For extraversion a correlation has been discovered together with the amount of Facebook friends a person has and Facebook groups a person belongs to (Amichai-Hamburger & Vinitzky, 2010)(Ross et al.,2009). For intensity of Facebook usage, two similar studies found that Facebook users tend to be more extraverted and less conscientious, particularly among the young adults (Gosling, Gaddis & Vazire, 2007)(Ryan & Xenos, 2011)(Correa, Hinsley & de Zúñiga, 2009). Also, neurotic people have been found to spend more time on Facebook than non-neurotic people (Ryan & Xenos, 2011). For social media use in general, openness also appeared as an important personality predictor of social media use, but only for the more mature individuals (Correa, Hinsley & de Zúñiga, 2009).

Some studies state that the Big Five might be too broad for reflecting the small differences in Facebook behavior patterns and additional personality traits are required to determine these nuances (Ross et al, 2009)(Ryan & Xenos, 2011). Additional research has therefore examined more narrow personality traits including shyness, narcissism and loneliness. In those studies, narcissism, shyness and loneliness all appear positively correlated to Facebook use (Buffardi & Campbell, 2008)(Mehdizadeh, 2010)(Orr et al., 2009)(Sheldon, 2008)(Ryan & Xenos, 2011). The correlation between narcissism and Facebook use is explained by Facebook's encouragement for self-promoting and superficial behavior, such as posting status updates and uploading photos, stimulating the narcissistic part of an individual to express itself (Buffardi & Campbell, 2008)(Mehdizadeh, 2010). It could be suggested that shy or socially anxious individuals tend to feel more comfortable to maintain social relationships online rather than face-to-face, explaining the increased Facebook use (Ebeling-Witte, Frank & Lester, 2007). Another explanation for the increased use of Facebook could be an increased amount of time spent on less social behavior, for instance playing games like Farmville and Candy Crush (Ryan & Xenos, 2011). Finally, Facebook users show less signs of loneliness than non-Facebook users, indicating the role Facebook plays in combatting loneliness (Ryan & Xenos, 2011).

For Twitter, only one study has been retrieved that directly investigates the relationship between personality and actual Twitter use. This study shows that significant correlations are found between individuals Twitter usage and an increased score on openness and a decreased score on conscientiousness (Hughes, Rowe, Batey & Lee, 2011). This supports the research by Correa, Hinsley and de Zúñiga who also found an increased score on openness as related to an increased use of social media in general (Correa, Hinsley & de Zúñiga, 2009).

2.7.3 Social media smartphone applications

Several differences in social media behavior exist for devices like PCs and smartphones, due to their own specific characteristics (Malinen & Ojala, 2012). For instance, people use mobile internet mostly for reading email and following some social media sites. Desktop computers on the other hand are used for active contribution to social websites, which was less common when using mobile devices. Participants of this research noted that mobile web sessions are shorter and more prone to interruptions, making mobile web sessions suitable for update checking and desktop computer sessions more suitable for situations that require more attention and privacy (Kaikkonen, 2008). Cui and Roto describe these short mobile web sessions as micro breaks, which are usually associated with attention spans of about four seconds and primarily used for checking for new notifications (Cui & Roto, 2008). The character of micro breaks also explains the relatively high usage of Twitter on smartphones compared to Twitter usage on desktops. The brief and momentary character of tweets fits the short attention span of smartphone users, making micro-blogging an attractive activity for a micro break (Grace, Zhao and Boyd, 2010)(Malinen & Ojala, 2012).

2.8 Social smartphone use and social context

The following section will present the findings of papers that focus on the social situations a smartphone user is involved in, including social networks and physical social situations.

2.8.1 Creating social networks

Another example of an application that examines social relationships is the Android application Nobido, designed at detecting social networks within a group of 27 graduating high school students (Bell, McDiarmid & Irvine, 2011). The social context data being captured for this research consists of phone call logs, text messages, Bluetooth proximity detection, WiFi-signals and cell tower IDs. Additionally, the directionality of the calls and text messages are recorded, along with the associated phone number and the duration of the conversation or length of the message. While examining the different interactions among the study group, the researchers were able to plot social graphs based on the interaction links between students. Their preliminary results show visualizations based on SMS, call, proximity interactions and all combined, in which they identify a person’s importance within the social group using betweenness centrality. Further examination of the data set is not presented for this study, while its main goal was to show that the openness and processing power of smartphones makes it feasible to capture social context of a smartphone user.

2.8.2 Social networks and trend analysis

Chronis and Pentland centralize social influence behavior in their study, and more specifically focus on the question why certain hypes catch on in certain social groups, but are rejected by other groups. For this reason they developed SocialCircuits, a platform designed for Windows mobile 6.x smartphones, which is capable of measuring face-to-face and phone-based communication network of a real-world community (Chronis and Pentland, 2011). The platform uses Bluetooth signals, WiFi signals, the music player, phone and SMS logs as their primary data sources, along with build-in links to web-based surveys that measure the subject’s personal ideas and opinions. As a test case, the social ties between 65 individuals where measured, along with the individual’s adoption of political opinions. The results indicated that among students in general, exposure to other social ties explains the variance of the topics; ‘interest in politics’, ‘ political party preference’, ‘liberal or conservative’ for 15%, 9% and 6% respectively. For freshman students, influence of exposure noted for the same topics a variance of 22%, 25% and 30% respectively. The authors indicate that the platform offers possibilities for both long- and short-term surveys to measure shifts in individual habits, opinions, health and friendships influenced by the observed social ties.

2.8.3 Social network analysis and user classification

Gupta, Trifunovic and Plattner developed an application called SocialMine, which abstracts social metadata from five data sources: Phone-Logger, SMS-Collector, Location-Tracker, Contacts-Fetcher and Facebook-Miner (Gupta, Trifunovic & Plattner, 2011). Using data from 9 subjects and a time span of a week, the authors created visualizations for three social dimensions: contact graphs, interaction graphs and communication pattern graphs. The conclusions drawn from the graphs are the following. The contact graph shows that there is a significant difference in composition of Facebook friends and the telephone contact list. The authors suggest that virtual friends always imply a personal relationship in real life, while people in the contact list represent individuals with whom the user communicates directly. In the context of social interactions, the authors concluded that communication with people over divergent channels indicates the strength of the relationship. I.e. a person you are calling, texting and is listed among your Facebook friends is more likely to be a close friend then somebody only present in the call history. Lastly, frequency and duration of medium usage where measured and summarized into averages for every medium. The authors indicate the usefulness of the collected data for user classification, but did not further extent their research to actually giving examples of classifying users, mainly because their sample size can be considered as too small.

2.8.4 Sensing social situations

In 2006, Nicolai and Kenn describe a simple way of recognizing broad social situations based entirely on Bluetooth signals, by making an overview of the dynamics in familiar and strange devices. The authors argue that by evaluating the data with the subject, specific activities can be identified by peaks in the amount of sensed devices, particularly when information is available on the familiarity of the devices. The familiarity of devices makes for instance distinction possible between family dinners and conference receptions. They performed one test scenario while attending a conference in Tokyo, from which they were able to identify every activity except for a workshop group whose behavior appeared to be too homogeneous and did not reveal the measured dynamic. The method makes identification of different social situations possible, but a drawback of this method is that the collected data is too high-leveled to perform stand-alone identification of activities; interference with users is still required to discover the type of activity.

Yan, Yang and Tapia created the so called CoSoBlue framework, which focuses on sensing social situations and is also based on Bluetooth-signals (Yan, Yang & Tapia, 2013). Input data consists of each identified Bluetooth signal in the surroundings, including MAC-address, device name, device class, strength of the signal (RSSI) and the time of registration. By using the CoSoBlue framework, Bluetooth entropy maps can be created that give an insight in the user’s Bluetooth environment during the week. By using the k-means algorithm the authors created a classification for entropy maps, of which they argue that this classification could play an additional role in quantifying a user’s sociability.

2.8.5 Critical side note

An important issue most of the cited papers face in the pronation to error is the use of self-reporting. As the study by De Reuver indicates; the largest advantage of this type of studies is that seldom the actual relationship is measured with actual smartphone use, because self-reporting delivers subjective data, i.e. data observed from the subject’s perspective. In their study, De Reuver et al found that at least 62% of respondents are off-base when asked to make an assessment of their own smartphone behavior and therefore should be handled with care when interpreted in a social behavior context. The authors argue that behavioral intention rather than actual usage is measured and should therefore be treated in this way, both theoretically as practically. In the authors’ opinion, using objective handset study data will lead to alternative (acceptance) models, leaving an increased research gap which overlaps with already performed research that based their conclusions on subjective, self-reported data.

2.9 Smartphone location and movement mining

The following section presents the papers associated with smartphone-based localization of users and the creation of movement patterns. First the available data sources are distinguished, followed by several different methods to utilize these sources for localization purposes and subsequently the methods that use the same data sources for creating movement patterns.

2.9.1 Data sources

Several different data sources can be utilized to identify an individual’s movement behavior, including GPS, Wifi-signals, Bluetooth-signals, GSM and the accelerometer, of which the latter only measures smartphone movements rather than a smartphone’s location. The following section will describe the potentials and restrictions for each of the different sources when utilizing them for localization or movement mining purposes.

Of all sources, GPS is found the most used one throughout research studies. When being outside and having an un-obstructive view of the sky, GPS is able to localize a smartphone with an accuracy of 10m (Papliatseyeu & Mayora, 2009). A problematic issue however, is the high consumption of power when frequently retrieving the GPS coordinates, which enforces a reduced amount of localizing intervals (Bierlaire, Chen & Newman, 2010).

WiFi signals could be used as reference points, making localization possible with a median positioning error of less than 2 meters, but is not useable in less populated areas where WiFi coverage is very limited. Solutions using GSM could profit from a much higher coverage, but lack in precision; having a possible deviation up to hundred meters. Bluetooth-enabled devices make positioning possible with a high accuracy but in most cases other Bluetooth-enabled devices are non-stationary making localization increasingly difficult (Papliatseyeu & Mayora, 2009). Lastly, an accelerometer can sense any type of motion, but it does not collect any information of the smartphone’s current location or of the environment (Bujari, Licar and Palazzi, 2012).

To improve the reliability of results, researchers combine different data sources and techniques arguing that a combination of different positioning methods allows for more precise localization of users and increased accuracy of classifying user activities. This so called ‘sensor fusion’ is defined by Hightower and Boriello as:

“.. the use of multiple technologies or location systems simultaneously to form hierarchical and overlapping levels of sensing… [It] can provide aggregate properties unavailable when using location systems individually.” (Hightower & Boriello, 2001)

2.9.2 Localization

Mining smartphone data for analyzing the movement of the user can be done for several different purposes including identifying points of interest (POIs), distinguishing human activities and creating movement paths based on several different data sources delivered by a smartphone. The methods for these mining purposes differ and will be described separately below, along with several proposed mining techniques and useable data sources.

For the term ‘place of interest’ we maintain the definition by Kang et al.:

“A locale that is important to an individual user and carries important semantic meanings such as being a place where one works, lives, plays, meets socially with others, etc.”(Kang et al., 2004)

For identifying places of interest, two approaches can be distinguished when identifying a person’s location: the first is based on a *physical* location; the second is based on a *symbolic* location (Hightower & Boriello, 2001). Applications using physical locations, like GPS, collect the physical coordinates (absolute or relative) of a specific location, while symbolic locations consist of labels or names that are associated with certain places, as used by identifying WiFi- or Bluetooth-signals. To abstract meaningful information about places of interest, symbolic locations should be linked to their physical locations by using a database that links symbolic locations to their coordinates. However, considerable calibration effort is required for mapping new places, making the method less scalable. Physical places on the other hand, should be mapped onto a city plan to correctly identify the places of interest; this becomes a challenging task when room-level accuracy is required.

Ashbrook and Starner make use of two assumptions for identifying places of interest; a person is at a place of interest when GPS signal is lost for 10 minutes (because GPS signal loss is associated with entering buildings) or the speed of the person is registered below 1 mile per hour for 10 minutes (indicating the person stopped traveling)(Ashbrook and Starner, 2003). Windows of signal loss or movement loss segment the GPS-logs by clustering the GPS-location that was lastly available and the first available GPS-location as a candidate point. These candidate points are then merged using a variant of k-means clustering to create a list of locations. This clustering works as follows; one place point is taken out of the collection and a radius is set. All the points within the radius of the place are marked and the mean of these points is identified. This mean is then used as the new center point, for which the same process is repeated until the mean stops changing. When this mean is found, all other points within the radius are removed from consideration and the found cluster is used as a new location. This occurs for every candidate point until a collection of locations is left.

Although this method is low leveled, requiring only GPS and the accelerometer, the assumptions made make the method prone for error; both in the form of false positives and false negatives. Concerning false negatives, some locations will not be identified when GPS in fact is available at an indoor point of interest and some locations will not be identified when the point of interest requires the person to move; being for instance at a gym or when working at a building site. For false positives, some locations will be addressed as points of interest when the GPS signals are blocked due to other reasons than being in a building; for instance because of snowfall, or because of being in a forest. Other false positives will enter the data set when the phone has been left somewhere by the user; for example in the car.

Hightower et al. bring the concept of physical locations in practice by developing an algorithm called BeaconPrint, which uses a combination of GSM and WiFi fingerprints to learn the places a user visits and then detects when the user returns to these places (Hightower et al., 2005).

The authors concluded that BeaconPrint is accurate in learning and recognizing places for 90% of the cases. Also, in contrast to previous approaches (including the algorithm by Ashbrook and Starner), BeaconPrint appears to be more accurate for places that are visited infrequently or for short durations. This means 63% accuracy for places visited once or for less than 10 minutes and up to 80% for places visited twice.

Although being precise, the positioning method by Hightower et al. still remains driven only by rather symbolic locations. Papliatseyeu and Mayora use a similar approach using also raw GSM and WiFi fingerprints as a basis, but augment these fingerprints, when possible, with GPS-traces (Papliatseyeu

& Mayora, 2009). In this way, they instantly combine symbolic locations with a physical location to localize a person, without having to link the symbolic locations to a physical location database. Also, Papliatseyeu and Mayora use a more scalable approach in identifying places of interest, by not using a nominal variable, classifying them as either interesting or not, but instead using a continuous ordinal variable ranking the places based on their importance. The authors argue that the novelty of their approach is in the unique fusion of positioning methods, which should provide higher coverage and accuracy. The published paper however, is only based on conceptual design, for which no demonstrable results are available to support the authors' claim for higher coverage and accuracy.

An even more advanced example of sensor fusion is maintained in the application Lifemap, which combines the accelerometer, magnetometer, Wi-Fi-, GSM- and GPS-signals to identify places of interest, making localization possible with a room-level accuracy (Chon & Cha, 2011). The localization process is based on GPS signals, and is supplemented by three different combinations of data sources. The first component is the inertial provider component, which captures data from the accelerometer the magnetometer and the GPS sensor to implement smartphone-based dead reckoning. Second is the network provider component that combines data from cellular base stations (GSM) and Wi-Fi based positioning system (WPS) to localize the smartphone. Lastly, the logical provider component uses the available Wi-Fi signals in the surroundings in combination with context information from the database to aggregate the current place with other places visited earlier.

The authors performed a small experiment with three students to measure the accuracy of identifying places of interest. Lifemap was able to identify 54 points of interest, from which 85% was generated indoor, where the ground truth was obtained from combining sensor data with Google Maps. Of all indoor identified points of interest, 91% indicated the actual position within an error bound of 25.6 meters. After aggregating these points of interest, 18 POIs remained, of which 83% contained their reference location within a mean error of 17.7 meters. As indicated by the authors, the biggest drawback of the application is the strong dependency on GPS signals, while the initial location is based on GPS-localization.

2.9.3 Movement patterns

Bierlaire, Chen and Newman present a systematic method using a novel approach for matching a set of paths with GPS data. Conventionally, map matching algorithms were designed to cluster GPS points into one meaningful path. The authors however, present a new algorithm that generates a set of potential paths instead of one, and subsequently calculates the likelihood of each path by incorporating temporal information like speed and time (Bierlaire, Chen & Newman, 2010). They then combine these paths and associated predictions onto the transportation network from the website openstreetmap.org to select the best fitting path with the highest probability. By using real data, the authors already considered the probability of the actual path and the other paths realistic and meaningful. In addition, the authors did a comparison study to compare the method with a traditional map matching algorithm from which they concluded that the method is well suited for the sparse and sometimes inaccurate date collected from a smartphone's GPS utility.

2.9.4 Social rhythms

In addition to smartphone movement mining, Adams, Phung and Venkatesh and describes different algorithms that provide social context to a user's movement patterns in the forms of *social spheres*, *social rhythms* and *social ties* (Adams, Phung & Venkatesh, 2008). The collected data comes in the multimodal forms of GPS fixes, Bluetooth device discoveries and media files like photos, videos and blog entries, of which the authors claim that the awareness users create around those media files, references to a simplified mental model of the users' memories. We will explain the concepts of *social* spheres, *social rhythms* and *social ties* and their construction in more detail below.

The *social spheres* were formed by clustering GPS signals in combination with the labeling by the users if the places appeared to be of significance to the user. If unlabeled, the places were considered to be false positives, which were found in the form of unfiltered noise, car parks and clustering of short-time tourist-related GPS traces. The method appears to provide reliable conclusions for most of the important places visited by the users, with an exception rate varying between zero and ten percent of false positives.

The *social rhythms* describe the routines that are part of people's life which could be daily routines like having breakfast or going to bed, but also weekly, monthly or even yearly routines like work, school, going on vacation etcetera. Different characteristics of a place define these rhythms, including the time of arrival, duration of stay, presence of certain people or resources and being structured or unstructured. The activity 'shopping' for example can be considered as timetable-bound (i.e. bound to opening hours, work schedule etc.) and place-bound (visiting the same clothing or grocery store), but not people-bound or duration-bound, while shopping shows a too high variation in total duration and company. For their paper, Adams, Phung and Venkatesh (2008) divide *social rhythms* in *behavioral rhythms* and *relational rhythms* as will be further explained. For *behavioral rhythms*, Adams, Phung and Venkatesh distinguish two different dimensions: rare-frequent visits and timed-flexible visits. First, a place is classified as frequent when the number of enters reaches a certain threshold within a certain time period, where the term frequent is defined relatively in the context of the places that were visited rarely. Second, the frequently visited places are further specified into timed rhythms and flexible rhythms. Rhythms that show little variance in time tables are considered to be timed, whereas rhythms without a predefined time table are considered flexible.

Relational rhythms are an extension of behavioral rhythms, in the sense that they include both frequency and timeliness as rhythm dimensions, but add a third dimension to describe the dependency of the activity on the presence of other individuals. Rhythms are again clustered based on collocated people which allows, in combination with the aforementioned dimensions, for assessment on the nature of interpersonal relationships between the subject and other individuals. This assessment is done based on the strength and closeness of a relationship and is more specifically defined as a *social tie*.

As the most relevant conclusion, Adams, Phung and Venkatesh describe the usefulness for social scientists of utilizing the algorithms for getting cheap estimators of the social variables described. In short, social spheres are related to the clustering of GPS traces into significant, labeled places, while social rhythms expand this concept by combining patterns in time, duration, place and people as related to recurrent physical activities. As an extra, the authors give an innovative way of describing social ties, combining proximity, shared spheres and social rhythms, which can be used for more elaborate social network analysis.

2.10 Conclusion systematic literature review

This section will describe the usefulness for each of the systematic literature review subjects in the context of this research.

Smartphone use

The smartphone use section provides a first insight in the different determinants that support smartphone use in general. From here, we select the top predictors that may serve as confounding factors for the creation of a social profile. As the theory of behavior model suggests, we should determine the possible impact several categories have on our research, to avoid having confounding factors determining the social profile. The categories described by the theory of behavior include consumer attributes, user-context, service characteristics, intentions, and technology enablers (Maheshwaree et al.,2009). When observing people's social activities, the biggest impact is created by the person confounding factors, which include user characteristics and user demographics (Steg, Buunk & Rothengatter, 2008). These factors are user-specific, and are proven to influence social behavior in several ways. The social cognitive theory confirms that personal factors influence social behavior and adds the importance of environmental factors which partly overlaps with the user-context attributes described in the theory of behavior model (Bandura, 1986). The remaining categories 'intentions', 'service characteristics' and 'technology enablers' only indirectly influence social behavior through increased/reduced smartphone use and therefore are no confounding factors for a sociability profile. As an example of the category 'intentions', performance expectancy influences the consideration to use the smartphone for communication, but when the user decides not to use the smartphone for communication, he will choose a different medium for communication which does not make him less sociable. Also, having unlimited internet access or a smartphone with a high-capacity battery will increase overall smartphone use which will also result in increased social smartphone use. This however does not implicate that the person is more sociable, while a sociable person will again search for alternative ways of communication when the phone battery is fully drained or when internet access is unavailable. Concluding, only the personal factors and user-context factors are influences that should be accounted for when observing social smartphone use in more detail. We will explain the explicit factors in more detail in the chapters 4 and 5.

Social media usage

In the context of social media usage, research to date is limited to studies that describe social media usage regardless from platform like for instance a PC, smartphone or tablet. Considering again the Theory of Behavior model by Maheshwaree et al., the findings associate personal characteristics with social media usage, making personal factors again a potential confounding factor, in this case, for examining social media usage (Maheshwaree et al., 2009). No research however has been done investigating the influence of user-context on social media usage, making it unclear whether user-context has the same influence on social media usage as it has on smartphone use in general. Additionally, factors that could be placed under the remaining categories of the theory of behavior model; intentions, service characteristics and technology enablers, are not found in present literature.

As the largest difference between general social media usage for the PC and the smartphone, Kaikkonen concludes that people use mobile internet mostly for following social media sites. Desktop computers on the other hand are used for active contribution to social websites, which was less common when using mobile devices (Kaikkonen, 2008). Twitter usage was found to be used more extensively on the smartphone, which was explained due to the short attention span required for tweeting (Grace, Zhao and Boyd, 2010).

In short, this section indicates several research gaps exist concerning social media usage on smartphones, which underlines the possibilities for the data that is being collected for this study.

Social smartphone use and social context

Three studies show the various possibilities offered by social network analysis for smartphones. Social graphs like contact graphs, interaction graphs and communication graphs are some of the examples, which make use of different data sources like SMS messages, calls, proximity interactions (Bluetooth), Facebook friends and the contact list. Additionally, the telephone number could be used as an id or the contact list as a reference list to allow researchers to identify people across different applications and determine the diversity in interlocutors a user has. Using these same techniques allows for the creation of cross-platform social networks based on multiple sources and subsequently for the application of user classification to determine for instance the closeness of a friend. As an example, a user's friend can be identified as more important when being present in the contact list, the Facebook friend list and having a substantial amount of text message conversations in common. For our research the most interesting option is to use the telephone number as an id for identifying friends across Whatsapp-messages, telephone calls and SMS messages, because the registration of (encrypted) phone numbers is already incorporated in the first build of the application. In this way, social diversity, which we will be explained to be one of the sociability dimensions, can be made visible across different applications.

Using Bluetooth signals for sensing social situations

Two applications of Bluetooth signals were found to determine the type of social situations users were involved in. Nicolai and Kenn (2006) chose to identify activities afterwards during interventions with the users, based on the identification of other smartphones and the total amount of signals in the surroundings. Yan, Yang and Tapia (2013) used the same data sources, but applied several computational techniques to distinguish recurrent daily activities and to additionally create entropy maps visualizing the Bluetooth density of a user's environment during the week.

Both methods use a combination of Bluetooth signal identification and the quantity of Bluetooth signals in the surroundings as a base for their analysis but both in different manners, underlining the possibilities offered by Bluetooth signals for future studies.

Smartphone location and movement

According to the literature, all available data sources have their pros and cons when it comes to smartphone location mining, where it is the challenge to find the best possible combination of sources and techniques for research purposes to discover results with high reliability.

For localization of smartphone users, a combination of data sources is required that connects physical locations to symbolic locations or vice versa (Hightower & Boriello, 2011). Several examples exist in literature that achieve localization in distinctive ways, of which LifeMap can be considered the most promising one combining five different data sources leading to the identification of POIs with 91% accuracy within an error bound of 25,6 meters. As derived from best practices, it is common to use GPS as a base and add other data sources to fill data gaps caused by poor indoor GPS reception and to apply symbolic meaning to the physical coordinates of a GPS signal.

In extension of the localization process, although not one hundred percent accurate, it is possible to create movement paths onto street maps by an algorithm making use of predictive modeling. Such methods have the disadvantage of frequent location determination and the high battery consumption resulting from this high retrieval rate. Still, Bierlaire, Chen and Newman (2010) in their research perceive such a method to be well suited for the sparse and sometimes inaccurate data delivered by the smartphone's GPS utility. Further research should investigate this viewpoint by Bierlaire, Chen and Newman, while little research exists for smartphone-based localization.

Besides movement patterns as an extension of localization, Adams, Phung and Venkatesh (2008) extend the concept of localization by enriching locations with information about people in the environment, time and duration to discover so called social rhythms; recurrent activities that can be characterized by the place, the duration, the time of occurrence and other people present during the activity. In the context of sociability and health-care, researchers can use anomalies in social rhythms to identify social withdrawal or perhaps even mental illness exacerbation.

3 Research approach

The following section will present the research method for this study, which includes the overall design of the study and the data mining method used for reaching the objectives defined by the research method.

3.1 Research method

Peffers et al. (2007) developed a Design Science Research Process (DSRP) model, which shows the six process elements that are present in design-science research. These activities include *Problem Identification & Motivation*, *Objectives of a Solution*, *Design & Development*, *Demonstration*, *Evaluation* and *Communication.* The model also shows that the first four activities are possible starting points for research approaches. The main goal of the research is to discover how the application can be used to create a social profile of the smartphone's user. However, an exact definition of this social profile is unknown and should be developed by combining scientific literature, the knowledge of experts and the available data that could be collected by a smartphone application. Therefore, the details of the solution's objectives are unknown. Also, uncertainty exists about an approach for the validation of the method, while the formation of a test group is not completed from the start. For these reasons, this research starts with the activity *Objectives of a Solution*, aimed at defining the objectives in more detail. A more detailed representation of the model tailored for this research is shown in figure 2.

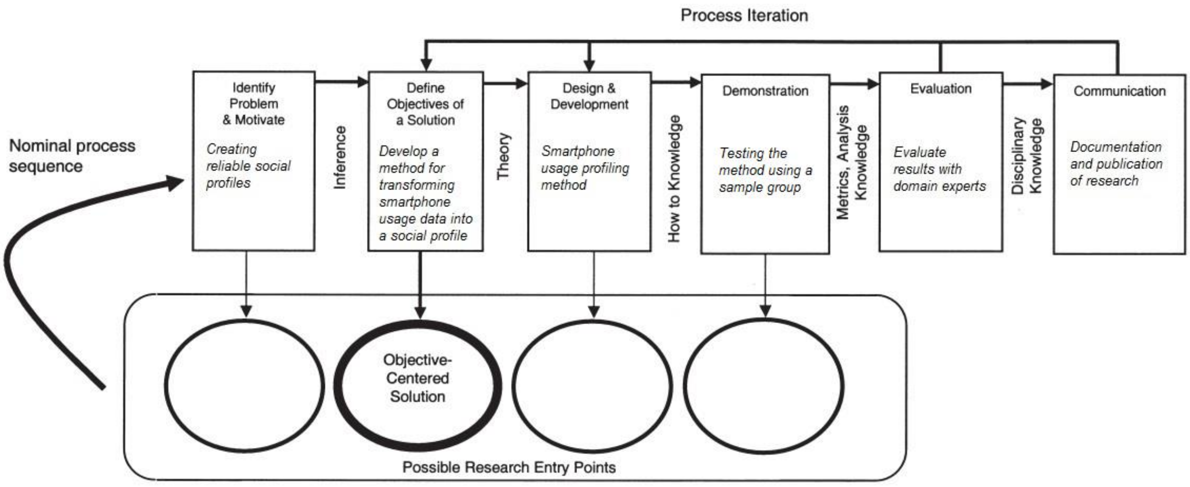

Figure 2: Peffers Design Science Research Process model applied to the research

3.2 Data mining method

To answer the main research question, a method is required that transforms raw smartphone data into useful knowledge that describes the smartphone's user. Several different data mining methods are available for knowledge discovery, including the Knowledge Discovery in Databases (KDD) process by Fayyad, Piatetsky-Shapiro, and Smyth (1996), the Sample Explore Modify Model Assess (SEM-MA) method as referred to in (Azevedo & Santos, 2008) and the Three Phases Method (3PM) by Vleugel, Spruit, and van Daal (2010). However, the most used and most widely adopted method is the CRoss Industry Standard Process for Data Mining (CRISP-DM) method (Chapman et al., 2000) (Shearer, 2000), which therefore will be utilized as the main guideline for the knowledge discovery process in this research.

Following the phases of CRISP-DM, the first step is to create a business understanding by defining a data mining problem and by creating a preliminary plan on how to achieve the objectives. This is done by interviewing several experts in the field of sociology and psychiatry and discuss the requirements and outcomes of the method. The second step is to build a general understanding of the data, for which interviewing is required with the developers of the application. This phase also includes the acceptance testing for verifying the validity and reliability of the data generated by the application. The testing will most likely lead to a new development phase, where bugs are fixed and additional features are implemented. Simultaneously, interviews with domain experts will be conducted to define the goals and required variables that are related to the social profile of the smartphone owner. Next, the collected data will be modeled and evaluated to get an impression of the final social profile and to make alterations to the previous definition of this profile if needed. When both the smartphone application is technically accepted and the method for defining a person's social profile is found acceptable, the research can continue with a second iteration of the CRISP-DM model. This time, the method will be used to create social profiles of 10 individuals, of which data will be collected over 1,5 week. Based on the results, the experts will provide their opinions on the satisfactory level the method provides for health care professionals as a part of the last evaluation phase.

Figure 3 explains the CRISP-DM model again in the context of this paper's structure. The business understanding phase is distributed among chapter 2 and 5, where chapter 2 includes the business understanding from a literature point of view, and chapter 5 from the expert's point of view. Chapter 4 then both includes the data understanding and data preparation phase, where data is cleansed, filtered and selected. The eventual modeling is described in chapter 5 and the concluding chapters 6, 7 and 8 evaluate the model and its future potential.

Note that the deployment phase is not part of this study, while this study is a pilot study that will be followed up by a longitudinal study, involving schizophrenic patients, after which the deployment will be considered.

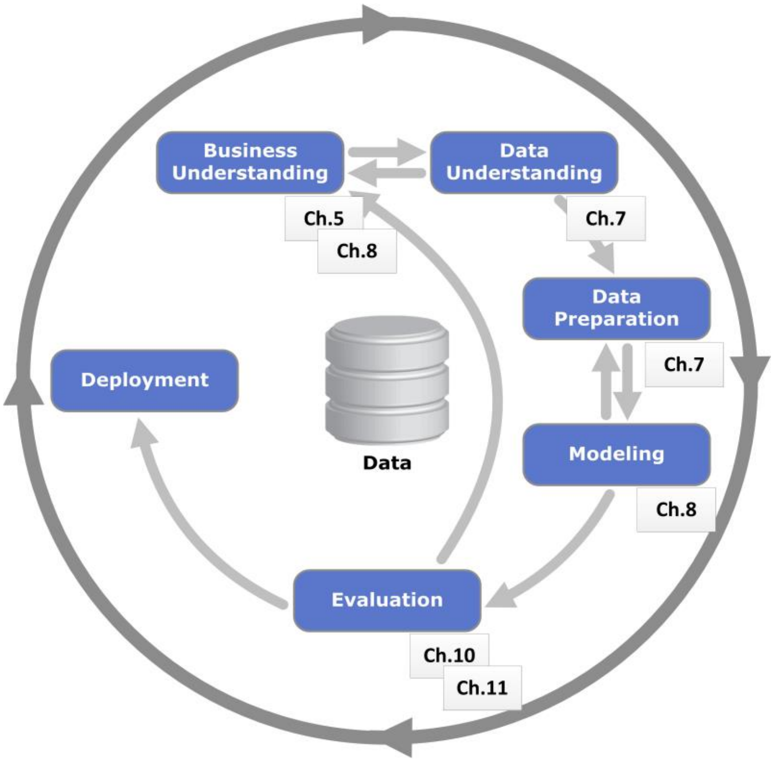

Figure 3: Structure of the paper in context of the CRISP-DM model

3.3 Data collection

From a software development point of view, this smartphone application is currently in the testing and evaluation phase, meaning that the different application functionalities are tested and improved from both a technical and a functional perspective. The first part of this study consists of the functional acceptance testing. Simultaneously, a sociability measurement method is constructed based on the requirements that are derived from the health care purposes.

As found during the literature study, the definition of the term ‘sociability’ that we will maintain during this study will be:

“The tendency to affiliate with others and to prefer being with others to remaining alone” (Cheek & Buss, 1981)

This definition should not be confused with shyness, which is the reaction to being with strangers or casual acquaintances: tension, concern, feelings of awkwardness and discomfort, and both gaze aversion and inhibition of normally expected social behavior (Buss, 1980).

In brief, sociability is a preference for affiliation or need to be with people, and shyness is the discomfort and inhibition that may occur in the presence of others (Cheek & Buss, 1981). This research will only be focused on social situations a user is involved in, disregarding the feelings a user may experience during these situations, as feelings are not directly measurable by smartphone devices.

3.4 The BeHapp application and its functionalities

The BeHapp application is a smartphone application for the Android operating system developed by the software development company HYS enterprise and will be used as data collection tool within this research to abstract data describing regular smartphone usage. The data collected for this research is presented in a list of different types of events that all represent specific data sources, which will be explained in more detail in the following section. Additional to each of the events, the time the event occurred and the location of the user, at the time the event occurred, is registered as an attribute.

3.4.1 Positioning event

To localize a user in a physical matter, the application stores the longitude and latitude of his position in the database each time the smartphone senses movement of the smartphone. Not only specific locations can be identified in this way, but also movement patterns can be visualized while the smartphone keeps moving when traveling. These movement patterns can then be complemented by the choice of transportation, while machine learning algorithms can use a combination of the smartphone’s location and movement speed to identify typical movement for transportation vehicles like the train, airplane, boat or car. This movement speed is measured in meters per second and is stored in combination with the total duration the smartphone moves at that particular speed in seconds.

We recall that effective positioning of users should be done by using a combination of physical and symbolic locations and can be approached from taking either of the two as a starting point (Hightower & Boriello, 2001). For this research we chose for a physical localization approach in combination with a manual addition of symbolic locations. Users will be asked to localize their most visited locations on the map like work, school and their closest supermarket. The GPS-data will then be compared with the user’s physical location to determine the presence of the user in a frequently visited location. If the application recognizes a manually entered symbolic location, this is stored in the database along with the rest of the positioning event data using the id of this so called base point.

3.4.2 Proximity count event

A proximity count is performed when the user holds his smartphone in a vertical position. Behapp then opens the camera application and counts the amount of people in the user's line of sight, using the face recognition functionality. The total amount of faces recognized is then stored in the database.

3.4.3 Call events

The application opens the call logs of the user's smartphone to register each type of call that can be found; incoming calls, outgoing calls and missed calls. Also the duration of the call is registered and the encrypted version of the telephone number the user is calling or is called by.

3.4.4 SMS/MMS/ Whatsapp messages

Again, Behapp uses logs to register SMS, MMS and Whatsapp messages that are sent and received by the user. Additionally, the other telephone number involved in the communication is again stored in an encrypted state. Note that only the occurrence of the event is registered, not the actual content of the message.

3.4.5 Application activity

To get a total overview of smartphone use, information about the user's application activity is stored including the process name of the application and the total duration the app is running on the fore-ground. This data serves as a background activity level against which the other, primary outcome measures can be analyzed.

3.4.6 Twitters events

When using the application, the users must provide authorization to register Twitter-based events. These events are collected using the application programming interface Twitter freely provides. The events include personal incoming and outgoing messages, personal tweets and re-tweets. For the personal messages the other person involved in the conversation is stored as the sender/recipient.

3.4.7 Facebook events

Again, specific authorization is required for the utilization of Facebook information, where information like Facebook posts and Facebook messages are obtained and stored. This information is directly retrieved from the Facebook servers so it must include any message existed in the Facebook account along with the time of occurrence and the sender/receiver.

3.4.8 Hyves messages

Originally, personal messages of the Dutch social media site Hyves were retrieved as well, but due to the transformation of the website into a gaming website, further information retrieval is excluded from the Behapp application.

3.4.9 Bluetooth event

As a measure of social density, the amount of Bluetooth signals in the surroundings is measured when Bluetooth is enabled on the smartphone and at least one Bluetooth signal is detected. Additionally, an encrypted version of the MAC-address is stored to enable determining the diversification in Bluetooth signals without violating privacy regulations.

3.5 Data processing and analysis

Several different tools were used for the processing and analysis of the data in preparation of determining the sociability score. First, all data collected by the BeHapp application was sent to and stored in a MySQL database with access through phpMiniAdmin. From the web application, csv-files were exported, which functioned as exchange files between the different analysis tools. Then, Rapidminer Studio, a data analytics application specialized in data mining, ETL, OLAP and BI, was used to cleanse, filter and transform the data and eventually analyze the data. For the creation of the final data set, the following processes were required:

- Removal of double entries
- Removal of empty entries
- Removal of unanswered outgoing phone calls
- Filter data outside the time period
- Filter unreliable test subjects
- Filter faulty data
- Change attribute types and formats (e.g. datetime)

Additionally, SPSS was used for statistical analysis purposes and to provide visualizations that could not have been created by the standard toolset of Rapidminer Studio. An operational version of the sociability scoring method was eventually created in Rapidminer (and a simplified version in Excel), to provide experts with a tool to score new test subjects. The only effort to be made for scoring new individuals is the replacement of the old CSV-file with a new CSV-file exported from the MySQL database.

4 Validity and reliability

The following section is dedicated to the pre-study performed to test the validity and reliability of the data generated by the Behapp application. The results of this testing phase were handed to the developers for further improvement of the application.

This section is structured as follows; for the validity, both the internal and external validity threats typical for social studies are described and assessed. The second part will examine the reliability of the data collected from each of the data sources and assess whether the data sources are useable for the sociability model.

4.1 Internal validity

To ensure internal validity several predefined threats should be eliminated on beforehand, while threats to internal validity compromise our confidence in saying that a relationship exists between the independent and dependent variables (Brewer, 2000). In social sciences, these threats are identified as history, maturation, statistical regression, selection, experimental mortality, testing, instrumentation, design contamination, compensatory rivalry and resentful demoralization (Blascovich, 2000). To apply some preliminary filtering; only the threats will be discussed for one group design studies with one test period. Therefore the threats testing, selection and design contamination are further omitted, while those threats only apply for multiple group or multiple test designs. We will explain each of the remaining threats in more detail and assess their relevance for this study.

Maturation

Maturation occurs when subjects experience a personal, developmental process throughout the study, which could explain differences in behavior over time. In this study however, the subjects are not observed performing prescribed activities, but are observed while performing their daily routines. The subjects therefore do not walk through a whole development process that makes them more experienced at the end of the study. For this reason, maturation is a non-applicable threat for this research.

Statistical regression and compensatory rivalry

When subjects are aware of being observed, they could possibly have the tendency to compensate for days of exceptional behavior when they take note of these extreme scores or they try to ‘outperform’ other subjects when they discover the performances of these other subjects. This might result in manipulative ways to reach a desired score, which in this case would be a desirable sociability score. In this research however, the subjects will be provided with no explanation about the way of scoring and will only be given a general idea of what is being measured. During measurement no feedback on any score is provided and the measurements itself are carried out in the background. Also, the subjects will not be given any hints on the performances of other subjects to avoid comparison and doubts about their personal performances. In this manner, statistical regression and compensatory rivalry will not function as threats when controlling for internal validity within this study.

Experimental Mortality

During the execution of a study with multiple participants, it is possible that some of these participants drop out due to any reason. Subconsciously, this reason could be an unintentional filter that makes participants with certain characteristics drop out. For instance when an experiment appears too complicated for some subjects, one could argue that the research design unintentionally filters the more experienced or the higher-educated people. In this research the only reason for subjects to drop out was a technical malfunction within the software, which caused the application on some devices to consume an unacceptable amount of battery power or CPU usage. These subjects decided to participate no longer in the study, while normal functioning was impeded. This being the only reason for drop out, only smartphone device filtering could be argued as being applied here and while we assume device filtering does not automatically mean the filtering of people with certain personal characteristics, we assess experimental mortality as a controlled threat.

Instrumentation

Instrumentation can be a threat when changes occur in the way sociability is measured during the study. However, for this study the actual measuring of sociability happens only once after the observation period and is therefore not subject to any changes during the observation period. Consequently, this threat is not applicable for this research.

Resentful demoralization

The last threat includes the development of feelings like resentment or demoralization, when subjects learn that they receive less desirable goods or services. However, while no reward system is integrated in this study, the threat can be considered as non-applicable.

4.1.1 Summary Internal validity

To conclude internal validity, all the threats described by Blascovich and their applicability for this research are presented in Table 1. In this table, a plus sign (+) means the threat to validity is controlled. A minus sign (–) indicates a definite weakness in this design concerning the threat to validity. A question mark (?) means a possible threat exits. The word ‘no’ indicates the threat is likely not relevant.

As the table shows, the biggest threat for this research is the history of the user. When users are unable to identify events that occurred during the observation period, the risk increases for results to be explained in a faulty manner. Further threats are either not applicable for this research or easily controlled by the chosen research design.

	Applicable?
Maturation	No
Testing	No (2tests)
Instrumentation	No
Regression	+
Selection	+ (2group)
Mortality	+
Contamination	No (2group)
Rivalry	+
Demoralization	No

Table 1: Applicability internal validity threats

4.2 External validity

As explained by Campbell (1986), external validity refers to "the degree to which results of an empirical investigation can be generalized to and across individuals, settings and times". For this research it means that the following factors should be accounted for to make presumptions about the research generalizability: personal characteristics of the user, the settings the smartphone is used in during the observation period, and the time span and time period the users are observed in. We will explain these factors in two sections: population validity and ecological validity.

4.2.1 Population validity

As stated, this research will observe 10 individuals for 1,5 weeks. Although this can be considered a relatively small test group, this test group is composed of individuals that share similar personal characteristics to preserve external validity. These characteristics consist of the same age group (20-26 years old), the same gender (males only), the same education level (academic level), the same profession (students), a similar level of smartphone use experience (length of smartphone ownership is at least one year to exclude novice smartphone users) and the same psychological condition (psychologically healthy, no social deficits that might affect the outcome). Less relevant for this study, but very relevant for the follow-up study; the test group consists of people from the same culture. This is relevant for the follow-up study, while cultural differences, no matter how small, play an integral role in the appearance and manifestation of social diseases. For example, for schizophrenic patients, the content of hallucinations and delusions appeared to be culturally specific (Ascoli et al.,2014)(Bartocci, 2014)(Jones & Gray, 1986).

4.2.2 Ecological validity

Ecological validity can be defined as the degree to which the results of an empirical study can be generalized to and across settings and times. Several treats are predefined here including multiple-treatment interference, reactive effects of experimental arrangements, interaction effect of testing, interaction of history, measurement of the dependent variable, interaction of time and measurement (Bracht & Glass, 1968)(Gall, Borg & Gall, 1996). Again we will apply some preliminary filtering were threats are excluded that apply to multiple testing or multiple treatment designs only. These factors include multiple treatment interference and testing interaction. We will examine the remaining factors in more detail in the following section.

Reactive effects of experimental arrangements

The way a research is designed can have several influential effects on the behavior of subjects participating in the study. The most noteworthy example is the Hawthorne effect, which warns for the possibility that subjects may behave differently when they know that they are being observed. This effect could be a threat for the outcome of this study, because participants could deliberately choose to communicate more during the observation period to get a desirable outcome, even though the subjects were specifically asked to act normally. We believe however that the influence of the Hawthorne effect on the ecological validity will be too small to be a threat for the interpretation of the results. The biggest reason is the lack of information the subjects receive on the eventual sociability scoring method. Therefore, the subjects will not have a clue about what their scores could be and how they perform compared to other subjects until the end of the study. Additionally, the subjects cannot win or fail during the observation, e.g. no incentives are involved that might stimulate subjects to change their natural habits. For these reasons we ought the impact of this threat to be negligible.

Interaction of history

History can be a threat for any study with a one group design if certain events occur during the observation period that might have effect the dependent variable, which is in this case the sociability metric of the user. Unanticipated events like birthdays, vacations, family issues could all be the cause of spikes in the communication level of a certain user. To restrain this threat, the subjects were asked after the observation period to indicate specific events that occurred during the observation period which could have caused a significant increase or decrease in smartphone communication. However, this still leaves room for subjective errors, while some subjects may be more successful in indicating potential influential factors. For this reason, history remains a possible internal validity threat.

Measurement of the dependent variable

In some cases, results only appear evident with specific types of measurements, while other types of measurements would have resulted in the rejection of these same results. To ensure the so called construct validity for this study, the dependent variable 'sociability' is broken down into different dimensions (frequency, diversity, duration and social density), which are all measured based on the available data that could be delivered by a smartphone application. This means that a concept like 'frequency of social situations' in this research is restricted to the social situations that can be identified by a smartphone. A disadvantage is that not all social situations of an individual can be included for this research, since it is impossible for smartphones to capture every single social interaction. Therefore, more extensive measurements can be created that both capture social interactions in a physical and a smartphone setting, which could provide more complete insight into a person's sociability. We assume however, with a target group in the age of 20-25, which are known for the high social smartphone use, that conversations over smartphones form an important percentage of the user's social life, making the results reliable enough to generalize towards a user's overall sociability. While this assumption cannot be supported entirely by literature, we label the threat caused by the measurement of the dependent variable as 'potential'.

Interaction of time and measurement

Another issue is the actual duration of the observation period in which data is collected from the subjects' smartphones. In order to preserve generalizability, the length should be chosen to be representable enough for a longer time period. Having a data set with three subjects for nine months, the stability of the incoming data can be determined to calculate the minimum amount of observation time required to be reliable and generalizable. To realize this, we performed some permutation testing for the most frequently occurring events to discover the most efficient time period duration which appeared to be around a 11 day minimum. For this permutation testing, one test subject with data from a time period of 193 days was observed. The data was divided over groups of X days for which the average deviation was calculated with respect to the total average. After that, the smallest deviations were highlighted to indicate the minimum observation length to gain high representativeness of the overall data set. The results of these tests are presented in appendix B.

Experimenter effects

The last external validity threat concerns the influence of experimenter actions or presence on the subjects during the observation period. In this study however, the experimenters aren't present or involved in the observation period, as subjects are being monitored automatically. Additionally, experimenters only contacted the subjects to provide assistance if technical malfunctions occurred, like repeated application crashes, or fast battery depletion. This call for help might slightly increase the amount of social interactions in total, but calling for help could also be considered as an act of sociability, while some subjects may decide to ignore the technical malfunctions. For this reason we still believe this threat is well controlled.

4.2.3 Summary external validity

Like in the internal validity section, the applicability for each threat is presented in a table.

Again, a plus sign (+) means the threat to validity is controlled. A minus sign (–) indicates a definite weakness in this design concerning the threat to validity. A question mark (?) means a possible threat exits. The word ‘no’ indicates the threat is likely not relevant.

Table 2 shows only two factors form a potential risk for the generalizability of the results. The first factor indicates the potential effect of special events that were unreported by subjects and which may have had a positive or negative influence on the amount of social interactions the subject had during the observation period. Although the chance is small, there is still room for human error. The second factor includes the fact that we have no proof for smartphone social interactions to be representative for all of an individual’s social interactions. This may be a restriction for now, but considering the follow-up study will compare a group of schizophrenic patients and this test group as a control group, this ‘measurement of the dependent variable’-threat will not be relevant for this follow-up.

	Applicable?
Multiple treatment inference	No (multiple treatment)
Reactive effects	+
Testing interaction	No (multiple testing)
History interaction	?
Measurement dependent variable	?
Time interaction	+
Experimenter effects	+

Table 2: Applicability external validity threats

In conclusion of external validity, the results of this study will be generalizable for the complete population that complies with the following characteristics: academic, male students in the age between 20-26 years old, with at least 1 year of smartphone use experience and a healthy mental condition.

4.3 Reliability

This section is aimed at determining the reliability of the data collected by the Behapp application. The validation is done by performing a pre-study that examines each of the different data points and assesses their usefulness for the actual follow-up. First, the completeness of the data will be determined for each of the data sources, followed by the effectiveness of the Behapp application in collecting all events belonging to the data sources. Then, the stability of the data is tested to ensure the homogeneity of the overall dataset. Additionally, while two different versions of the Behapp application were used between test subjects, the internal consistency has to be assessed to allow for interchangeable data usage. Then, the internal consistency for variables that contribute to the same concept is assessed. Finally, the summery describes the reliability of each of the data sources and whether they are included for the remainder of this study.

4.3.1 Data completeness

For our data set to be sufficiently complete each event needs to occur frequently enough to be useable and the data set must be representative for the parent population. These aspects will be highlighted in the next paragraphs; event occurrence and representativeness of the data set.

Data collection over time

Figure 4 presents the collection of data for each of the different events on a time scale. The most remarkable fact is the absence of Whatsapp data after 24/02/2014. The developers of the Behapp application explained that recent updates of the Whatsapp application prevented the log data from being read by the Behapp application. For this research it means the Whatsapp events have to be excluded, given that the next Behapp application update was postponed until after the research study. Furthermore the figure shows some data gaps for multiple events at certain dates. The process for dealing with these gaps is described in the data preparation phase.

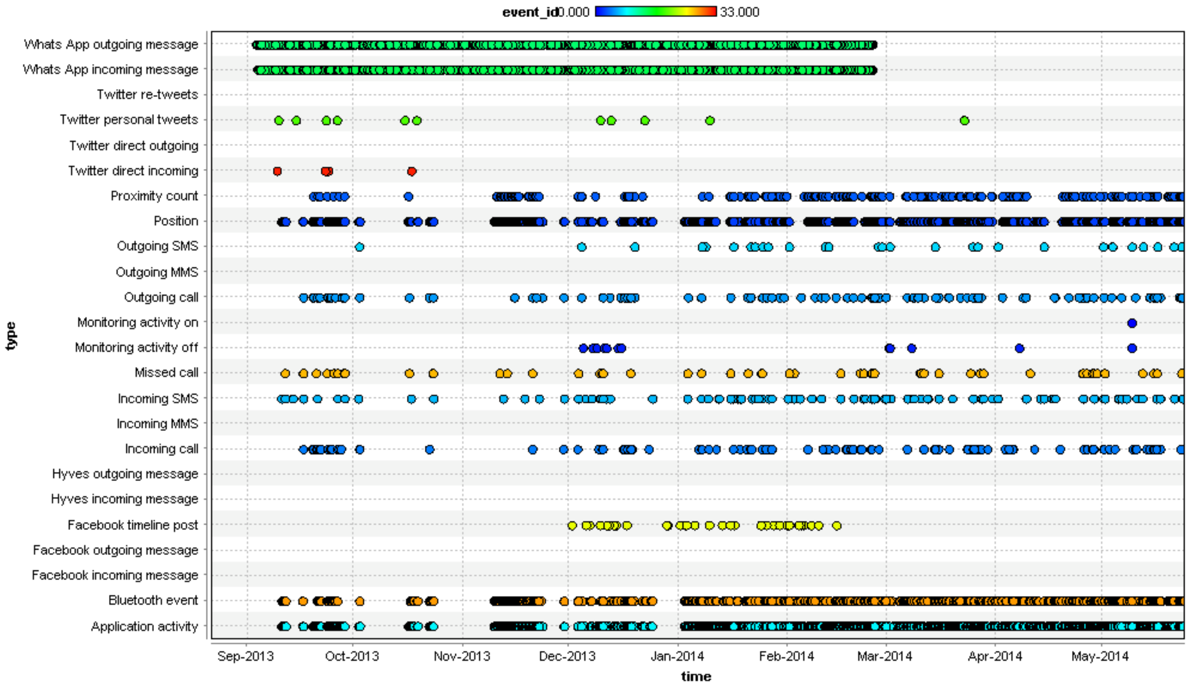

Figure 4: *Data collection over time per data source*

Event occurrence

Appendix C shows the average amount of data point occurrences per day per person. The total amount of occurrences is divided by the total amount of observation days for the involved data point.

For determining the value of a data point, we consider the boundary of having at least one occurrence in three weeks, while a chance of 50% for one occurrence in the time period of 1,5 week is too small. This boundary means that the distribution of an event should equal 0,0476 occurrences per day, meaning that the following data points are considered invaluable: Twitter, Facebook, Hyves and MMS. This concludes the involvement of social media in this research, due to lack of data.

Representativeness of the dataset

Appendix D provides an overview of all data associated with social events that were present in the database on 14-05-2014 sorted by rank of occurrence, regardless of person_id. It shows Whatsapp messages are dominating in presence, followed by calls and SMS messages. Least present are Facebook messages, Twitter and MMS messages.

The estimate proportion indicates what percentage of the real total value is expected to be present in the database, based on the examination of one or multiple persons' data. This examination has been performed differently for each of the data points.

The calls and SMS messages in the database are compared with those in the logs to determine the estimated proportion. Tweets and Facebook posts were counted on the timeline and subsequently compared with the registered amounts. Whatsapp, Twitter and Facebook messages were examined by taking a sample from the message history and calculating the percentage of the messages that are also present in the database. For validating the completeness of the smartphone activity, a one person diary was kept that described the user activities on the smartphone, which can be found in Appendix U. The comparison with the results in the database formed the basis for the estimated proportion. The estimated proportions are listed in the final column of the table in appendix D.

As the table shows, percentages below 40% have been found for CO, CI, SI, CM, SO, FI, FO, TO and TR. The highest estimated proportions of data completeness are represented by AA, WI, WO and FT.

4.3.2 Measurement effectiveness

The first step is assessing the effectiveness of the Behapp application as a research instrument; is the application measuring what it is supposed to measure? We will assess the different data points that were selected: Position, Proximity count, Calls, SMS, Application activity, Whatsapp and Bluetooth events. Also additional attributes like user speed and duration of the different events are reviewed.

Calls incoming, outgoing and missed

As we recall, sociability is the tendency to affiliate with others and to prefer being with others to remaining alone (Cheek & Buss, 1981). From this definition we derive that it is possible to consider every type of telephone call (incoming/outgoing/missed) an act that represents a person's sociability to a certain extent. However, we should note that the Behapp application registers every telephone call, including those that involve conversations between users and interactive voice response systems (IVRS). One may argue that conversations with IVRSs are not acts of sociability. Therefore, a sample set has been taken of 50 phone calls to determine the presence of conversations with IVRSs, which showed that only 1 out of 50 calls included a conversation with an IVRS. Therefore, we assume the influence of IVRSs to be too small to have a significant effect on the eventual sociability outcome.

Another phenomenon that should be dealt with is the occurrence of unanswered phone calls, which are also stored as outgoing phone calls. It is arguable to treat outgoing phone calls and unanswered phone calls the same, while one could say that an unanswered phone call only postpones the conversation and it would be unfair to count those conversations as two separate ones. For this reason we decided to apply a filter on the outgoing calls, where the duration of the conversation is registered as zero.

SMS incoming and outgoing

The same experiment has been done for SMS messages of which the results are shown in Appendix E. It shows that almost 50% of the 150 different messages originated from computer aided services: 16 activation codes, 48 voicemail notification messages, 10 messages from the telephone service provider and 3 messages from stores and sport facilities. While it not possible to perform content analysis on the SMS messages with the current version of the mobile application, the SMS data cannot be related with sociability in a reliable matter. Therefore, further examination of this data source is omitted.

Whatsapp incoming and outgoing

For Whatsapp messages it has to be mentioned that the Behapp application does not distinguish group messages from personal messages. As a consequence, subtle differences in utterances between these two different events cannot be observed directly. An additional algorithm is required to distinguish group chats from personal chats based on the ratio incoming/outgoing messages, where the amount of incoming messages is significantly higher for group chats.

Proximity count

Face detection works up till the head is turned a corner of 60 degrees. This means that in the most optimal situation, 66.6% of the people cannot be detected, due to their position towards the camera. Additionally, several errors can be made in the detection of faces were both false positives and false negatives can be restrictive for the effectiveness of the functionality. Having a range of 1 to 5 faces detected, the influence of errors can be significant, while errors on a small scale have big consequences for the total representativeness. For instance, the chance of 5 human faces being recognized , when the position of the head is randomized, is 13.2%. For 1 person this chance is 66.7%, making the effectiveness of this event varying between 13.2-66.7%, which we consider as too small to be useful.

Application activity

As explained by the developers, the Behapp application only registers the application that runs on the foreground as an application activity event. Therefore, the application activity event can be considered as sufficient effective. Originally, the Behapp applications would register the category an application could be put in according to the Google Play store categorization, but halfway the study the Behapp application failed to register this category correctly. This categorization of applications is further omitted for this study.

Bluetooth signals

The first step in verifying the amount of Bluetooth signals in the surroundings is to examine the range in which the amounts appear for each person and to link the symbolic locations to these physical locations by identifying the position on the map. This is done by taking a random sample of the highest and the lowest quantities for each device, removing the duplicates, after which the effectiveness of each measurement can be assessed. The results are presented in Appendix F.

The tables show some remarkable events, as several locations can be found in both the highest quantities sample and the lowest quantities sample, making for instance the hospital UMC Utrecht a place where crowdedness varies between 1 and 188. The same occurs for three street addresses in the cities of Utrecht, Culemborg and Zeist. Another surprising observation is the appearance of low social densities at train stations like Maastricht and Amersfoort, which you would expect to be crowded. Additional clustering analysis is required to determine the true value of the Bluetooth signals event, where using the DBSCAN or the OPTICS algorithm would be recommended to group the different positions and link them to a symbolic location. Then, when determining the average amount of Bluetooth signals at the symbolic locations, a more in-depth overview can be created that would enable improved assessment of the BT event's effectiveness. For now, we consider the data to be manageable provided it is treated with the right transformation processes, which will be further described in the sociability method chapter.

Positioning and Travel analysis

When examining the reliability of the speed measure we conclude that the reported numbers are too big to be found reliable. For instance, the speed measured for a regular passenger train varied between 75 and 105 meters per second or 270-378 km/h, where 60-70km/h was expected. A similar deviation can be found for airplanes. From data examination, we could conclude that the speed of an Airbus A320 varies between 1850 and 2948 km/h. However, literature indicates that the Airbus A320 has a maximum speed of 817 km/h (Peltzer, Nitsche and Suttan, 2008). Therefore, the speed measured by the Behapp application can be used as an ordinal attribute (using categories like slow, fast and very fast), but not as a ratio attribute.

Duration analysis

There are different types of duration in this study including, AA duration, CI and CO duration and PO duration. We will assess the duration in separately in each of these contexts.

In the diary, which is used to test the representativeness of the dataset, the duration of application usage is also registered. A summary of the events and their observed duration versus their stored duration is presented in Table 1 of Appendix G. It should be noted that the observed durations are manually estimated and are not strictly measured using a stopwatch. Also, the Behapp application only registers the duration of application that runs on the foreground, The table shows that the stored duration of the application usage is fairly similar to the estimated values. It appears that the estimations of the duration are consistently a bit higher than the stored versions ($p=0,000$; $r^2=0,899$). The only outlier mentionable is the ING app session which took less time than estimated. From this perspective the data seems to be useable for this study.

Now we will examine the same AA duration from the perspective of the data, seeing if the database shows any irregularities by looking at the range the duration appears in. A random sample of 10 AA events and their duration range is presented in table 2 (Appendix G) in descending order of maximal duration. It shows that the minimum duration for application usage is 9 seconds in all cases, which seems like a remarkable coincidence and should be explained as the threshold the Behapp application uses for registering the use of an application as an event. Even more remarkable are the high maximum durations for most of the applications. When translating the seconds in hours, the maximum durations include application usage for about 3 hours, 5 hours and even 20 hours. These numbers seem too extreme to be realistic. While these outliers could marginally influence a person's average smartphone use time, duration as an attribute for AA is further omitted.

Furthermore, duration also is an attribute of CIs and COs, of which the reliability should also be tested. This is done by comparing taking a sample of both CIs and COs and compare the duration of these events with the duration registered by the telephone service provider. This sample is shown in table 3 (Appendix G). As the table shows, the Behapp application seems very accurate at registering the total duration of phone calls with a standard deviation of 1 second. For this reason, duration of the events CI and CO are approved for using them in the sociability model.

The last duration attribute can be found for travel events which will be assessed in the next section.

Travel analysis

The data presented in Appendix H was registered from a trip from Utrecht to Houten and from Houten back to Utrecht. The travel included 5 minutes by bike, a 2 minute walk to the train station, a 10 minute train ride and a 2 minute walk to the destination. The results from this trip are presented in table 1 and 2 (Appendix H), as recorded in the database. These tables show a variation in registration for similar trips. For the first trip the application only created three positioning events, while for the second trip it created nine events. This difference is significant when concluding for different sociability factors including for instance movement patterns, transportation choices and travel times. As a conclusion, a higher frequency of positioning events is required during the trip to create a reliable representation of the trip in the database.

Another issue is the duration which appears to be several fold higher than reasonable. As also can be seen in Appendix H, several events overlap with each other, for instance in the case of event 76694, 76696 and 76701. Event 76694 starts at 12:11 and takes 85 minutes, while the next event is triggered at 12:16 and the event after that at 12:26. These last two events also take longer than what can be possibly considered as reasonable (15minutes and 98 minutes).

Because of these two reasons mentioned, movement pattern analysis is omitted from the study.

4.3.3 Stability

To test the reliability of the study over time, we applied the test-retest method to assess whether each test person gives similar results over time for each of the different data points. As we expect that smartphone behavior will only change slowly over time, we expect a high correlation between two independent samples of data from a certain social event. In line with this expectation, we performed test-retest reliability testing for each of the social data points, involving person 13 and 14 of which the results are presented in appendix I. In the cases of both person 13 and 14, no significant deviations in averages were found between the two time period samples, of which we conclude that an individual's dataset is stable enough to compare it with other individuals' dataset collected in other time periods.

4.3.4 Instrument reliability

While a second version of the application was released during the study, which was used by three out of ten test persons, it is necessary to determine a coefficient of variability between the two different application versions to preserve the repeatability of the study. If required and appropriate, this variation can be used as an explanatory factor for any discrepancies between the group of three individuals and the rest of the test group.

Again the test-retest method is applied to capture the similarities between the two Behapp versions of which the results are shown in Appendix J, along with each of the separate tests. As the results show, there is no proof for any of the data points within the two data sets to be significantly different when comparing the means, using a maximum p-value of 0,01. Therefore, we assume the data sets generated by both versions of the Behapp application to be useable interchangeably throughout the rest of the study.

4.3.5 Internal consistency reliability

As several data points contribute to the same concept, a correlation is expected between these data points. For this research, the Bluetooth signals event and the Proximity Count event should provide complementary results for the concept of social density. However, as the events do not occur at the same time, permutation testing had to be performed to discover the best regression model between the two data points. Appendix K shows the first steps towards a permutation test to find the best model that describes the relationship between the amount of camera-observed faces and the recorded Bluetooth signals in the area. Pairs for the linear regression are created based on the time of occurrence and the difference between the PC and the BT event. The maximum association value varies between 1 and 60 minutes and is described in the left column of the table in Appendix J. We expect an interval time larger than one hour between the BT event and the PC event to be too large for a relationship to exist.

The table shows that the best model describing the relationship between the PC and the BT event lies between 25 and 30 minutes. However, the effect size appears too small for the data points to actually fit the regression model. Therefore, using a combination of both PC and BT to describe the social density dimension is unjustifiable, and while PC has already been found ineffective only BT will be used to describe social density.

4.3.6 Summary reliability

To summarize the reliability section, we created a list for both all the data sources approved and the data sources disapproved for the realization of the sociability model. These lists are presented below.

Concluding from the reliability section we can approve the following data sources for the sociability method:

- Call incoming/outgoing
- Call missed
- Call duration
- Application activity
- GPS signal event
- Bluetooth signal event

The following sources are omitted due to a lack of reliability, with the reliability issue between brackets:

- SMS incoming/outgoing (effectiveness)
- Proximity count (effectiveness)
- Speed (effectiveness)
- Duration (effectiveness)
- Travel analysis/movement patterns (unsufficient data available)
- Application Activity categorization (API change during the study)
- Whatsapp incoming/outgoing (API change during the study)
- MMS incoming/outgoing (event registration error)
- Twitter personal (completeness)
- Twitter re-tweet (completeness)
- Twitter direct outgoing (completeness)
- FB incoming/outgoing (completeness)
- FB timeline post (completeness)
- Hyves incoming/outgoing (deprecated social medium)

5 The Sociability model

The first step towards the creation of the sociability model is defining the factors that can be used to describe the concept of sociability. We retrieved these factors as requirements from the healthcare domain by holding expert interviews with a biologist and a physician, whose profiles are presented in table 3. Subsequently, we combine the requirements with the information gained by the literature study and the possibilities offered by the collected data from the Behapp application to create the first version of the sociability model.

Expert 1: Associate Professor Translational Behavioral Genetics	Expert 2: Psychiatrist and Child and Adolescent Psychiatrist
Is an independent research group leader at the Department of Neuroscience and Pharmacology of the University Medical Centre in Utrecht.	Divides his time between his clinical work as a Child and Adolescent Psychiatrist, and his research in the field of genetics, concerning autism or schizophrenia.
Received his PhD degree in Behavioral Neuroscience, with the thesis entitled: "Sleep and circadian timekeeping in Octodon degus; behavioral and photic determinants of activity phase preference."	Received his PhD degree by researching the genetic and psychiatric aspects of the 22q11.2 deletion syndrome.
Has published 82 articles in international, peer reviewed journals	Has (co-)published 40 papers within the domain of genetics of developmental disorders and psychosis

Table 3: Expert introductions

5.1 Step 1: Sociability break-down

Recalling, the definition of sociability we use for this study is:

“The tendency to affiliate with others and to prefer being with others to remaining alone.” (Cheek & Buss, 1981)

This definition consists of two parts; ‘the tendency to affiliate with others’, which expresses itself in social acts that contribute to certain social situations. And ‘the tendency to prefer being with others to remaining alone’, which can be explained by the crowdedness of situations an individual puts himself into. As we derive from this definition, utterances of sociability can be divided into social acts and social exploration, which will both be explained in more detail below.

5.1.1 Social acts

During the expert interviews, the experts concluded that when describing a user’s social acts you can identify three metrics; frequency of social acts, duration of the interaction and diversity of communication partners. These metrics were derived from the following quote that came after a discussion of possible metrics for the concept of social activities. The term ‘social environment’ was later adjusted to ‘social exploration’ as will be explained hereafter.

Exp1: "I can imagine there are multiple metrics, diversity, frequency, duration and social environment"

The reason for choosing duration as a metric came from the following quote, in which expert 2 reacts to the hypothesis that the conversation duration decreases when schizophrenic patients are involved:

Exp2: "I think that's a very good hypothesis. .. There are studies performed that observe schizophrenia and the length of utterance; how long is the average sentence. … There are schizophrenic patients that generally show shorter utterances. So this will have an effect on the eventual conversation duration."

5.1.2 Social exploration

In line with the definition part 'to prefer being with others to remaining alone', the expert added social environment as a measure of the amount of people present during the user's daily situations. The term social environment later transformed into social exploration, which includes social density, but also additional requirements like the movement range, the variation in places visited and the diversification in movement patterns. The contribution of these additional requirements to the concept of sociability is explained below.

The movement range was added under the assumption that people with social deficits have a limited movement range; they have a lower tendency to travel large distances to attend a certain social situation. Or as one of the experts states:

Exp2: "Still, to my experience, I see this occurring for the people I know with schizophrenia, that having a car or not, their moving range is limited. They do not travel that far. … The question is, if it is possible to assign an average span. Then you can say, well this is the diameter in which the subject is moving".

The variation in places visited is added to capture the diversity in places a person normally visits during a certain time span. As the same expert indicates:

Exp2: "What I want to know is how much variation is there … is he visiting the grocery store two times a day or his mother once a week. … Diversity"

Also, one of the experts mentioned duration to uncover the subjects' attitude towards the presence of other people for an extended period of time. As explained by the first expert:

Exp1: "And I am also wondering how you can add a third dimension; the duration. … How long is an individual present in social dense areas. … So the difference between going to the grocery store while living in the city center, or spending a weekend at the countryside."

Finally, movement patterns also became part of social exploration, while people with social deficits like schizophrenia tend to avoid crowded places, and therefore altering their routes based on the crowdedness of a certain situation. The need is implied by the following quote:

Exp2: "I want to know, how far does an individual travel from his home base. Or is it just a small trip around the church. And how much variation is there in the routes he takes."

5.1.3 Summary

To conclude, sociability presents itself in two forms: social acts and social exploration. We define the three dimensions that comprise social acts as contact duration, contact frequency and contact diversity. Within social exploration, we distinguish movement range, the variation in places visited, the duration of place visits, the diversification in movement patterns and the social density of the places visited.

The next step is to link the smartphone data points that were found reliable enough (Chapter 4: reliability) to the four dimensions of sociability as will be done in the following section.

5.2 Step 2: Bridging the gap between requirements and the available data

From the literature study, data collected from smartphones can be categorized into the following categories: social media activity, communication data and localization and movement data, of which the latter also includes social density of the user's environment. These categories led to the research questions 1.1 to 1.4, which imply examining the added value of the categories for the concept of sociability. From these categories, social media has been omitted, while eventually no social media data was collected by the Behapp application.

5.2.1 Communication data

Concerning communication, only data describing phone call behavior has been found reliable enough to add as a data source for the sociability model. From this data source, all aforementioned dimensions frequency, diversity and duration can be used as factors describing overall call behavior. A distinction will be made here in calls that are incoming and calls that are outgoing to distinguish between active senders and active receivers. As the experts make specific statements about the role of the user in a conversation; being either a sender or as a receiver. An example from a discussion about outgoing calls:

Exp 2: "It could be a clue that something is going on. For instance, a good friend of mine with schizophrenia calls me, my parents and his own parents. I know there are not many people he calls on a regular basis and this holds for the last ten years now."

5.2.2 Localization and movement data

As derived from the expert interviews, the factors describing social exploration are movement range, the variation in places visited, the duration of place visits, the diversification in movement patterns and the social density of the places visited.

5.2.3 Localization

As literature states, localization of users can be approached by determining either the physical or the symbolic location of the user and subsequently linking the other (manually or automatically) to the one observed (Hightower and Boriello, 2001). For the sociability model we decided not to apply physical localization, because creating a score out of physical places would require additional knowledge about the particular places, which would make the scoring unnecessarily complex.

For the scoring method we chose to focus only on symbolic locations which are formed by the variables social density, duration and the distance from home. The biggest advantage of these variables is that the numbers can be compared objectively regardless of what the exact physical location is. A consequence of this method is that the factor 'variation in places visited' becomes redundant, as the variation in symbolic locations can be described by comparing the values of the associated attributes.

As duration appeared to be an unreliable variable, an alternative way had to be found to determine symbolic locations and to give value to the social density and distance. We did this by assigning a score to both variables separately as we will explain in more detail in the following section.

In the context of movement mining, it appears too early to sort out a user's movement paths or (recurrent) physical activities for now, mainly because of the complexity caused by the low position registration rate as stated in Chapter 7.

5.3 Step 3: the Sociability Model

This step combines all information from the previous sections to create the conceptual version of the sociability model, which is presented in figure 5. It shows the different dimensions of sociability and the variables derived from the expert interviews that contribute to these dimensions. The model has been designed under the assumption that every data source is available. However, in the context of Behapp, several parts of the model could not be tested, due to technical restrictions of the application. For this reason, an overlay is created in figure 5 filtering the variables disapproved in Chapter 4. We will describe the representation of the variables in the model in more detail below.

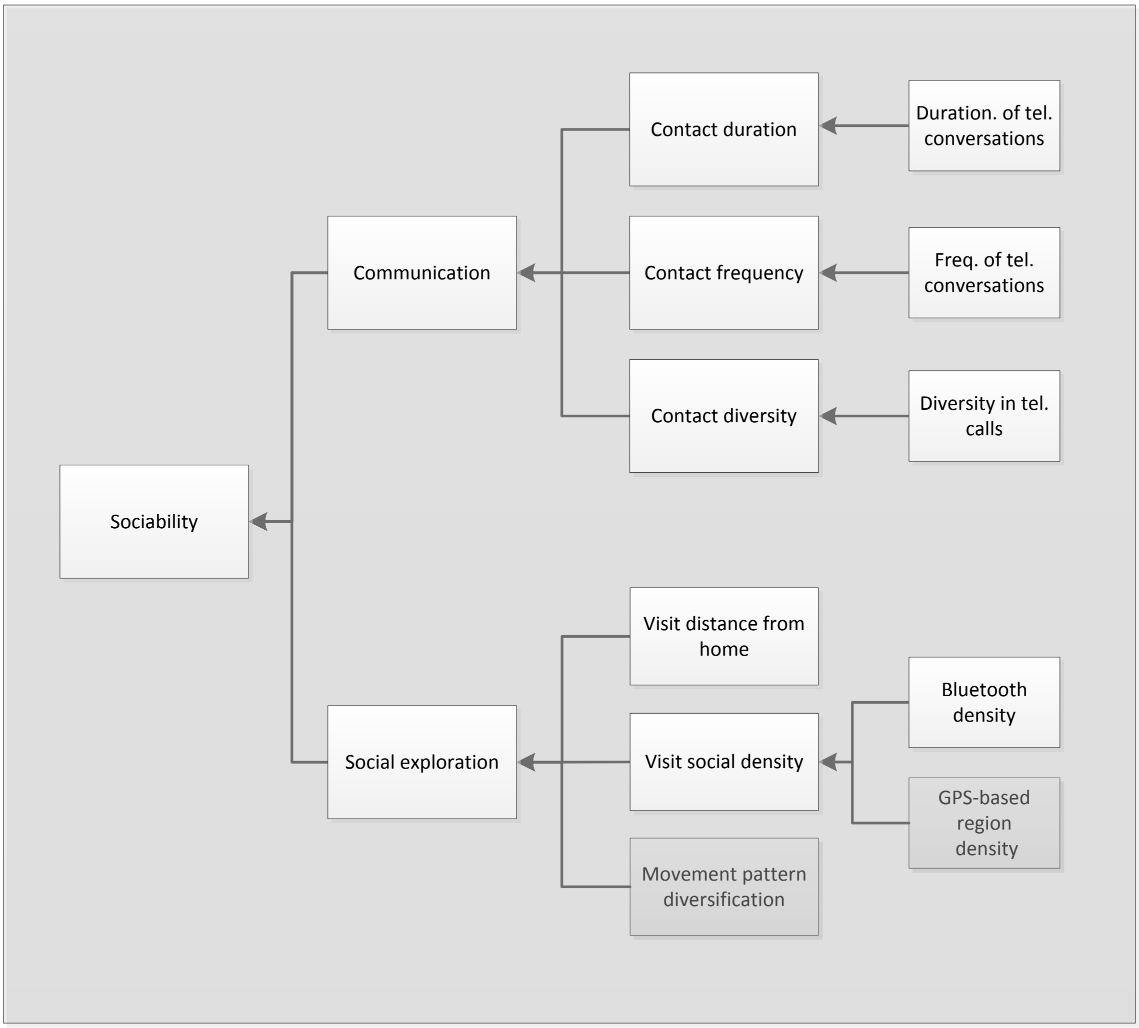

Figure 5: Hypothesized model with tested model overlay

5.3.1 Variables scores

The remaining variables include the frequency of CIs and COs, the diversity of CIs and COs. the duration of CIs and COs, the average travel distance and the average Bluetooth density. We will explain the formulas and their application in more detail below.

Social acts scoring

This social acts formula first calculates the standard score for the particular user and a specific event, using the average and the standard deviation of the total population for that same event. This standard score can be explained as the amount of standard deviations the particular user deviates from the average in a normal distribution. In order to avoid a negative score, all scores have to be shifted to a positive domain by adding a factor i to the scores. Note however, that in a normal distribution, it is only possible to shift all scores to a positive domain if the distribution is shifted with $i = \infty$, while a Gaussian curve includes all possible scores within the domain of -∞ to ∞. Therefore, boundaries have to be set for what are expected to be possible scores per research.

Another reason to limit the domain is that the wider the score range chosen, the more the scores will cluster together, making it harder to separate subtle differences between test subjects. Therefore, the factor i should be chosen considerately to avoid the scores from either clustering or falling outside the score range.

The first consideration was to choose the six sigma strategy, a term frequently used in business performance management, which prescribes to use a maximum of 6 standard deviations to maintain an efficiency of 99,99966% (or 3,4 errors per million scores)(Barney & McCarty, 2003). However, in case of this research, clustering of scores occurred under this strategy, which led to the decision to shift the scores by adding 3 to each standard score, as in 99,73% of the cases the standard score deviates from -3 to +3. In this case, there still exists a small chance that 1 person out of 370 falls outside of this scale, causing an error, but we assume this chance to be too small in a sample set of 10 subjects. After the score calculations, this assumption was verified, as the test subject scores deviate from a minimum of 15,93 to a maximum of 95,82.

In case the same formula will be used for a bigger sample set, one might consider increasing the amount of standard deviations, making again the tradeoff between the subtlety in score differences and the probability of errors to find the optimal balance for that particular situation.

To come to a score eventually, we divide the shifted standard score by the maximum standard score, which equals two times i (i.e. two times the amount of standard deviations used for the shift). Which would be six for this research as i=3. Finally, the score is multiplied by a hundred to create a score between 1 and 100.

$$social\ act\ score = (((\frac{X-\mu}{\sigma}) + i)/2i) * 100$$

$$social\ act\ score = (((\frac{X-\mu}{\sigma}) + 3)/6) * 100$$

Besides the scoring of social act frequencies, the average call duration is also transformed using the same formula, where in this case the value of X is equal to the average conversation duration in seconds over all either incoming or outgoing telephone calls.

Travel distance scoring

To give a score to the distance travelled by a user, first for all of the GPS-positions the distance had to be calculated to the subject's home. The subjects had to fill in the GPS-coordinates of their home before participating in the study. Then, we use a clustering method on the available data to group the data per hour and per day respectively, and taking the average distance for each of these steps. As a threshold we chose for a minimum of 3 data points before grouping, meaning that if for instance the average over an hour was derived from only 2 data points, the whole hour was omitted from further grouping. Also, if a subject only has effective data from 2 days in total, the person did not get a distance score assigned.

The total average distance of a subject is subsequently transformed into a score using the same formula used for social act scores.

Bluetooth density scoring

For the Bluetooth density score, a similar method is used as for the travel distance score, but instead of taking the distance average, the average Bluetooth signal count is taken. The clustering of the data occurs under the same circumstances just as the scoring of the average amount of Bluetooth signals.

5.4 Step 4: Confounding factors

As we recall from the systematic literature review, the personal factors and user-context factors are influences that should be accounted for when observing social smartphone use in more detail in the context of measuring sociability (Bandura, 1986)(Maheshwaree et al., 2009)(Steg, Buunk & Rothengatter, 2008).

Personal factors include gender, age, profession, culture etcetera, but these factors can be controlled by picking the right sample set. A personal factor which cannot be observed directly is personality, which consists of several different dimensions that should be tested separately to create an extra personality profile. Expert 1 added an extra motivation for measuring the personality of test subjects, by stating:

"You can also turn it around; it would be great to see that a certain personality profile exists for a certain patient population. Perhaps all schizophrenic patients are introverted people."

For both the preservation of validity and the additional exploratory reasons, a personality profile will form an essential part of the eventual sociability profile. This profile will show to what extent the scores can be explained by an individual's personality by using percentages.

Furthermore, user-context factors also play a role in overall smartphone use, while for example the presence of WiFi-signals, the smartphone battery capacity and the smartphone specifications may all indirectly play a role in the execution of social acts (Maheshwaree et al., 2009). Under the assumption that a linear relationship exist between smartphone use in general and social smartphone use if not influenced by personal or user-context factors, a profile of general smartphone use is required to put the social smartphone use into context. For instance, a low sociability score can in this way be explained when the subject is not a frequent smartphone user. This can be the case when the subject does most of his electronic communication using the telephone at work or at home.

Concluding, additional reference points are required in the form of a smartphone use profile and a personality profile to include the confounding factors and to put the results of the sociability profile into context. The personality profile will be created by filling in a questionnaire, which can be found in appendix V. The smartphone use profile will only consist of the AA frequency score, while the AA duration appeared not reliable enough to draw conclusions upon and the AA categorization (diversity) missed data due to a bug in the latest version of Behapp. The AA frequency score will be determined using the same method to describe the frequency of CIs and COs.

5.5 Step 5: the Sociability score

The last step is choosing a way of representing the sociability of a certain user in quantitative figures. However, the largest problem to cope with when creating scores is the fact that the application does not register every event properly and may miss a phone call or SMS message, as explained in the reliability section. For this reason, it is unreliable to conclude something about a person's sociability, while data may be missing. For instance, the database could contain 10 phone calls for a certain subject, of which could be concluded that the subject is an average caller, while literature states the average amount of phone calls per subject is 8 phone calls a week. In real life however, this person could have called way more frequently, but not having these extra calls registered, making this person in real life a more frequent caller. A possible solution for this issue could be to use prediction models, using manually gathered phone call data as a training set. However, we do not have a test group which is large enough to provide enough data for reliable prediction models. To deliver manually gathered data we have a maximum of three individuals. Additionally, registering every data source manually is impossible for data sources like the amount of Bluetooth signals in the surroundings.

An alternative way of scoring is to choose for the determination of a relative score for each data point using the rest of the test group as a reference point . A disadvantage is that the scores cannot be related to real data and are therefore useless as comparison material for future studies about general smartphone behavior. Within this study however, the use of relative scores for each data point gives the advantage that comparison between one data point and another can be done fast and efficient if the same scale is maintained (e.g. a score between 0 and 100), while scores can be used as complements or as counterweights when creating a social profile. For instance, this would enable sociability to be captured as one factor, which would speed up decision-making within the healthcare sector. Like expert 1 says:

"There are separate elements that we could measure, but maybe we could create some general, derived factor, which says something about an individual's sociability."

To finish the scoring process, the experts suggested adding some basic statistics describing the total population to create some contextual information for the individual scores. As basic statistics we add the following: the population average, standard deviation, confidence interval, range and the total sample size.

6 Results

The following section will present the results that show the application of the sociability method in practice. First some general descriptive statistics are presented about the data set obtained from the study. Then, the influence of factors that confound sociability as a concept are examined and described for the group of test subjects. Finally, the final sociability score is assigned to each of the subjects and presented along with the smartphone use profile and the personality profile.

6.1 Descriptive statistics

The Behapp application registered a total of 13.688 events cumulatively for 10 individuals over an average of 11,35 days. The event distribution for social events, social media events and other events can be found respectively in the three tables in Appendix L. The first Table 1 shows that the most frequent occurring social event is the outgoing call (152) followed by the incoming SMS (103). The lowest numbers can be found for Whatsapp messages, while the collection stagnated during the pre-study, due to an update of the Whatsapp application. Another remarkable statistic is the found MMS messages both incoming (38) and outgoing (24), which could be explained neither by the researchers nor by the test subjects. Further examination of the developers is required to determine the origin of these numbers and what the application is actually measuring.

Table 2 represents the social media events which is completely empty. The test subjects were instructed not to fill in their social media accounts, while the pre-study showed (Chapter 4) that most of the events are either not registered (FI, FO, HI, HO) or have a too low representativeness rate (FT, TI, TO, TP, TR).

The last table 3 gives an overview of the remaining data points where the most events are created by Application activities with a total of 9023 events. Second are the positioning events with 3081 events, followed by Bluetooth events and Proximity count events with a total of 2283 respectively 370 events.

Figure 6 shows the collection of data for each of the test subjects over time. First it should be noted that the data collected from only ten of the presented test subjects was found sufficient enough to continue the study with. The test subjects removed from the data set are the individuals with person_id 17, 24, 27, 28, 29 and 31. Furthermore, several data gaps can be found on the timeline which had to be closed afterwards, to avoid miscalculations over time. In most cases, if only a few data points where involved those data points were removed to close the gap. In the case of a gap in the middle of the time period, the empty space is removed under the assumption that the collection of data does not significantly differ per day (as seen in Chapter 4).

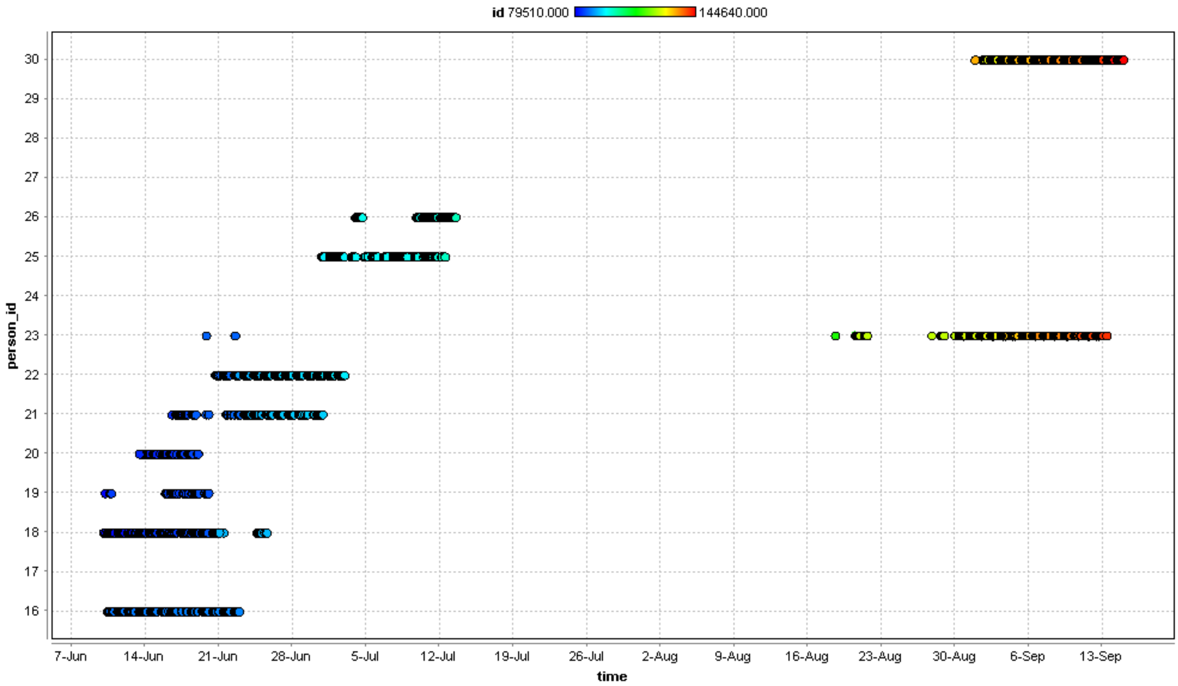

Figure 6: Data collection over time per subject

6.2 Statistical relationships within social acts

Linear regression analysis was performed to discover any statistical relationships between the data points that describe smartphone use. For the frequency dimension, the average occurrence of the social event per day is taken. For diversity, the unique amount of conversation partners is divided by the total social act frequency. Duration lastly, has been measured by taking the average amount of seconds the social act took.

The data points that were analyzed included all social acts in every of the three different dimensions (if relevant). An extensive version of the relevant results can be found in appendix M table 1.

In terms of frequency of occurrence, two strong relationships were found including SO_diversity/CI_diversity ($p=0{,}002^{**}$; $r^2=0{,}708$; $\beta=-0{,}841$) and CI_duration/CI_frequency ($p=0{,}004^{**}$; $r^2=0{,}828$; $\beta=-0{,}910$) when maintaining the significance levels $p<0{,}05^{*}$ and $p<0{,}01^{**}$. However, after further examination both cases appear to provide unsufficient evidence for a relationship to exist. In the case of SO_diversity/CI_diversity, the correlation seems mainly to be caused by the non-callers and non-SMS users. For the relationship CI_duration/CI_frequency, two extreme values are the main cause of the correlation. Further, one weak relationship has been found between CO_frequency and CM_frequency, which after filtering of extreme values remained a significant relationship ($p=0{,}024^{*}$; $r^2=0{,}539$; $\beta=0{,}734$).

6.3 Statistical relationships within social acts using scores

To discover any significant relationships between scores, several linear regression analyses were performed creating different matrices which can be found in appendix N. The first matrix includes all scores of the lowest level: the CI_frequency, CO_frequency, CI_duration, CO_duration, CI_diversity, CO_diversity, the distance and the density score. Then the second matrix aggregates the incoming (CI_frequency, CI_duration and CI_diversity) and outgoing (CO_frequency, CO_duration and CO_diversity) scores and compares them together with the distance and density score. The third matrix presents both the aggregated incoming and outgoing communication scores along with the aggregated social exploration score (distance and density score). The fourth matrix groups the incoming and outgoing communication scores, but separates the distance and density score. The final matrix groups both the communication scores and the social exploration scores and compares both scores in a bivariate regression analysis.

The first matrix (Appendix N: matrix A) shows four correlations between CI/CO, CI/CI_duration, CO/CI_duration and CO_duration/CO_diversity. However, none of these relationships holds after examining the corresponding plots. In all cases, the relationships are strongly influenced by extreme values, which after removal leave uncorrelated collections of data points.

The second matrix (Appendix N: matrix B) shows the relationships between the average incoming and outgoing communication scores, the distance score and the social density score. In this matrix, a correlation was found between the average incoming communication score and the outgoing communication score ($p=0,015^{*}$; $r^2=0,541$; $\beta=0,735$).

The remaining matrices were created involving all variables of matrix B, the overall social exploration score and communication score (Appendix N: matrices C, D & E), but no significant relationships were found for these scores.

6.4 Confounding factors

As specified in chapter 5, the largest confounding factors that could be of influence on the sociability profile are personality and general smartphone use. The impact of both factors is assessed in this section.

6.4.1 Personality

In order to determine the influence of a user's personality on his smartphone behavior, regression analysis is performed for each of the Big Five personality traits, the social acts and all available scores (both separated and aggregated). The results of these analyses can be found in appendices O, P, and Q. For these results, we maintain the following significance levels: $p<0,1^{*}$; $p<0,05^{**}$; $p<0,01^{***}$.

Concerning social acts, only one correlation has been found between inquisitiveness and the diversity in outgoing SMS message receivers, which is considered a strong relationship ($p=0,030^{**}$; $r^2=0,834$; $\beta=0,913$). This model however, is based on five subjects, which makes the reliability of the prediction model questionable.

When linked to any of the calculated scores, two correlations have been found for personality traits: the amount of outgoing SMS messages is positively correlated with extraversion ($p=0,097^{*}$; $r^2=0,307$; $\beta=0,554$), and a higher outgoing communication score is associated with higher inquisitiveness ($p=0,087^{*}$; $r^2=0,322$; $\beta=0,568$). However, in both cases the model can only explain about 30% percent of the variance, which decreases the potential of the prediction model.

Finally, two significant relationships have been found including personality traits only. First, we found extroversion and accommodation to be strongly related ($p=0,031^{**}$; $r^2=0,459$; $\beta=-0,678$). Secondly, orderliness and inquisitiveness show a weak relationship ($p=0,086^{*}$; $r^2=0,324$; $\beta=-0,569$), but the value of r-squared indicates a weak fit of the prediction model in both cases.

6.4.2 Smartphone use

To discover the role of smartphone use in the expression of an individual's sociability, we examine the statistical relationships between the created smartphone use score and the other scores, both separated and aggregated.

The results of the statistical analysis can be found in the appendix R.

As matrix A in appendix R shows, the smartphone use score (which is equal to application activity) shows a negative statistical relationship with the incoming ($p=0,021^{**}$; $r^2=0,505$; $\beta=-0,711$), outgoing ($p=0,028^{**}$; $r^2=0,475$; $\beta=-0,689$) and total communication score ($p=0,012^{**}$; $r^2=0,566$; $\beta=-0,752$). Maintaining the significance levels $p<0,1^{*}$, $p<0,05^{**}$ and $p<0,01^{***}$, all these relationships can be considered strong. However, after the removal of the extreme values for person 30 as observed in appendix R, all previous found correlations are gone. Therefore, we assume for this research the effect of smartphone use on overall sociability to be too small to be of influence.

6.5 Sociability profiling

The following section will first present all aggregated scores for each of the test subjects, divided over three different visualizations; a communication graph, a social exploration graph and a sociability graph. The communication graph shows how the incoming and outgoing communication score form the overall communication score and the social exploration graph shows how the Bluetooth score along with the distance score forms the social exploration score. The sociability score graph then presents how the communication and social exploration score are aggregated to create the final sociability score.

At the end of this section the social profiles of the test subjects will be presented, as created by using the sociability model.

6.5.1 Communication

Figure 7 shows the communication scores for all test subjects in a bubble chart, including the incoming communication score on the x-axis, the outgoing communication score on the y-axis and the overall communication score represented by the size and color of the bubble. The overall communication score is visualized by the color and size of the bubbles. To emphasize the differences between the communication scores, the color is chosen relatively to the highest and lowest value in the score range (in this case, 29,7-64,6). To show the differences in scores relatively to the entire score domain (i.e. 0-100), a difference in bubble size is depicted. Note that the black lines indicate the average for both scores, which because of the chosen score calculation always equals 50, but can be slightly higher or lower due to missing scores (in the case of the incoming and outgoing communication the averages are 49,22 and 50,28).

The subjects shown in figure 7 can be divided into four groups: 1 subject scoring low on both outgoing and incoming communication compared to the average, 5 subjects scoring about average, 3 higher scoring subjects on either outgoing or incoming communication and 1 subject scoring higher on both incoming and outgoing communication.

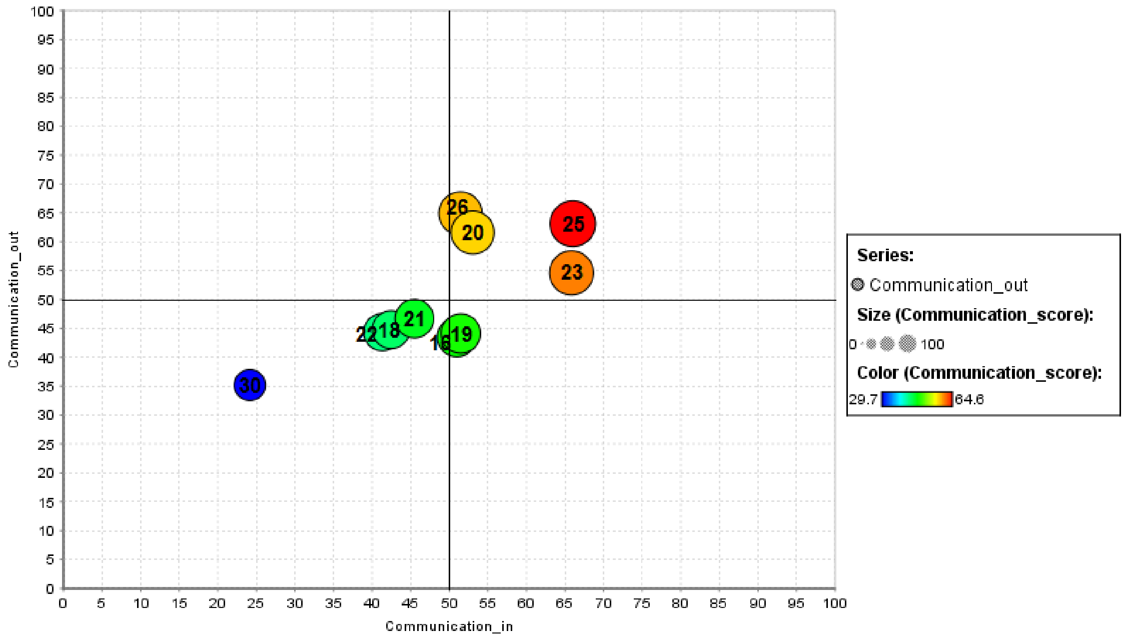

Figure 7: Communication score per subject

6.5.2 Social exploration

The Bluetooth scores, distance scores and the aggregated social exploration scores are presented in figure 8. Several subjects had to be omitted due to a lack in Bluetooth or distance score, these subjects are person 19, 20, 23 and 30. Again the averages are indicated by the black lines, which in this case both equal the score 50.

The figure shows that for social exploration the scores are diverged from the graph's center, meaning that a large diversity is present in the expression of social exploration. Two subjects stand out here, as scoring either relatively low on the Bluetooth score (person 21) or scoring relatively high on the distance score (person 26).

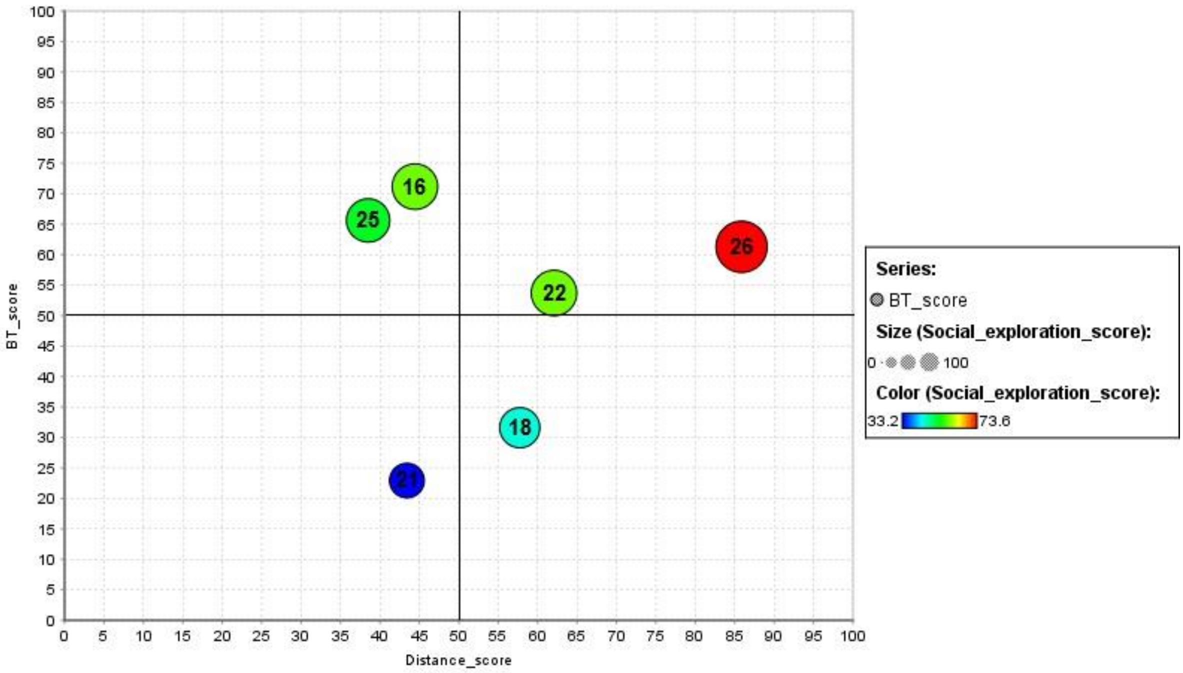

Figure 8: Social exploration score per subject

6.5.3 Sociability

The final sociability score for each test subject is visualized in figure 9. As shown by the lines in the graph the average social exploration score is found to be 47,87 and the average communication score is 49,75. Note that person 23 is omitted while we were unable to create a social exploration score due to unsufficient GPS and Bluetooth signal data.

As shown by figure 9, the differences between the subjects in sociability scores are marginal as the subjects all cluster around the center. Still a distinction can be made between subjects that score either below or above the averages. Four subjects score below average on both social exploration and communication score (person 18, 19, 21 and 30), one subject scores only below the social exploration score average (person 20) and two subjects score only below the average on communication (person 16 and 22). Two subjects score above average for both social exploration and communication which are person 25 and 26.

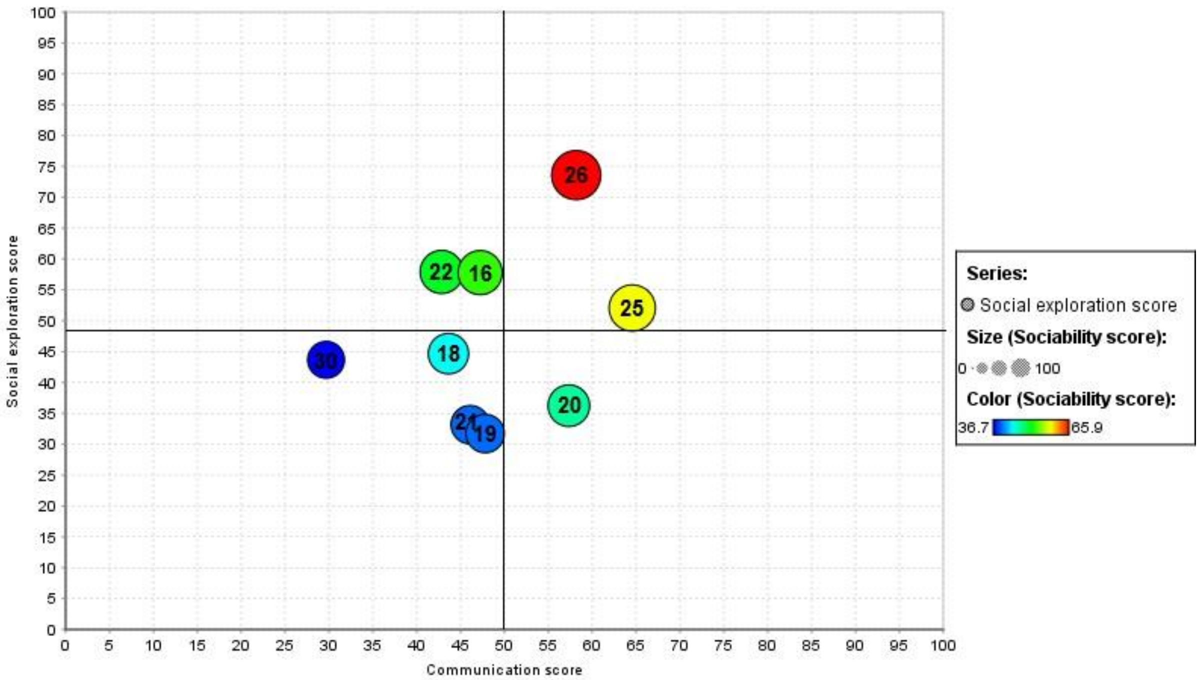

Figure 9: Sociability score per subject

6.5.4 Sociability profile

This section will present a summary of the highest-level score that will function as the final sociability profile of a subject, which is in this case for person 16.

Person 16	*Score*	*Average*	*Standard deviation*	*Sample size*	*Lower Bound*	*Upper Bound*	*Min*	*Max*	*Range*
Communication score	47,23	49,75	9,85	10	43,65	55,85	29,67	64,56	34,89
Social exploration score	57,80	47,87	12,98	9	39,39	56,35	31,73	73,58	41,85
Sociability score	52,51	49,43	9,29	10	43,67	55,19	36,67	65,88	29,20

Table 4: Sociability profile of person 16

6.6 Summary

In this section, we presented the results from applying the sociability model to 10 test subjects and visualized their eventual sociability scores. As expected, a large amount of data was retrieved having a dataset containing 13.688 events with a minimum of 38 registrations for one event (missed calls). Surprisingly, we did not find any evidence for the supposed confounding factors; personality traits and total smartphone use, in contrast to the information found in literature describing several relationships between personality traits and social acts. Further examination is required in this case to confirm or reject this finding. Then, for the calculated scores, we found a relationship between incoming and outgoing communication scores, which can be expected when assuming that active senders are also more likely to be active receivers. Finally, in line with our expectations, we found the final sociability scores to be fairly distributed among the four quadrants in a way easy distinction is possible between different test subjects.

7 Conclusions per RQ

The aim of this research is best reflected by the main research question:

1. How can a social profile of an individual be created for psychological healthcare purposes based on smartphone usage behavior?

To answer this research question, the first step encloses the determination of the social profile contents. Maintaining the term sociability and the corresponding definition by Cheek & Buss (1981), we came to the distinction of the first two categories: communication and physical social exploration. During the business understanding phase, the expert interviews in accordance with the results from the systematic literature review led to the definition of the following category dimensions: as part of the communication category, the dimensions frequency, diversity and duration were defined, in the case of social exploration, the dimensions visit distance, social density and movement pattern diversification were chosen. These categories and dimensions later formed the basis for the sociability model. With the specification of the term 'sociability' the sub question 1.1 was answered:

1.1 What factors can be defined that determine a healthcare-related sociability profile?

The next step was to examine the smartphone data during the data understanding phase and select, transform and cleanse the data to create a final data set. The data selected for this data set includes phone call data, application activity, GPS events and Bluetooth signal events.

Then, the data sources needed to be linked to the previously defined categories and dimensions in correspondence with the concept of sociability, of which the result can be found in the completion of the sociability model. This ended the CRISP-DM modeling phase and concludes the research questions 1.2, 1.3 and 1.4.

1.2 How can mobile social media use contribute to the creation of a social exploration profile?

1.3 How can smartphone communication data contribute to the creation of a social exploration profile?

1.4 How can GPS location in combination with social environment density contribute to the creation of a social exploration profile?

Then, a scoring mechanism was constructed to assign values to the different dimensions of sociability and to come to an eventual sociability score by aggregating the underlying scores. In addition to the sociability score, the influence of possible confounding factors was evaluated, and if relevant, added to the list of final scores to form the eventual sociability profile. For this matter, neither personality nor smartphone use appeared to influence sociability enough to conclude that either should be included in the final sociability profile.

As a test case, we subsequently applied the sociability model on data collected from a group of 10 students to assess the usefulness of the eventual model. To limit the influence of other confounding factors, we picked test subjects based on the same user characteristics (age, gender, education level, mental condition and level of smartphone experience).

The results from this test case reveal a weak relationship between outgoing calls and missed calls, which may be caused by the fact that people who miss a phone call are likely to return the call to discover the reason of the first call. Furthermore, one weak relationship has been found between the incoming communication score and outgoing communication score, which could indicate that a person's communication profile can be reflected by both the incoming and outgoing communication. Finally, the sociability profiles of the 10 students were successfully created using the sociability model, which shows that the model is a possible answer for the main question.

8 Discussion

The discussion chapter is divided into two parts; the limitations section, describing the boundaries of the current research, and the future research section, dedicated to the possibilities for future studies to exploit the sociability model for innovative purposes.

8.1 Limitations

For this research we distinguish two types of limitations; instrumental limitations, which are concerned with the restrictions imposed by the Behapp application, and general research design limitations. We will expand both types in the following section below.

The instrumental limitations are the consequence of the Behapp application still being in the alpha development phase. Several test reports were written during this research with additional requirements, but the actual version update came too late to be useable from the start. The first instrumental limitation encloses the deficient data retrieval from several data sources, including for instance WhatsApp messenger, Facebook and Twitter. Therefore, these data sources could not have been tested, and for now, cannot play a role in the creation of a sociability profile.

Also, bugs in the alpha version caused the application or even the entire smartphone to crash at certain moments, which forced several test subjects to drop-out of the study when the smartphone became inoperable. In replacement, new test subjects had to be found, which caused research delay and led to differential observation periods of test subjects.

Another disadvantage of the first version is the rapid battery depletion which discouraged test subjects to use their smartphone, making them generate less research data.

The first research design limitation is the sample size (n=10), which can be explained by multiple factors. The most important condition for applying as a test subject is the willingness to give up some personal data in return for a small compensation. The rest of the conditions involve being compliant with the prescribed user characteristics; having an Android-based smartphone, not suffering from a mental illness and using the smartphone on a daily basis. The lack in test subjects resulted in the specification of test subject characteristics (age, gender, etc.) to ensure internal validity. A consequence is that only a small part of the population could be represented, leaving room for additional research to examine for instance differences across gender and education level. The second limitation is the time restrictions; participants where observed over a time period of two weeks, which raises the question whether the same results hold over a longer period of time. Then, there is the diversity in smartphone type the participants own, varying from Samsung, Sony, HTC and LG devices. As performance testing is not performed strictly for each of these devices, it is unknown whether differences exist in the registration of events. As an example, it could be the case that for some devices, the Bluetooth component can register more Bluetooth-enabled devices during a scan than the Bluetooth component of other devices does.

8.2 Future research

This study is a pilot study for a study that will test the method in a subsample of an ongoing longitudinal youth cohort, involving patients diagnosed with a form of schizophrenia. From that research conclusions will be derived about the usefulness of the current model version in a practical, clinical matter. Finally and ideally, the validated method can formally be deployed in a clinical context for profiling patients and can subsequently be used as an addition for the diagnoses of several mental illnesses. However, the results from this research can also be extended in several other directions. We will walk through these directions based on the size of impact in an ascending order.

First, the sociability model can be complemented with new variables from new data sources. Acts on social media for instance would be an interesting addition, as presumptions arise from existing scientific studies that describe relationships between extraversion, social anxiousness, loneliness and Facebook use (Aspendorpf & Wilpers, 1998)(Ebeling-Witte, Frank & Lester, 2007)(Ryan & Xenos, 2011). Other additional data sources include text-messenger applications like WhatsApp (500+m users worldwide), WeChat (438+m users worldwide) and Line (400+m users worldwide)(TNW, 2014)(TNW, 2014)(Forbes, 2014), which form an essential part of modern communication and can be added as new communication variables both in the frequency and diversity dimension.

Another way of adding new variables to the sociability model, is the exploitation of the same data sources in innovative manners. For instance, GPS data can be exploited in several different ways, creating scores based on location visits, movement patterns or travel analysis. Recalling from chapter 5, for movement patterns, a presumption about variation was mentioned during the expert interviews in which one of the experts states that more variety in movement patterns is expected among schizophrenic patients, as they have the tendency to avoid crowded places.

When adding new variables, it could also be the case that some variables need to be replaced, which could be the case with social density. Other data sources like WiFi-signal density and GPS-based region density are implementable, which could be complementary or replacing factors for the concept of social density.

A final interesting concept mentioned in the literature is the discovery of social rhythms or social patterns in a user's life, by combining for instance the day of the week with repetitive values retrieved from multiple data sources, like the location and the identification of Bluetooth signals. When focusing on anomalies in these social rhythms, social withdrawal or perhaps even mental illness exacerbation can be identified more easily.

Another direction for future research would be the improvement of the sociability model. A good start would be the addition of weights to the existing and/or newly added factors. For this research, the aggregated scores are created by taking the average of other scores, maintaining the assumption that each score has an equal weight. For now, we have no reason to presume that some variables are more important than others within this aggregation. For instance, we have no proof that the frequency of conversations is of more significance to the sociability score than the duration of conversations. These weights can be established in a follow-up study, when comparing the scores of this study's test group with the scores of a group of people diagnosed with social deficits. This comparison will show that some differences in particular scores between the groups may be of more significance than other scores. It could also be concluded that a score does not differ between the two groups, meaning that the score does not contribute to the sociability score at all. To determine the exact weight, the strength of the relationship between the two groups can be used inversely to create a number between 0 and 1 that describes the influence of the category or dimension on the concept of sociability.

Although no evidence was found during this research that proofs relationships exist between personality and sociability or smartphone use and sociability, still further research is required to confirm these findings, as previous studies did find relationships between sociability and both personality and smartphone usage. In case these relationships exist, one could cope with these relationships by using the strength of the relationship as an explanatory factor for the sociability score. Personality then can be integrated in the model, by reducing the sociability score equal to the influence of the personality traits on the separated communication or social exploration scores.

The third suggestion for future research is scaling the usefulness of the model by creating a baseline for a more diverse test group, including for instance differences across gender, age, culture, educational level and profession. In this way, potential patients can be compared with a more diverse group making eventual diagnoses more reliable. To involve all user demographics, we suggest randomly selecting 40 test subjects at minimum, ensuring that at least a large portion of the user demographics is represented.

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Appendix A: Systematic literature review - Keyword combinations

The combinations of search words can be captured in the following expression:

[Cat. X] + (([Cat. B] || ([Cat. D] || [Cat. E] || [Cat. F] || NULL) + ([Cat. A] || [Cat. C]))

Category/ Keywords	**Cat. X General research characteristics**	**Cat. A Social deficits**	**Cat. B Confounding factors**	**Cat. C Data mining**	**Cat. D GPS tracking**	**Cat. E Social media**	**Cat. F Smartphone usage**
Behavior monitoring	X						
Bluetooth					X		
Classification				X			
Context provider					X		
Crowdedness					X		
Data analysis				X			
Data mining				X			
Environment density					X		
Facebook						X	
GPS					X		
Human activity recognition					X		
Localization					X		
Location-based					X		
Loneliness		X					
Movement patterns					X		
Navigation paths					X		
Personality			X				
Psychotic patients		X					
Psychosis		X					
Schizophrenia		X					
Schizophren-		X					

ic							
Smartphone usage							X
Social behavior							
Social exploration	X						
Social exclusion		X					
Social interaction		X					
Social isolation		X					
Social media						X	
Social media usage							
Social profiling	X						
Social withdrawal		X					
Twitter						X	
Whatsapp							X

Appendix B: Interaction of time and measurement

Groups of X days	Bluetooth average deviation from total average	Phone call average deviation from total average
1	27,49347	0,577343
2	25,35126	0,36369
3	22,39525	0,286541
4	21,56482	0,278955
5	18,43864	0,203402
6	16,98257	0,237405
7	20,63466	0,203133
8	16,69887	0,207581
9	19,00031	0,193683
10	19,29471	0,158481
11	17,49197	0,138906
12	16,68872	0,139831
13	16,55847	0,150013
14	19,45309	0,140862
15	18,73276	0,132393
16	18,11881	0,12131

Appendix C: Event occurrence

	Person 13	Person 14	Person 16
0. Monitoring on	0	0	0,0069
1. Monitoring off	0	0	0,077
2. Position	22,061	43,848	18,481
3. Proximity count	0,151	2,597	0,107
4. Incoming call	0,381	0,252	0,097
5. Outgoing call	0,323	0,417	0,128
6. Incoming SMS	0,132	0,176	0,212
7. Outgoing SMS	0,021	0,122	0,042
8. Application activity	7,224	17,185	39,163
13. Whatsapp incoming	6,948	6,023	126,665
14. Whatsapp outgoing	1,158	2,310	29,177
19. Twitter personal	0,074	0	0,0069
20. Twitter re-tweet	0	0	0
21. Twitter direct outgoing	0	0	0
22. FB incoming	0	0	0
23. FB outgoing	0	0	0
24. FB timeline post	0	0,161	0,069
25. Hyves incoming	0	0	0
26. Hyves outgoing	0	0	0
27. Missed call	0,267	0,048	0,063
28. Bluetooth event	5,795	12,934	11,764
30. Incoming MMS	0	0	0
31. Outgoing MMS	0	0	0
32. Twitter direct incoming	0,079	0	0,0069

Appendix D: Representativeness of the dataset

Event (id)	**Person 13**	**Person 14**	**Person 16**	**Total**	**Est. Prop.**
Whatsapp incoming (13)	1,301	671	29,398	31,370	58,6%
Application activity (8)	1,758	3,192	6,242	11,192	46% (8/20)
Whatsapp outgoing (14)	945	321	6.769	8,035	67,7%
Call outgoing (5)	76 (9,5%)	75	17 (19,5%)	168	14,5%
Call incoming (4)	90	44	14 (22%)	148	22,2% (14/63)
SMS incoming (6)	32	31	31 (18%)	94	18%
Call missed (27)	62	8	8 (17%)	78	17,0%
FB timeline post (24)	0	29	10 (59%)	39	59%
SMS outgoing (7)	2	19	4 (6,5%)	25	6,5%
Twitter personal (19)	9 (11%)	0	1 (50%)	10	<12% (10/82)
Twitter direct incoming (32)	3	0	1 (100%)	4	?%
FB incoming (22)	0	0	0 (0%)	0	0% (0/400+)
FB outgoing (23)	0	0	0 (0%)	0	0% (0/400+)
Twitter direct outgoing (21)	0	0	0	0	?%
Twitter re-tweets (20)	0	0	0	0	0% (0/132)

Appendix E: SMS sample experiment

Type of SMS	**Quantity**
Personal	73
Voicemail	48
Bank	11
Telco	10
Activation codes	5
Sport facilities	2
Web shop	1
Total	150

Appendix F: Bluetooth signal analysis

Person 13

Latitude	Longitude	Quantity	Symbolic location
52.065692	5.143693	211	Train station Utrecht Lunetten
51.959089	5.237489	188	Marijkestraat, Culemborg
44.206759	5.944634	188	Route de la Motte du Caire, Ribiers, South-France
43.579237	1.399434	188	University de Toulouse
47.421731	5.170673	148	Bois de Boulois, France
…	…	…	
51.95905	5.237069	1	Marijkestraat, Culemborg
52.088112	5.182205	1	UMC Utrecht, Utrecht
51.959261	5.236962	1	Marijkestraat, Culemborg
50.850332	5.706071	1	Train station Maastricht, Maastricht
52.328166	4.792942	1	Road junction Badhoevedorp, Badhoevedorp

Person 14

Latitude	Longitude	Quantity	Symbolic location
52.071736	5.191821	74	Van Merkensteijngaarde, Bunnik
52.06374	5.172551	74	Restaurant Vroeg, Vechten
52.086351	5.177179	74	Stratenum UMC, Utrecht
43.696847	7.268009	74	Rue Paradis, Nice
52.087575	5.245531	74	Antonlaan, Zeist (center)
…	…	…	…
52.083348	5.17656	1	Bolognalaan, Utrecht
52.069562	5.214925	1	Koelaan, Bunnik
52.08693	5.177414	1	Stratenum UMC, Utrecht
52.153197	5.371897	1	Train station Amersfoort, Amersfoort
52.0716384	5.1915278	1	Van Merkensteijngaarde, Bunnik

Person 16

Latitude	Longitude	Quantity	Symbolic location
52.099318	5.118714	93	Koekoekstraat, Utrecht
52.095423	5.215603	83	Duifhuis, Zeist

52.087001	5.18098	74	UMC, Utrecht
51.94402	5.229639	74	Train track around Culemborg
52.100328	5.115595	74	Merelstraat, Utrecht
…	…	…	…
52.095347	5.215659	1	Duifhuis, Zeist
52.095432	5.215547	1	Duifhuis, Zeist
52.099312	5.118754	1	Koekoekstraat, Utrecht
52.307192	5.141376	1	Gooimeer, Naarden
52.094788	5.122298	1	Boothstraat, Utrecht

Appendix G: Duration analysis

Person_id	Activity	Duration min (in sec)	Duration max (in sec)
14	com.sonyericsson.home.	9	72834
18	com.whatsapp.COMMUNICATION	9	39378
20	com.whatsapp.COMMUNICATION	9	38724
29	com.facebook.katana.SOCIAL	9	35889
14	com.sonyericsson.home.PRODUCTIVITY	9	35509
13	nl.sanomamedia.android.nu.NEWS_AND_MAGAZINES.	9	29206
23	com.google.android.youtube.ENTERTAINMENT" titl	9	11438
26	com.whatsapp.COMMUNICATION	9	19162
14	com.sonyericsson.android.socialphonebook.	9	13288
14	com.google.android.googlequicksearchbox.TOOLS	9	139

Table 1: Application duration analysis extremes

ID	Person	Event	Time	Duration (database)	Duration (service provider)
71699	16	4	2014-04-03 13:46:08	84	85
71738	16	4	2014-04-04 14:30:56	163	164
72276	16	4	2014-04-19 01:42:56	24	25
72911	16	4	2014-04-28 12:08:00	44	45
72228	16	5	2014-04-17 11:27:28	37	38
72588	16	5	2014-04-24 09:55:44	166	167

Table 2: Call duration analysis

Time	Event_id	Activity	Duration (observed)	Duration (stored)
8.15	8	9292	15	9
10.50	8	Gstrings	30	20
10.50	8	GuitarTuna	20	19
10.50	8	Pitchlab	20	20
11.35	8	ING	10	19
14.40	8	Facebook	60	50
14.45	8	Facebook	40	29
19.30	8	Facebook	15	9
21.45	8	Facebook	70	49

Table 3:Application duration analysis diary

Appendix H: Travel analysis

Trip Utrecht-Houten

ID	Event_ID	Time	Speed	Duration
76701	2	2014-05-23 12:26:17	1	900
76696	2	2014-05-23 12:16:21	1	5900
76694	2	2014-05-23 12:11:41	21	5100

Trip Houten-Utrecht

76725	2	2014-05-23 14:48:01	14	3400
76724	2	2014-05-23 14:45:27	0	7900
76723	2	2014-05-23 14:40:05	105	4200
76722	2	2014-05-23 14:39:20	75	7000
76714	2	2014-05-23 14:35:55	82	3500
76712	2	2014-05-23 14:34:55	2	1300
76711	2	2014-05-23 14:32:54	0	3300
76709	2	2014-05-23 14:31:23	6	1400
76707	2	2014-05-23 14:31:04	0	400

Appendix I: Stability of data

P-values	Person 13	Person 14
PC frequency	0,000	0,000
PC soc. Density	- (sd=0)	0,000
BT frequency	0,000	0,000
BT soc. Density	0,000	0,000
Call in frequency	0,000	0,000
Call out frequency	0,000	0,000
SMS in frequency	0,000	0,000
SMS out frequency	0,000	0,000
AA frequency	0,000	0,000

PC 13 freq

One-Sample Test

	Test Value = 0					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
PC_freq_1	5,870	14	,000	1,60000	1,0154	2,1846
PC_freq_2	16,000	14	,000	1,06667	,9237	1,2097

PC 13 average quantity

One-Sample Test

	Test Value = 0					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
PC_quantity_2	16,000	14	,000	1,06667	,9237	1,2097

PC 14 freq

One-Sample Test

	Test Value = 0					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
PC_freq_1	12,583	70	,000	7,14085	6,0090	8,2727
PC_freq_2	11,970	71	,000	5,73611	4,7806	6,6917

PC 14 average quantity

One-Sample Test

	Test Value = 0					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
PC_quantity_1	5,558	70	,000	3,72490E+15	2,3882E+15	5,0616E+15
PC_quantity_2	4,131	71	,000	2,40066E+15	1,2420E+15	3,5593E+15

BT freq 13

One-Sample Test

	Test Value = 0					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
BT_freq_1	5,974	40	,000	25,43902	16,8324	34,0456
BT_freq_2	7,401	41	,000	17,64286	12,8286	22,4571

BT 13 average quantity

One-Sample Test

	Test Value = 0					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
BT_quantity_1	7,813	41	,000	41,43333	30,7235	52,1432
BT_ quantity _2	17,720	40	,000	16,50732	14,6246	18,3900

BT freq 14

One-Sample Test

	Test Value = 0					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
BT_freq_1	12,076	81	,000	21,92683	18,3141	25,5395
BT_freq_2	7,665	82	,000	23,56627	17,4503	29,6823

BT 14 average quantity

One-Sample Test

	Test Value = 0					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
BT_quantity_1	29,242	82	,000	29,90000	27,8659	31,9341
BT_quantity_2	30,953	81	,000	31,28171	29,2709	33,2925

CI freq 13

One-Sample Test

	Test Value = 0					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
CI_freq_1	6,950	21	,000	2,09091	1,4652	2,7166
CI_freq_2	6,472	21	,000	2,54545	1,7276	3,3633

CI freq 14

One-Sample Test

	Test Value = 0					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
CI_freq_1	8,579	23	,000	1,33333	1,0118	1,6548
CI_freq_2	7,855	23	,000	1,62500	1,1970	2,0530

CO freq 13

One-Sample Test

	Test Value = 0					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
CO_freq_1	8,107	19	,000	1,60000	1,1869	2,0131
CO_freq_2	6,430	19	,000	2,65000	1,7874	3,5126

CO freq 14

One-Sample Test

	Test Value = 0					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
CO_freq_1	7,554	36	,000	1,78378	1,3049	2,2627
CO_freq_2	10,396	36	,000	1,70270	1,3705	2,0349

SI freq 13

One-Sample Test

	Test Value = 0					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
SI_freq_1	12,344	16	,000	1,17647	,9744	1,3785

SI freq 14

One-Sample Test

	Test Value = 0					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
SI_freq_1	8,335	24	,000	1,92000	1,4446	2,3954
SI_freq_2	15,126	25	,000	1,19231	1,0300	1,3546

AA freq 13

One-Sample Test

	Test Value = 0					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
AA_freq_1	8,966	48	,000	26,48980	20,5497	32,4299
AA_freq_2	7,775	48	,000	20,46939	15,1763	25,7625

AA freq 14

One-Sample Test

	Test Value = 0					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
AA_freq_1	12,029	81	,000	46,71951	38,9919	54,4471
AA_freq_2	9,543	81	,000	33,17073	26,2550	40,0865

Appendix J: Instrument reliability

P-values	Person 13	Person 14
PC frequency	-	0,000
PC soc. Density	-	0,000
BT frequency	0,000	0,000
BT soc. Density	0,000	0,000
Call in frequency	0,000	0,005
Call out frequency	0,000	0,000
SMS in frequency	0,000	0,000
SMS out frequency	- (sd =0)	0,006
AA frequency	0,000	0,000

Appendix K: Internal consistency reliability

Time interval	P	R^2	N
60 min	0,098	0,001	2985
40 min	0,053	0,002	2046
35 min	0,067	0,002	1823
30 min	0,038	0,003	1590
25 min	0,056	0,003	1333
20 min	0,076	0,003	1082
15 min	0,203	0,002	860
10 min	0,000	0,000	567
5 min	0,000	0,000	288
1 min	0,000	0,000	143

Appendix L: Descriptive statistics

Social event	Frequency
5. Outgoing call	152
6. Incoming SMS	103
4. Incoming call	76
27. Missed call	38
30. Incoming MMS	38
7. Outgoing SMS	33
31. Outgoing MMS	24
13. WhatsApp incoming message	0
14. WhatsApp outgoing message	0

Table 1: Social event frequencies

Social media event	Frequency
22. Facebook incoming message	0
23. Facebook outgoing message	0
24. Facebook timeline post	0
25. Hyves incoming message	0
26. Hyves outgoing message	0
32. Twitter direct incoming	0
21. Twitter direct outgoing	0
19. Twitter personal tweet	0
20. Twitter re-tweet	0

Table 2: Social media event frequencies

Other event	Frequency
8. Application activity	9023
2. Position	3081
28. Bluetooth event	2283
3. Proximity count	370

Table 3: Other event frequencies

Appendix M: Statistical relationships within smartphone use based on real values

Correlations

		Call_in_freq	Call_out_freq	Call_miss_freq	Call_in_div	SMS_out_div	Call_in_dur
Call_in_freq	Pearson Correlation	1	,553	,599	-,191	,462	,910**
	Sig. (2-tailed)		,098	,067	,598	,179	,004
	N	10	10	10	10	10	7
Call_out_freq	Pearson Correlation	,553	1	,733*	-,171	,396	,633
	Sig. (2-tailed)	,098		,016	,636	,258	,127
	N	10	10	10	10	10	7
Call_miss_freq	Pearson Correlation	,599	,733*	1	-,396	,501	,494
	Sig. (2-tailed)	,067	,016		,258	,140	,260
	N	10	10	10	10	10	7
Call_in_div	Pearson Correlation	-,191	-,171	-,396	1	-,841**	-,361
	Sig. (2-tailed)	,598	,636	,258		,002	,426
	N	10	10	10	10	10	7
SMS_out_div	Pearson Correlation	,462	,396	,501	-,841**	1	,433
	Sig. (2-tailed)	,179	,258	,140	,002		,332
	N	10	10	10	10	10	7
Call_in_dur	Pearson Correlation	,910**	,633	,494	-,361	,433	1
	Sig. (2-tailed)	,004	,127	,260	,426	,332	
	N	7	7	7	7	7	7

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Call_in_dur vs Call_in_freq

Model Summary

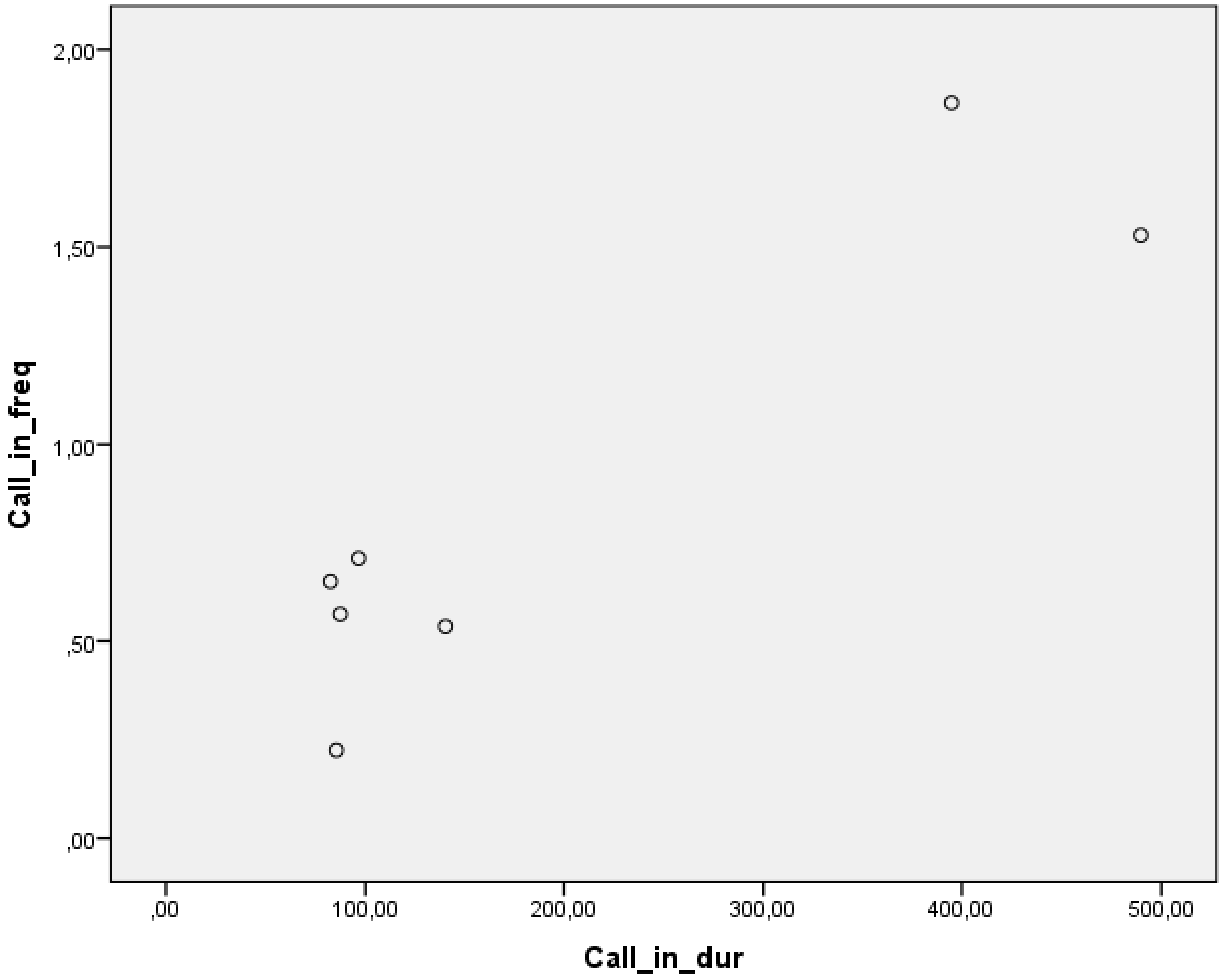
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,910[a]	,828	,793	,27033

a. Predictors: (Constant), Call_in_dur

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	,248	,163		1,521	,189
	Call_in_dur	,003	,001	,910	4,904	,004

a. Dependent Variable: Call_in_freq



Call_in_div vs SMS_out_div

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,841[a]	,708	,671	,15824

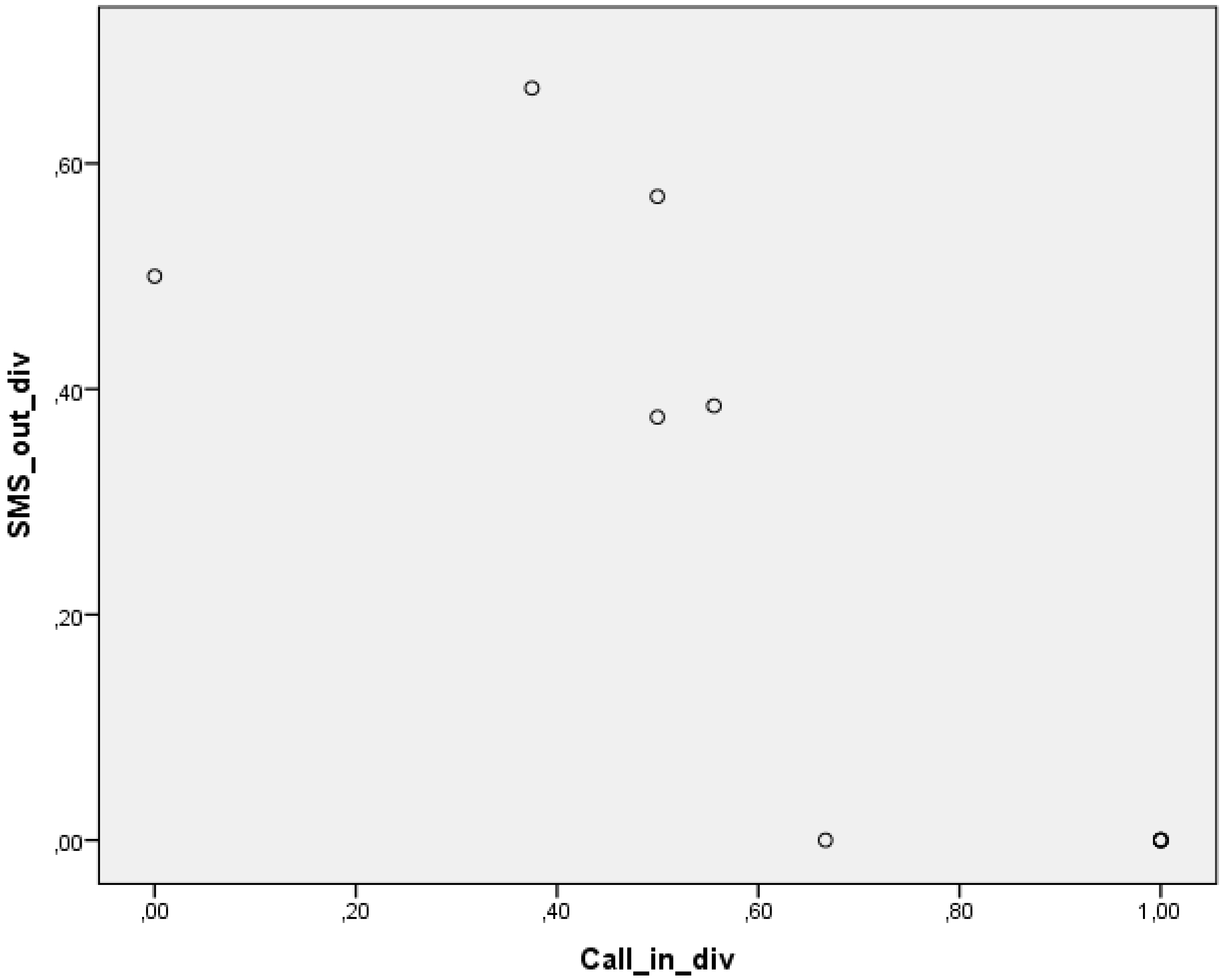
a. Predictors: (Constant), Call_in_div

Coefficients[a]

Model	Unstandardized Coefficients	Standardized Coefficients	t	Sig.

		B	Std. Error	Beta		
1	(Constant)	,700	,114		6,149	,000
	Call_in_div	-,683	,155	-,841	-4,403	,002

a. Dependent Variable: SMS_out_div



Call_miss_freq vs Call_out_freq

Model Summary

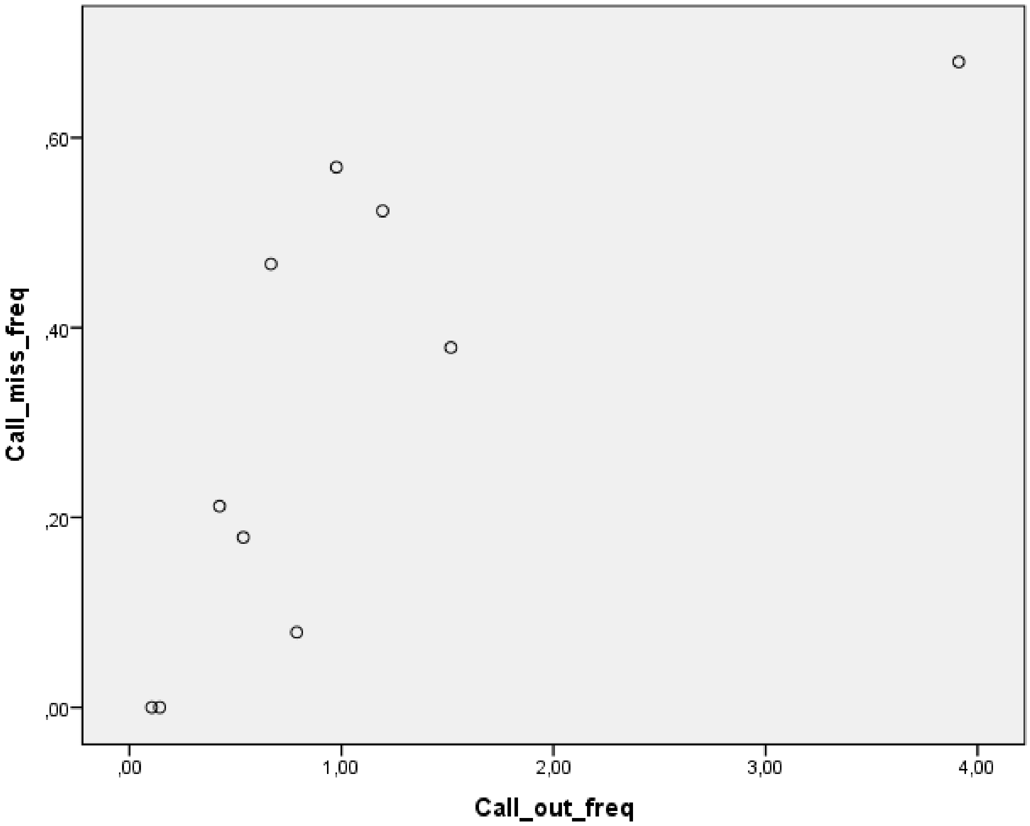
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,733[a]	,537	,479	,79822

a. Predictors: (Constant), Call_miss_freq

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	,015	,417		,036	,972
	Call_miss_freq	3,275	1,075	,733	3,046	,016

a. Dependent Variable: Call_out_freq



After removing extreme value (person_id=25)

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,734[a]	,539	,474	,34041

a. Predictors: (Constant), Call_miss_freq

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	,292	,184		1,592	,155
	Call_miss_freq	1,545	,540	,734	2,863	,024

a. Dependent Variable: Call_out_freq

Appendix N: Statistical relationships within the different scores

Matrix A:

Correlations

		Call_in	Call_out	Call_in_div	Call_out_div	Call_in_dur	Call_out_dur	BT	Distance
Call_in	Pearson Correlation	1	,765**	-,191	-,139	,910**	,437	,096	-,465
	Sig. (2-tailed)		,010	,598	,702	,004	,279	,838	,246
	N	10	10	10	10	7	8	7	8
Call_out	Pearson Correlation	,765**	1	-,181	-,315	,862*	,164	,195	-,351
	Sig. (2-tailed)	,010		,616	,375	,013	,698	,675	,393
	N	10	10	10	10	7	8	7	8
Call_in_div	Pearson Correlation	-,191	-,181	1	,553	-,361	,431	,377	-,044
	Sig. (2-tailed)	,598	,616		,097	,426	,287	,404	,918
	N	10	10	10	10	7	8	7	8
Call_out_div	Pearson Correlation	-,139	-,315	,553	1	,170	,776*	,314	,648
	Sig. (2-tailed)	,702	,375	,097		,716	,024	,493	,083
	N	10	10	10	10	7	8	7	8
Call_in_dur	Pearson Correlation	,910**	,862*	-,361	,170	1	,307	,734	-,322
	Sig. (2-tailed)	,004	,013	,426	,716		,503	,266	,534
	N	7	7	7	7	7	7	4	6
Call_out_dur	Pearson Correlation	,437	,164	,431	,776*	,307	1	,290	-,223
	Sig. (2-tailed)	,279	,698	,287	,024	,503		,636	,671
	N	8	8	8	8	7	8	5	6
BT	Pearson Correlation	,096	,195	,377	,314	,734	,290	1	,091
	Sig. (2-tailed)	,838	,675	,404	,493	,266	,636		,864
	N	7	7	7	7	4	5	7	6
Distance	Pearson Correlation	-,465	-,351	-,044	,648	-,322	-,223	,091	1
	Sig. (2-tailed)	,246	,393	,918	,083	,534	,671	,864	
	N	8	8	8	8	6	6	6	8

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Call_in vs Call_out

Model Summary

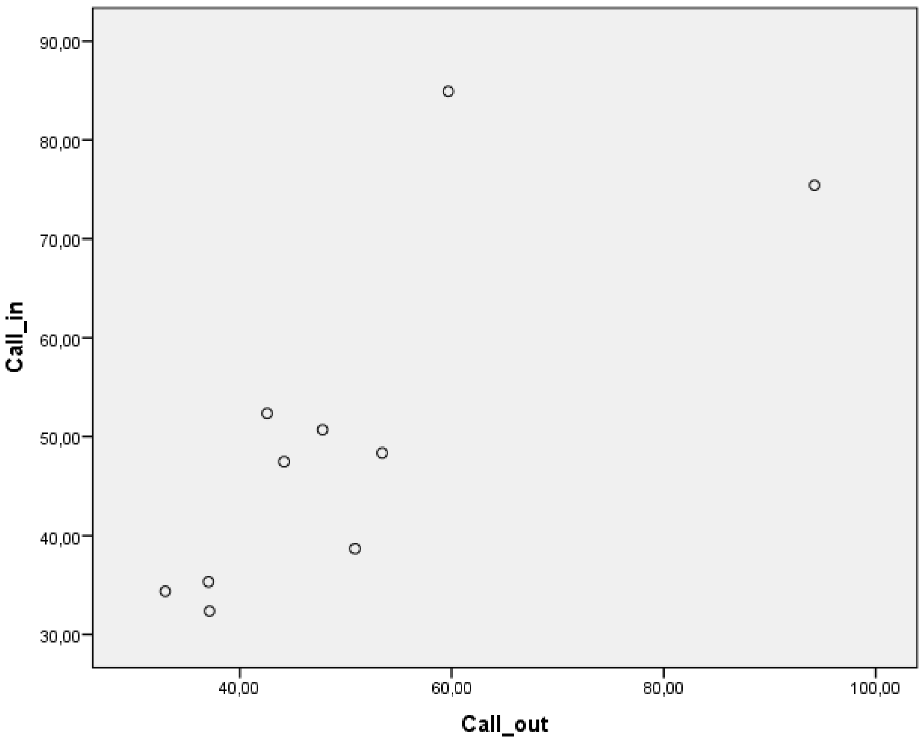
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,765[a]	,585	,533	12,00520

a. Predictors: (Constant), Call_out

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	11,760	12,005		,980	,356
	Call_out	,765	,228	,765	3,358	,010

a. Dependent Variable: Call_in



After removing extreme values (person_id=23 and person_id=25):

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,625[a]	,391	,290	6,81719

a. Predictors: (Constant), Call_out

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	12,149	15,623		,778	,466
	Call_out	,701	,357	,625	1,964	,097

a. Dependent Variable: Call_in

Call_in vs Call_in_duration

Model Summary

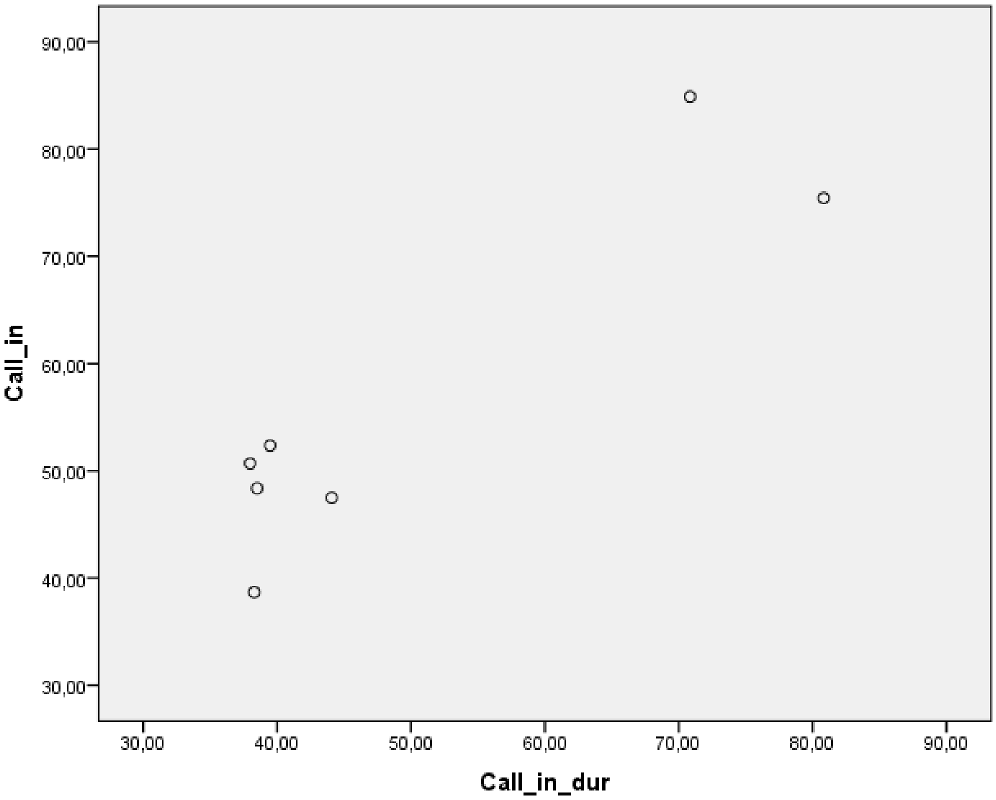
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,910[a]	,828	,794	7,60142

a. Predictors: (Constant), Call_in_dur

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	14,555	9,085		1,602	,170
	Call_in_dur	,846	,172	,910	4,906	,004

a. Dependent Variable: Call_in



Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,089[a]	,008	-,323	6,09524

a. Predictors: (Constant), Call_in_dur

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	40,143	47,877		,838	,463
	Call_in_dur	,186	1,205	,089	,154	,887

a. Dependent Variable: Call_in

Call_out vs Call_in_duration

Model Summary

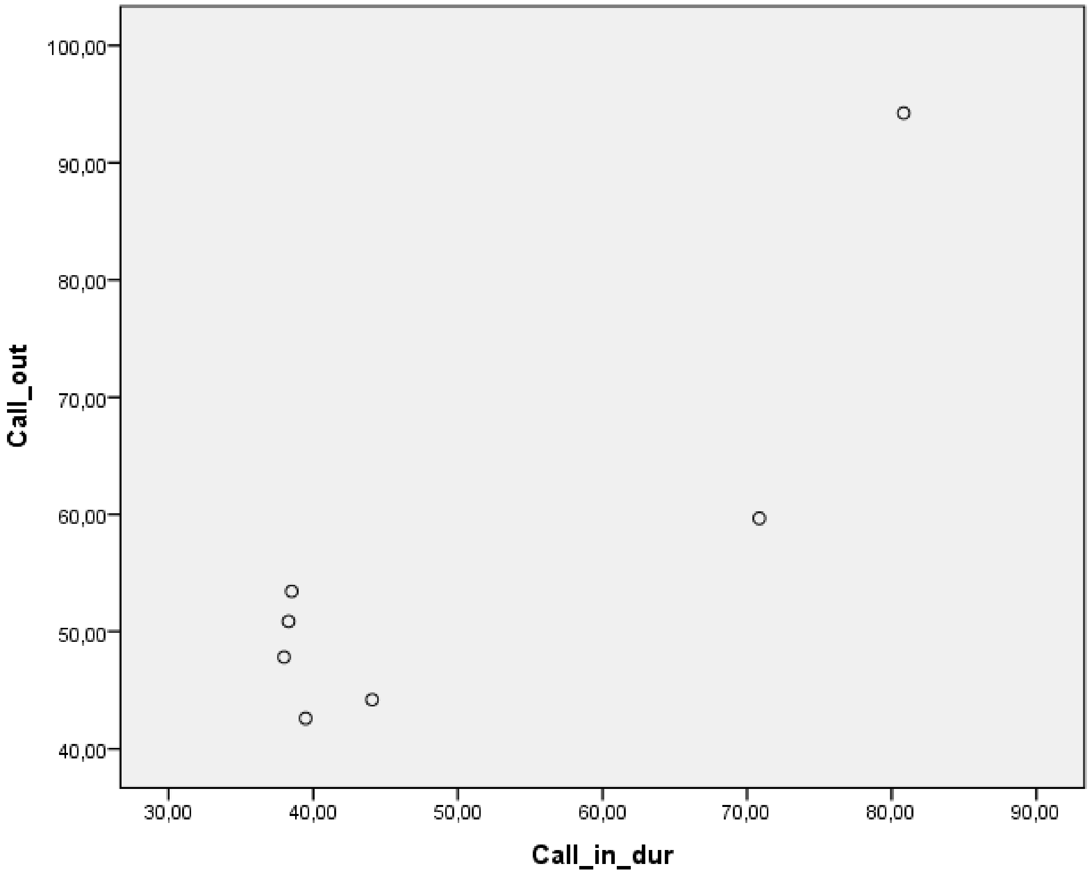
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,862[a]	,743	,691	9,87206

a. Predictors: (Constant), Call_in_dur

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	13,589	11,799		1,152	,302
	Call_in_dur	,851	,224	,862	3,799	,013

a. Dependent Variable: Call_out



After removing extreme values (person_id=23 and person_id=25)

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,565[a]	,319	,092	4,29753

a. Predictors: (Constant), Call_in_dur

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	87,718	33,757		2,599	,080
	Call_in_dur	-1,007	,850	-,565	-1,185	,321

a. Dependent Variable: Call_out

Call_Out_diversity vs Call_Out_duration

Model Summary

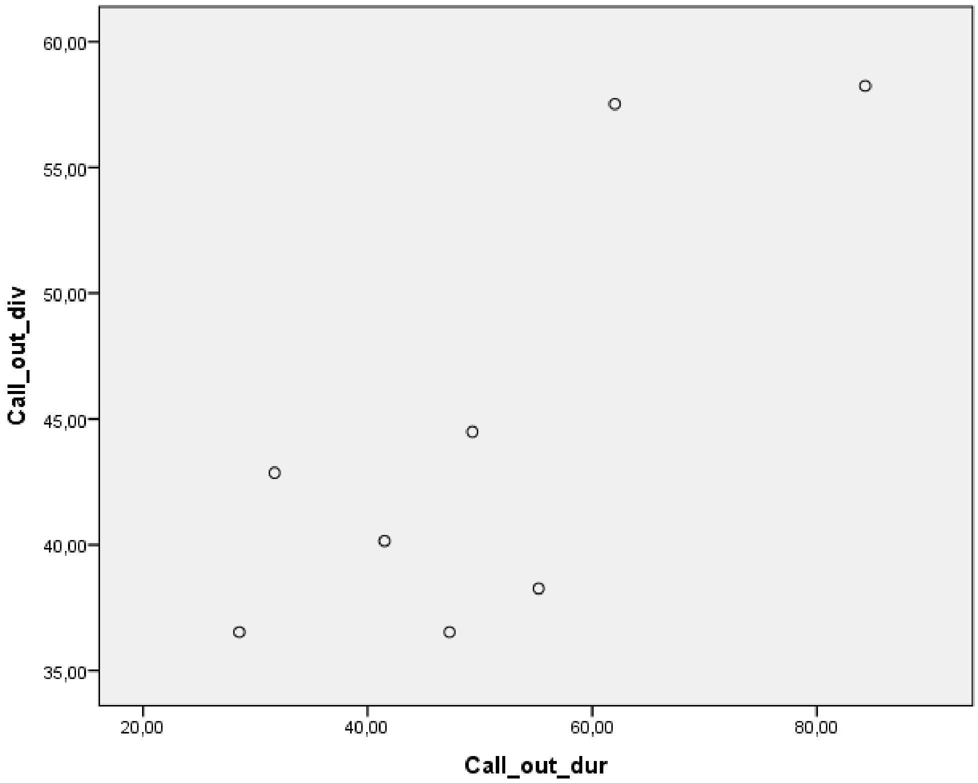
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,776[a]	,602	,536	6,01628

a. Predictors: (Constant), Call_out_dur

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	25,099	6,726		3,731	,010
	Call_out_dur	,384	,128	,776	3,012	,024

a. Dependent Variable: Call_out_div



Unreliable after removing extreme values (person_id=20 and person_id=23)

Matrix B:

Correlations

		Communication_in	Communication_out	BT	Distance
Communication_in	Pearson Correlation	1	,735*	,496	-,351
	Sig. (2-tailed)		,015	,258	,394
	N	10	10	7	8
Communication_out	Pearson Correlation	,735*	1	,418	,233
	Sig. (2-tailed)	,015		,351	,579
	N	10	10	7	8
BT	Pearson Correlation	,496	,418	1	,091
	Sig. (2-tailed)	,258	,351		,864
	N	7	7	7	6
Distance	Pearson Correlation	-,351	,233	,091	1
	Sig. (2-tailed)	,394	,579	,864	
	N	8	8	6	8

*. Correlation is significant at the 0.05 level (2-tailed).

Communication_in vs Communication_out

Model Summary

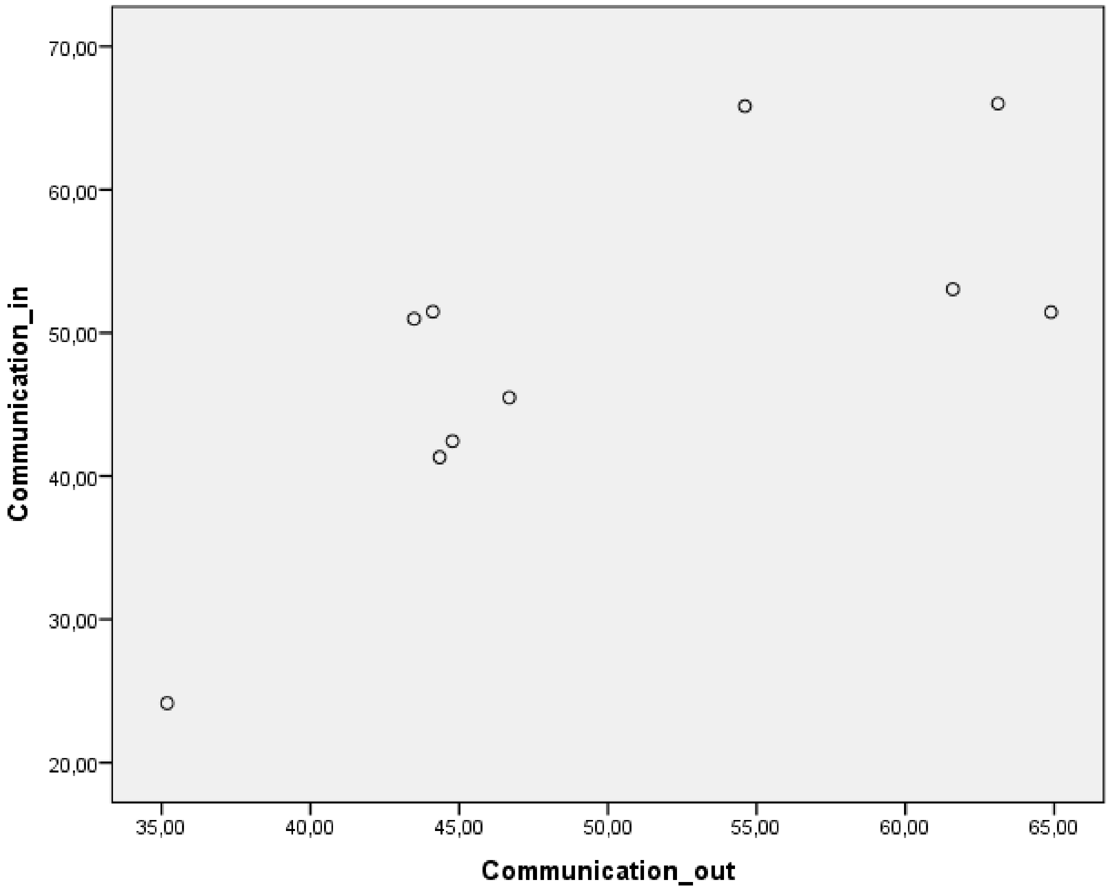
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,735[a]	,541	,483	8,75892

a. Predictors: (Constant), Communication_out

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	4,550	14,818		,307	,767
	Communication_out	,888	,290	,735	3,069	,015

a. Dependent Variable: Communication_in


70,00
60,00
50,00
40,00
30,00
20,00
Communication_in
35,00
40,00
45,00
50,00
55,00
60,00
65,00
Communication_out

Matrix C:

Correlations

		Communication_in	Communication_out	Social_exploration
Communication_in	Pearson Correlation	1	,735*	,210
	Sig. (2-tailed)		,015	,690
	N	10	10	6
Communication_out	Pearson Correlation	,735*	1	,503
	Sig. (2-tailed)	,015		,309
	N	10	10	6
Social_exploration	Pearson Correlation	,210	,503	1
	Sig. (2-tailed)	,690	,309	
	N	6	6	6

*. Correlation is significant at the 0.05 level (2-tailed).

Matrix D:

Correlations

		Communication	Distance	Density
Communication	Pearson Correlation	1	,482	-,030
	Sig. (2-tailed)		,273	,944
	N	10	7	8
Distance	Pearson Correlation	,482	1	,091
	Sig. (2-tailed)	,273		,864
	N	7	7	6
Density	Pearson Correlation	-,030	,091	1
	Sig. (2-tailed)	,944	,864	
	N	8	6	8

Matrix E:

Correlations

		Communication	So-cial_exploration
Communication	Pearson Correlation	1	,164
	Sig. (2-tailed)		,651
	N	10	10
Social_exploration	Pearson Correlation	,164	1
	Sig. (2-tailed)	,651	
	N	10	10

Appendix O: Personality and social acts

		Extroversion	Orderliness	Emotional_stability	Accomodation	Inquisitiveness
Call_in	Pearson Correlation	,162	-,009	,330	,193	,034
	Sig. (2-tailed)	,655	,980	,351	,594	,926
	N	10	10	10	10	10
Call_out	Pearson Correlation	,287	-,003	-,178	-,089	,263
	Sig. (2-tailed)	,422	,994	,623	,808	,464
	N	10	10	10	10	10
SMS_in	Pearson Correlation	,107	-,086	,184	,253	,018
	Sig. (2-tailed)	,768	,813	,611	,481	,961
	N	10	10	10	10	10
SMS_out	Pearson Correlation	,521	,004	,410	-,061	,095
	Sig. (2-tailed)	,122	,991	,239	,866	,794
	N	10	10	10	10	10
AA	Pearson Correlation	-,252	,202	,500	-,126	-,364
	Sig. (2-tailed)	,483	,575	,141	,728	,301
	N	10	10	10	10	10
Call_miss	Pearson Correlation	-,159	-,239	-,010	,028	,075
	Sig. (2-tailed)	,661	,506	,979	,938	,837
	N	10	10	10	10	10
Call_in_div	Pearson Correlation	,225	-,024	,386	,153	-,081
	Sig. (2-tailed)	,560	,952	,304	,694	,835
	N	9	9	9	9	9
Call_out_div	Pearson Correlation	,271	-,070	-,065	,142	,304
	Sig. (2-tailed)	,448	,847	,859	,695	,393
	N	10	10	10	10	10
SMS_in_div	Pearson Correlation	,205	-,185	,531	,144	,050
	Sig. (2-tailed)	,597	,633	,141	,712	,899
	N	9	9	9	9	9
SMS_out_div	Pearson Correlation	,631	,354	-,540	,439	,913*
	Sig. (2-tailed)	,254	,559	,348	,459	,030
	N	5	5	5	5	5
Call_miss_div	Pearson Correlation	-,419	-,191	,357	,370	,131
	Sig. (2-tailed)	,301	,650	,386	,367	,757
	N	8	8	8	8	8
Extroversion	Pearson Correlation	1	-,234	,297	-,678*	,301
	Sig. (2-tailed)		,515	,404	,031	,398
	N	10	10	10	10	10
Orderliness	Pearson Correlation	-,234	1	,305	,300	-,569
	Sig. (2-tailed)	,515		,391	,399	,086
	N	10	10	10	10	10
Emotional_stability	Pearson Correlation	,297	,305	1	-,353	-,369
	Sig. (2-tailed)	,404	,391		,317	,294
	N	10	10	10	10	10
Accomodation	Pearson Correlation	-,678*	,300	-,353	1	,046
	Sig. (2-tailed)	,031	,399	,317		,900
	N	10	10	10	10	10
Inquisitiveness	Pearson Correlation	,301	-,569	-,369	,046	1
	Sig. (2-tailed)	,398	,086	,294	,900	
	N	10	10	10	10	10

SMS_out_div vs inquisitiveness

Model Summary

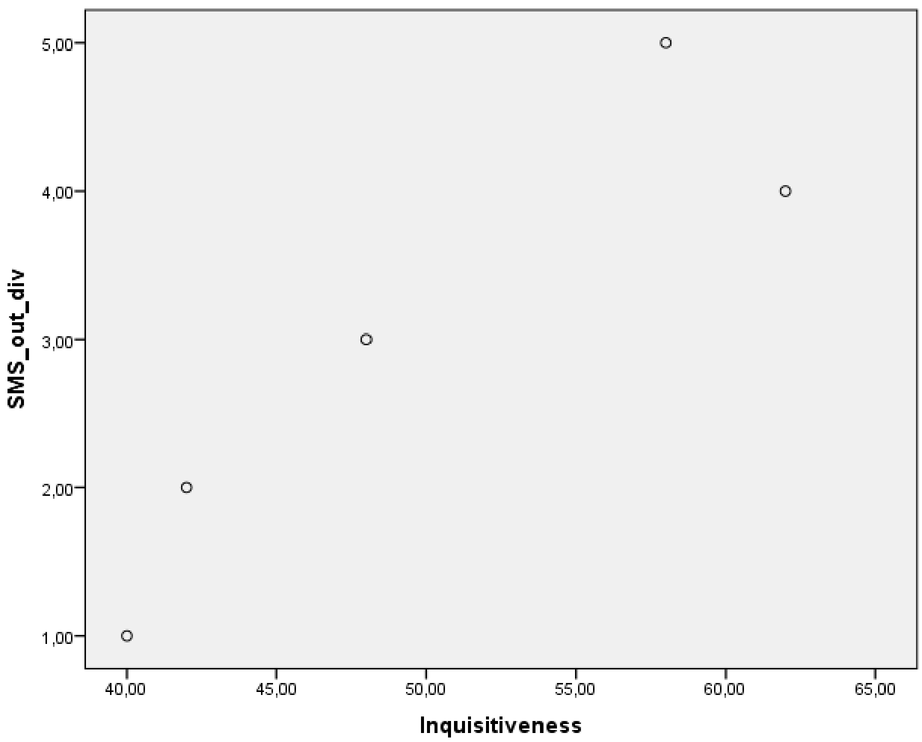
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,913[a]	,834	,779	,74377

a. Predictors: (Constant), Inquisitiveness

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-4,447	1,946		-2,285	,106
	Inquisitiveness	,149	,038	,913	3,883	,030

a. Dependent Variable: SMS_out_div



Extroversion vs accommodation

Model Summary

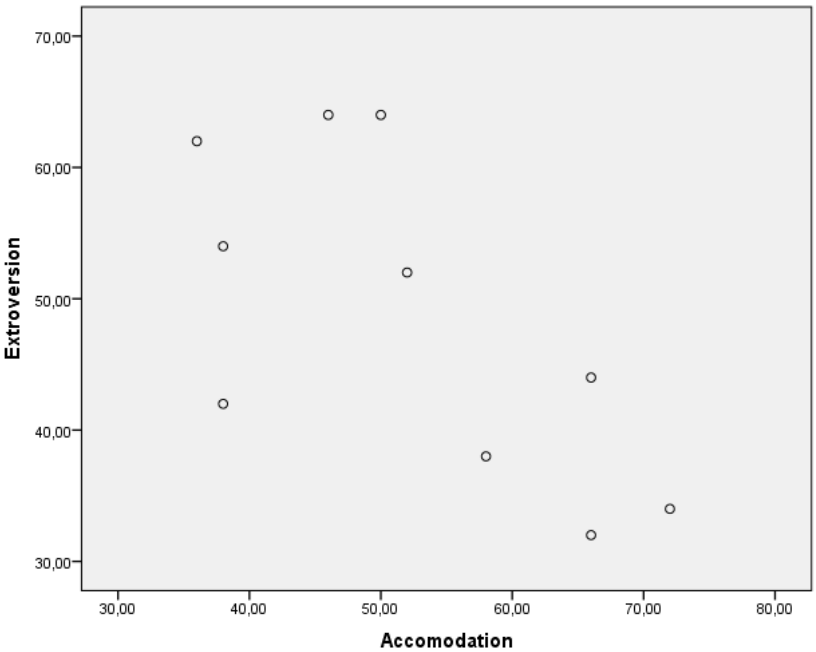
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,678[a]	,459	,392	9,58832

a. Predictors: (Constant), Accomodation

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	82,119	13,209		6,217	,000
	Accomodation	-,642	,246	-,678	-2,607	,031

a. Dependent Variable: Extroversion



Orderliness vs inquisitiveness

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,569[a]	,324	,240	4,25542

a. Predictors: (Constant), Inquisitiveness

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	62,018	6,080		10,201	,000
	Inquisitiveness	-,222	,113	-,569	-1,960	,086

a. Dependent Variable: Orderliness

Appendix P: Personality and separated smartphone use scores

		Extroversion	Orderliness	Emotional_stability	Accomodation	Inquisitiveness
Call_in	Pearson Correlation	,204	-,003	,186	,157	,000
	Sig. (2-tailed)	,573	,992	,606	,664	,999
	N	10	10	10	10	10
Call_out	Pearson Correlation	,243	-,007	-,173	-,003	,155
	Sig. (2-tailed)	,498	,984	,633	,993	,669
	N	10	10	10	10	10
SMS_in	Pearson Correlation	,016	,041	-,014	,259	-,210
	Sig. (2-tailed)	,964	,911	,970	,470	,560
	N	10	10	10	10	10
SMS_out	Pearson Correlation	,554	,011	,371	-,098	,121
	Sig. (2-tailed)	,097	,975	,292	,787	,740
	N	10	10	10	10	10
AA	Pearson Correlation	-,254	,181	,481	-,200	-,394
	Sig. (2-tailed)	,479	,616	,159	,579	,260
	N	10	10	10	10	10
Call_miss	Pearson Correlation	-,188	-,167	-,181	,011	-,056
	Sig. (2-tailed)	,603	,646	,617	,976	,878
	N	10	10	10	10	10
Call_in_div	Pearson Correlation	-,212	,158	-,470	,394	,207
	Sig. (2-tailed)	,556	,663	,170	,260	,566
	N	10	10	10	10	10
Call_out_div	Pearson Correlation	,290	-,176	,195	-,150	,349
	Sig. (2-tailed)	,416	,628	,589	,679	,322
	N	10	10	10	10	10
SMS_in_div	Pearson Correlation	-,194	,177	-,035	,164	-,248
	Sig. (2-tailed)	,591	,625	,923	,651	,490
	N	10	10	10	10	10
SMS_out_div	Pearson Correlation	,370	,012	,547	-,490	-,229
	Sig. (2-tailed)	,293	,974	,102	,151	,524
	N	10	10	10	10	10
Call_miss_div	Pearson Correlation	,101	-,514	-,039	-,010	-,102
	Sig. (2-tailed)	,782	,129	,915	,977	,780
	N	10	10	10	10	10
Extroversion	Pearson Correlation	1	-,234	,297	-,678*	,301
	Sig. (2-tailed)		,515	,404	,031	,398
	N	10	10	10	10	10
Orderliness	Pearson Correlation	-,234	1	,305	,300	-,569
	Sig. (2-tailed)	,515		,391	,399	,086
	N	10	10	10	10	10
Emotional_stability	Pearson Correlation	,297	,305	1	-,353	-,369
	Sig. (2-tailed)	,404	,391		,317	,294
	N	10	10	10	10	10
Accomodation	Pearson Correlation	-,678*	,300	-,353	1	,046
	Sig. (2-tailed)	,031	,399	,317		,900
	N	10	10	10	10	10
Inquisitiveness	Pearson Correlation	,301	-,569	-,369	,046	1
	Sig. (2-tailed)	,398	,086	,294	,900	
	N	10	10	10	10	10

SMS_out vs extroversion

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,554[a]	,307	,220	15,51758

a. Predictors: (Constant), Extroversion

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	11,552	21,027		,549	,598
	Extroversion	,791	,421	,554	1,880	,097

a. Dependent Variable: SMS_out

Appendix Q: Personality and aggregated scores

		Extroversion	Orderliness	Emotional_stability	Accomodation	Inquisitiveness
Communication_in	Pearson Correlation	,109	,146	-,093	,365	,248
	Sig. (2-tailed)	,764	,688	,798	,300	,490
	N	10	10	10	10	10
Communication_out	Pearson Correlation	,511	-,324	-,136	-,169	,568
	Sig. (2-tailed)	,131	,362	,708	,642	,087
	N	10	10	10	10	10
BT	Pearson Correlation	-,057	,630	,213	-,012	-,166
	Sig. (2-tailed)	,903	,130	,647	,980	,721
	N	7	7	7	7	7
Distance	Pearson Correlation	,130	-,325	,483	-,490	,365
	Sig. (2-tailed)	,759	,433	,225	,218	,374
	N	8	8	8	8	8
Social_exploration	Pearson Correlation	-,009	,149	,403	-,370	-,139
	Sig. (2-tailed)	,986	,778	,428	,470	,793
	N	6	6	6	6	6
Communication	Pearson Correlation	,312	-,072	-,121	,132	,421
	Sig. (2-tailed)	,380	,844	,740	,716	,225
	N	10	10	10	10	10

Communication_out vs inquisitiveness

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,568[a]	,322	,238	8,80531

a. Predictors: (Constant), Inquisitiveness

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	26,350	12,580		2,095	,070
	Inquisitiveness	,457	,234	,568	1,950	,087

a. Dependent Variable: Communication_out

Appendix R: Smartphone use and aggregated scores

Correlations

		Application_activity	Communication_in	Communication_out	Communication_score	Social_exploration_score	Sociability_score
Application_activity	Pearson Correlation	1	-,711*	-,689*	-,752*	,244	-,247
	Sig. (2-tailed)		,021	,028	,012	,526	,491
	N	10	10	10	10	9	10
Communication_in	Pearson Correlation	-,711*	1	,735*	,944**	,133	,673*
	Sig. (2-tailed)	,021		,015	,000	,732	,033
	N	10	10	10	10	9	10
Communication_out	Pearson Correlation	-,689*	,735*	1	,917**	,347	,743*
	Sig. (2-tailed)	,028	,015		,000	,360	,014
	N	10	10	10	10	9	10
Communication_score	Pearson Correlation	-,752*	,944**	,917**	1	,252	,756*
	Sig. (2-tailed)	,012	,000	,000		,514	,011
	N	10	10	10	10	9	10
Social_exploration_score	Pearson Correlation	,244	,133	,347	,252	1	,854**
	Sig. (2-tailed)	,526	,732	,360	,514		,003
	N	9	9	9	9	9	9
Sociability_score	Pearson Correlation	-,247	,673*	,743*	,756*	,854**	1
	Sig. (2-tailed)	,491	,033	,014	,011	,003	
	N	10	10	10	10	9	10

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Application activity vs Communication_in

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,711[a]	,505	,444	13,10440

a. Predictors: (Constant), Communication_in

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	100,451	18,125		5,542	,001
	Communication_in	-1,025	,359	-,711	-2,859	,021

a. Dependent Variable: Application_activity

Application activity vs Communication_out

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,689[a]	,475	,409	13,50511

a. Predictors: (Constant), Communication_out

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	110,349	22,848		4,830	,001
	Communication_out	-1,200	,446	-,689	-2,689	,028

a. Dependent Variable: Application_activity

Application activity vs Communication_score

Model Summary

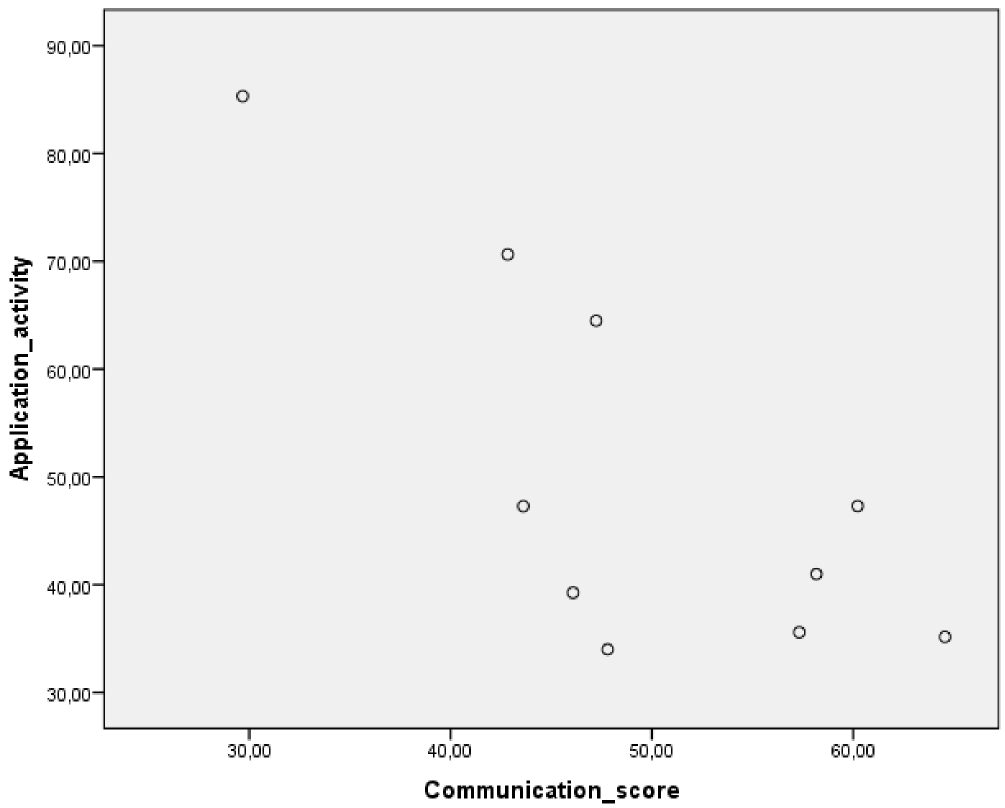
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,752[a]	,566	,511	12,28154

a. Predictors: (Constant), Communication_score

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	113,331	20,005		5,665	,000
	Communication_score	-1,273	,394	-,752	-3,227	,012

a. Dependent Variable: Application_activity



Smartphone use and aggregated scores after removing the extreme value (person_id=30)

Correlations

		Application_activity	Communication_in	Communication_out	Communication_score	Social_exploration_score	Sociability_score
Application_activity	Pearson Correlation	1	-,410	-,527	-,524	,462	,120
	Sig. (2-tailed)		,274	,145	,148	,249	,758
	N	9	9	9	9	8	9
Communication_in	Pearson Correlation	-,410	1	,735*	,894**	,133	,673*
	Sig. (2-tailed)	,274		,015	,001	,732	,033
	N	9	10	10	9	9	10
Communication_out	Pearson Correlation	-,527	,735*	1	,898**	,347	,743*
	Sig. (2-tailed)	,145	,015		,001	,360	,014
	N	9	10	10	9	9	10
Communication_score	Pearson Correlation	-,524	,894**	,898**	1	,240	,683*
	Sig. (2-tailed)	,148	,001	,001		,567	,043
	N	9	9	9	9	8	9
Social_exploration_score	Pearson Correlation	,462	,133	,347	,240	1	,854**
	Sig. (2-tailed)	,249	,732	,360	,567		,003
	N	8	9	9	8	9	9
Sociability_score	Pearson Correlation	,120	,673*	,743*	,683*	,854**	1
	Sig. (2-tailed)	,758	,033	,014	,043	,003	
	N	9	10	10	9	9	10

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Appendix S: Scores

Separated scores

Frequency	16	18	19	20	21	22	23	25	26	30
Incoming call	34,39	38,68	48,37	47,49	52,36	50,69	84,90	75,44	35,32	32,38
Outgoing call	35,97	52,67	57,78	42,23	46,23	49,21	44,29	95,82	35,36	40,44
Incoming sms	34,68	50,27	70,94	42,84	85,61	45,20	62,08	40,53	31,73	36,12
Outgoing sms	37,38	37,38	37,38	37,38	88,34	49,51	63,88	66,95	37,38	44,41
Application Activity	64,49	47,28	34,00	35,59	39,26	70,63	47,29	35,16	40,99	85,31
Missed call	28,08	65,17	54,98	40,79	33,68	68,51	61,21	76,36	28,08	43,15
Incoming MMS	37,87	71,98	37,87	37,87	87,04	61,53	43,41	37,87	37,87	46,69
Outgoing MMS	40,95	40,95	60,07	95,14	40,95	40,95	40,95	58,11	40,95	40,95
Diversity	**16**	**18**	**19**	**20**	**21**	**22**	**23**	**25**	**26**	**30**
Incoming call (div)	67,57	50,36	67,57	67,57	44,62	35,29	41,75	41,75	67,57	15,93
Outgoing call (div)	51,00	40,15	42,86	58,24	44,49	36,53	57,52	38,26	94,42	36,53
Incoming SMS (div)	71,50	37,75	36,07	71,50	36,22	52,52	50,79	51,25	20,88	71,50
Outgoing SMS (div)	34,10	34,10	34,10	34,10	58,58	76,53	57,97	70,47	34,10	65,93
Missed call (div)	22,87	54,33	44,89	66,91	66,91	48,03	66,91	39,38	22,87	66,91
Duration	**16**	**18**	**19**	**20**	**21**	**22**	**23**	**25**	**26**	**30**
Incoming call (dur)	x	38,29	38,50	44,08	39,47	37,98	70,85	80,83	x	x
Outgoing call (dur)	x	41,51	31,71	84,31	49,33	47,29	62,01	55,24	x	28,58
Social exploration	**16**	**18**	**19**	**20**	**21**	**22**	**23**	**25**	**26**	**30**
BT	71,16	31,61	x	x	22,93	53,72	x	65,62	61,30	43,67
Distance	44,43	57,74	31,73	36,24	43,42	62,08	x	38,50	85,87	x

Aggregated scores

Communication score	16	18	19	20	21	22	23	25	26	30
Communication_in	50,98	42,44	51,48	53,05	45,48	41,32	65,83	66,00	51,45	24,15
Communication_out	43,49	44,78	44,12	61,59	46,69	44,34	54,61	63,11	64,89	35,19
Communication score	**16**	**18**	**19**	**20**	**21**	**22**	**23**	**25**	**26**	**30**
Communication score	47,23	43,61	47,80	57,32	46,08	42,83	60,22	64,56	58,17	29,67
Social exploration score	**16**	**18**	**19**	**20**	**21**	**22**	**23**	**25**	**26**	**30**
SE score	57,80	44,67	31,73	36,24	33,17	57,90	x	52,06	73,58	43,67

Sociability scores

Sociability	16	18	19	20	21	22	23	25	26	30
Sociability score	52,51	44,14	39,76	46,78	39,63	50,37	60,22	58,31	65,88	36,67

Appendix T: Scores descriptive statistics

Separated scores

Frequency	Average	Standard deviation	Sample size	Confidence coff.	Margin of error	Upper Bound	Lower Bound	Max	Min	Range
Incoming call	50,00	16,67	10	1,96	10,33	60,33	39,67	84,90	32,38	52,52
Outgoing call	50,00	16,67	10	1,96	10,33	60,33	39,67	95,82	35,36	60,46
Incoming sms	50,00	16,67	10	1,96	10,33	60,33	39,67	85,61	31,73	53,88
Outgoing sms	50,00	16,67	10	1,96	10,33	60,33	39,67	88,34	37,38	50,96
Application Activity	50,00	16,67	10	1,96	10,33	60,33	39,67	85,31	34,00	51,31
Missed call	50,00	16,67	10	1,96	10,33	60,33	39,67	76,36	28,08	48,29
Incoming MMS	50,00	16,67	10	1,96	10,33	60,33	39,67	87,04	37,87	49,17
Outgoing MMS	50,00	16,67	10	1,96	10,33	60,33	39,67	95,14	40,95	54,19

Diversity	Average	Standard deviation	Sample size	Confidence coff.	Margin of error	Upper Bound	Lower Bound	Max	Min	Range
Incoming call (div)	50,00	16,67	10,00	1,96	10,33	60,33	39,67	67,57	15,93	51,65
Outgoing call (div)	50,00	16,67	10,00	1,96	10,33	60,33	39,67	94,42	36,53	57,89
Incoming SMS (div)	50,00	16,67	10,00	1,96	10,33	60,33	39,67	71,50	20,88	50,62
Outgoing SMS (div)	50,00	16,67	10,00	1,96	10,33	60,33	39,67	76,53	34,10	42,43
Missed call (div)	50,00	16,67	10,00	1,96	10,33	60,33	39,67	66,91	22,87	44,04

Duration	Average	Standard deviation	Sample size	Confidence coff.	Margin of error	Upper Bound	Lower Bound	Max	Min	Range
Incoming call (dur)	50,00	16,67	7,00	1,96	12,35	62,35	37,65	80,83	37,98	42,85
Outgoing call (dur)	50,00	16,67	8,00	1,96	11,55	61,55	38,45	84,31	28,58	55,73

Social exploration	Average	Standard deviation	Sample size	Confidence coff.	Margin of error	Upper Bound	Lower Bound	Max	Min	Range
BT	50,00	16,67	7,00	1,96	12,35	62,35	37,65	71,16	22,93	48,24
Distance	50,00	16,67	8,00	1,96	11,55	61,55	38,45	85,87	31,73	54,14

Aggregated scores

Communi-cation	Average	Standard deviation	Sample size	Confidence coff.	Margin of error	Upper Bound	Lower Bound	Max	Min	Range
Communi-cation_in	49,22	11,56	10,00	1,96	7,16	56,38	42,05	66,00	24,15	41,85
Communi-cation_out	50,28	9,57	10,00	1,96	5,93	56,21	44,35	64,89	35,19	29,71

Communi-cation score	Average	Standard deviation	Sample size	Confi-dence coff.	Margin of error	Upper Bound	Lower Bound	Max	Min	Range
Communi-cation score	49,75	9,85	10,00	1,96	6,10	55,85	43,65	64,56	29,67	34,89

Social exploration score	Average	Standard deviation	Sample size	Confidence coff.	Margin of error	Upper Bound	Lower Bound	Max	Min	Range
SE score	47,87	12,98	9,00	1,96	8,48	56,35	39,39	73,58	31,73	41,85

Sociability score

Sociability	Average	Standard deviation	Sample size	Confidence coff.	Margin of error	Upper Bound	Lower Bound	Max	Min	Range
Sociability score	49,43	9,29	10,00	1,96	5,76	55,19	43,67	65,88	36,67	29,20

Appendix U: Diary

Diary (23-05-2014)

Time	Event_id	Activity	Duration (sec)	Observed?
8.15	8	9292	15	Y
8.20-8.45	8	9gag	1500	N
8.45-8.50	8	Clash of clans	300	N
8.50-8.53	8	Tinder	240	N
9.10	5	OC 088-2505000	223	N
9.15	13	WO Ody		Y
9.18	13	WO Ody		Y
9.23	13	WO Ody		Y
9.24	13	WO Ody		Y
9.47-10.00	8	Zoo disco	780	N
10.08	13	WO Zeist		Y
10.50	8	Gstrings	30	Y
10.50	8	GuitarTuna	20	Y
10.50	8	Pitchlab	20	Y
11.04	8	Tinder	50	N
11.06	8	Snapchat	30	N
11.15	13	WO Zeist		Y
11.15	13	WO Zeist		Y
11.15	13	WO Zeist		Y
11.32	8	Gmail	15	N
11.35	8	ING	10	Y
12.30-14.30		To Houten		
13.05	8	9292	25	N
14.40	8	Facebook	70	Y
15.17	8	Tinder	30	N
16.08	8	Clash of clans	80	N
16.23	8	Snapchat	20	N
18.05	8	Snapchat	30	N
19.30	8	Facebook	100	Y
21.45	8	Facebook	70	Y

Database data 23-05-2014

ID	Event_ID	Receiver	Time	Quantity	Speed	Duration
76754	2		2014-05-23 23:20:05	0	25	1700
76753	2		2014-05-23 23:18:17	0	11	2900
76752	2		2014-05-23	0	2	4800

			23:16:22			
76751	2		2014-05-23 23:15:30	0	15	1600
76750	8	com.android.chrome.COMMUNICATION	2014-05-23 22:42:16	0	0	20
76749	8	com.whatsapp.COMMUNICATION	2014-05-23 22:18:10	0	0	10
76748	8	com.whatsapp.COMMUNICATION	2014-05-23 22:15:27	0	0	10
76747	8	com.facebook.katana.SOCIAL	2014-05-23 21:44:24	0	0	49
76746	8	com.sonyericsson.home.	2014-05-23 21:13:50	0	0	10
76744	28	4daca18481b7c0ccc46e710ad275b7e0	2014-05-23 21:13:46	41	0	0
76745	8	com.sonyericsson.android.camera.	2014-05-23 21:13:40	0	0	9
76743	8	com.sonyericsson.android.camera.	2014-05-23 21:12:42	0	0	9
76742	8	com.sonyericsson.home.	2014-05-23 21:12:32	0	0	10
76741	8	com.sonyericsson.android.camera.	2014-05-23 21:12:12	0	0	19
76740	8	com.sonyericsson.home.	2014-05-23 21:04:27	0	0	464
76739	28	4daca18481b7c0ccc46e710ad275b7e0	2014-05-23 20:55:30	32	0	0
76738	28	4daca18481b7c0ccc46e710ad275b7e0	2014-05-23 20:55:03	23	0	0
76737	8	com.sonyericsson.home.	2014-05-23 20:54:04	0	0	10
76736	8	com.sonyericsson.advancedwidget.onoff.	2014-05-23 20:53:54	0	0	9
76735	8	com.sonyericsson.home.	2014-05-23 20:48:35	0	0	318
76733	28	4daca18481b7c0ccc46e710ad275b7e0	2014-05-23 19:31:28	14	0	0
76734	8	com.facebook.orca.COMMUNICATION	2014-05-23 19:31:23	0	0	9
76732	28	d036c7422e53fa3aab13f5660e2760bc	2014-05-23 19:28:09	46	0	0
76731	8	com.whatsapp.COMMUNICATION	2014-05-23 19:27:07	0	0	39
76730	8	com.sonyericsson.home.	2014-05-23 18:09:06	0	0	4680
76729	8	com.tinder.LIFESTYLE	2014-05-23 18:08:36	0	0	29
76728	8	com.whatsapp.COMMUNICATION	2014-05-23 18:05:22	0	0	10
76726	28	4718419c3248c4c9b7f65577ac263bd1	2014-05-23	23	0	0

			14:48:01			
76725	2		2014-05-23 14:48:01	0	14	3400
76727	28	69eb48c4b97a0366f85c07e42b638082	2014-05-23 14:47:59	18	0	0
76724	2		2014-05-23 14:45:27	0	0	7900
76723	2		2014-05-23 14:40:05	0	105	4200
76722	2		2014-05-23 14:39:20	0	75	7000
76721	8	com.facebook.katana.SOCIAL	2014-05-23 14:38:48	0	0	29
76720	8	com.sonyericsson.advancedwidget.onoff.	2014-05-23 14:38:38	0	0	10
76719	8	com.facebook.katana.SOCIAL	2014-05-23 14:37:48	0	0	50
76718	8	com.google.android.gm.COMMUNICATION	2014-05-23 14:37:38	0	0	10
76717	8	com.whatsapp.COMMUNICATION	2014-05-23 14:36:40	0	0	10
76716	8	com.outlook.Z7.COMMUNICATION	2014-05-23 14:36:30	0	0	9
76714	2		2014-05-23 14:35:55	0	82	3500
76715	8	com.whatsapp.COMMUNICATION	2014-05-23 14:35:30	0	0	60
76713	28	c0266948aaad48dfd19a24ff216288c5	2014-05-23 14:35:02	5	0	0
76712	2		2014-05-23 14:34:55	0	2	1300
76711	2		2014-05-23 14:32:54	0	0	3300
76710	28	c0266948aaad48dfd19a24ff216288c5	2014-05-23 14:31:34	1	0	0

ID	Event _ID	Receiver	Time	Quantity	Speed	Duration
76709	2		2014-05-23 14:31:23	0	6	1400
76708	28	c0266948aaad48dfd19a24ff216288c5	2014-05-23 14:31:05	3	0	0
76707	2		2014-05-23 14:31:04	0	0	400
76706	8	com.google.android.googlequicksearchbox.TOOLS	2014-05-23 14:13:30	0	0	29
76705	8	com.whatsapp.COMMUNICATION	2014-05-23 14:03:06	0	0	624
76704	8	com.sonyericsson.home.	2014-05-23 13:14:51	0	0	2895
76703	28	bc6cdbaada191f608daacdb1e9205a56	2014-05-23 12:26:25	3	0	0
76702	28	65eb08771663e5c54f8d98abe6b6d189	2014-05-23 12:26:23	29	0	0
76701	2		2014-05-23 12:26:17	0	1	900
76700	28	bc6cdbaada191f608daacdb1e9205a56	2014-05-23 12:24:07	2	0	0

76699	28	65eb08771663e5c54f8d98abe6b6d189	2014-05-23 12:24:05	29	0	0
76698	28	bc6cdbaada191f608daacdb1e9205a56	2014-05-23 12:17:14	2	0	0
76697	28	65eb08771663e5c54f8d98abe6b6d189	2014-05-23 12:17:12	23	0	0
76696	2		2014-05-23 12:16:21	0	1	5900
76694	2		2014-05-23 12:11:41	0	21	5100
76695	8	com.whatsapp.COMMUNICATION	2014-05-23 12:11:33	0	0	19
76693	8	com.sonyericsson.home.	2014-05-23 12:07:57	0	0	100
76692	2		2014-05-23 12:02:13	0	3	3600
76691	8	com.sonyericsson.home.	2014-05-23 11:58:38	0	0	20
76690	8	com.whatsapp.COMMUNICATION	2014-05-23 11:57:50	0	0	48
76689	2		2014-05-23 11:57:31	0	2	2200
76688	2		2014-05-23 11:54:27	0	0	1500
76686	3		2014-05-23 11:42:35	2	0	0
76687	8	com.sonyericsson.home.	2014-05-23 11:35:03	0	0	485
76685	8	com.ing.mobile.FINANCE	2014-05-23 11:34:43	0	0	19
76684	8	com.whatsapp.COMMUNICATION	2014-05-23 11:25:41	0	0	412
76683	8	com.sonyericsson.home.	2014-05-23 11:07:00	0	0	450
76682	8	com.symbolic.pitchlab.MUSIC_AND_AUDIO	2014-05-23 10:55:31	0	0	20
76681	8	com.ovelin.guitartuna.TOOLS	2014-05-23 10:54:20	0	0	19
76680	8	com.android.vending.	2014-05-23 10:54:00	0	0	19
76679	8	com.sonyericsson.home.	2014-05-23 10:52:55	0	0	20
76678	8	org.cohortor.gstrings.TOOLS	2014-05-23 10:51:46	0	0	20
76677	8	com.sonyericsson.home.	2014-05-23 10:51:16	0	0	29
76676	8	com.whatsapp.COMMUNICATION	2014-05-23 10:50:56	0	0	19
76675	8	com.sonyericsson.home.	2014-05-23 10:42:35	0	0	500
76674	8	com.android.chrome.COMMUNICATION	2014-05-23 08:29:06	0	0	9
76673	8	com.sonyericsson.home.	2014-05-23 08:19:55	0	0	29
76672	8	com.android.vending.	2014-05-23 08:19:45	0	0	9
76671	8	com.whatsapp.COMMUNICATION	2014-05-23 08:19:35	0	0	9
76670	8	com.android.chrome.COMMUNICATION	2014-05-23 08:15:21	0	0	9
76669	8	nl.negentwee.TRAVEL_AND_LOCAL	2014-05-23 08:15:11	0	0	9

Appendix V: Personality test

Answering these questions accurately requires honest reflection on how you really think, feel, and act <u>in general</u> and maybe taking the test on more than one occasion. Some of the questions on this test measure personality traits differently than you might guess so trying to answer the test in a way you think would be ideal is just going to screw up your results, so just focus on being honest if you want the most accurate results.

PLEASE NOTE: SELECTING THE MIDDLE ANSWER MEANS A STATEMENT IS AROUND 50% ACCURATE

Very Inaccurate ○ ○ ◉ ○ ○ Very Accurate

1) I take things seriously.

Very Inaccurate ○ ○ ◉ ○ ○ Very Accurate

2) I am messy.

Very Inaccurate ○ ○ ○ ○ ○ Very Accurate

3) I get stressed out easily.

Very Inaccurate ○ ○ ○ ○ ○ Very Accurate

4) I am not easily bothered by things.

Very Inaccurate ○ ○ ○ ○ ○ Very Accurate

5) I talk for no reason.

Very Inaccurate ○ ○ ○ ○ ○ Very Accurate

6) I am talkative.

Very Inaccurate ○ ○ ○ ○ ○ Very Accurate

7) I am often late.

Very Inaccurate ○ ○ ○ ○ ○ Very Accurate

8) I can be unsympathetic.

Very Inaccurate ○ ○ ○ ○ ○ Very Accurate

9) I put the needs of everyone ahead of my own.

Very Inaccurate ○ ○ ○ ○ ○ Very Accurate

10) My thoughtfulness and charitable nature are my foundation.

Very Inaccurate ○ ○ ○ ○ ○ Very Accurate

11) I am a brainiac.

Very Inaccurate ○ ○ ○ ○ ○ Very Accurate

12) I will do anything for others.

Very Inaccurate ○ ○ ○ ○ ○ Very Accurate

13) I would take a 10% raise to move to a job where I did theoretical research all day.

Very Inaccurate ○ ○ ○ ○ ○ Very Accurate

14) I would rather please myself than others.

Very Inaccurate ○ ○ ○ ○ ○ Very Accurate

15) I am unphased by setbacks in life.

Very Inaccurate ○ ○ ○ ○ ○ Very Accurate

16) I dislike routine.

Very Inaccurate ○ ○ ○ ○ ○ Very Accurate

17) I prefer very structured environments.

Very Inaccurate ○ ○ ○ ○ ○ Very Accurate

18) I don't like to draw attention to myself.

Very Inaccurate ○ ○ ○ ○ ○ Very Accurate

19) I am reserved.

Very Inaccurate ○ ○ ○ ○ ○ Very Accurate

20) I am unplanned.

Very Inaccurate ○ ○ ○ ○ ○ Very Accurate

21) I take time out for others.

Very Inaccurate ○ ○ ○ ○ ○ Very Accurate

22) I keep in the background.

Very Inaccurate ○ ○ ○ ○ ○ Very Accurate

23) I don't mind being the center of attention.

Very Inaccurate ○ ○ ○ ○ ○ Very Accurate

24) I am attracted to solving complex problems.

Very Inaccurate ○ ○ ○ ○ ○ Very Accurate

25) I use difficult words.

Very Inaccurate ◯ ◯ ◯ ◯ ◯ Very Accurate

26) I find theoretical physics interesting.

Very Inaccurate ◯ ◯ ◯ ◯ ◯ Very Accurate

27) I am more relaxed than stressed.

Very Inaccurate ◯ ◯ ◯ ◯ ◯ Very Accurate

28) I talk nonsense.

Very Inaccurate ◯ ◯ ◯ ◯ ◯ Very Accurate

29) I keep my emotions under control.

Very Inaccurate ◯ ◯ ◯ ◯ ◯ Very Accurate

30) I am scientific.

Very Inaccurate ◯ ◯ ◯ ◯ ◯ Very Accurate

31) My own happiness and success are more important than the happiness and success of others.

Very Inaccurate ◯ ◯ ◯ ◯ ◯ Very Accurate

32) I love large parties.

Very Inaccurate ◯ ◯ ◯ ◯ ◯ Very Accurate

33) I have many fears.

Very Inaccurate ◯ ◯ ◯ ◯ ◯ Very Accurate

34) I am not sympathetic of the feelings of everyone.

Very Inaccurate ◯ ◯ ◯ ◯ ◯ Very Accurate

35) I am usually prepared.

Very Inaccurate ◯ ◯ ◯ ◯ ◯ Very Accurate

36) I am easily hurt.

Very Inaccurate ◯ ◯ ◯ ◯ ◯ Very Accurate

37) I say little.

Very Inaccurate ◯ ◯ ◯ ◯ ◯ Very Accurate

38) I am more interested in intellectual pursuits than anything else.

Very Inaccurate ◯ ◯ ◯ ◯ ◯ Very Accurate

39) I tend to be the life of the party.

Very Inaccurate ◯ ◯ ◯ ◯ ◯ Very Accurate

40) I am disorganized.

Very Inaccurate ◯ ◯ ◯ ◯ ◯ Very Accurate

41) I get upset easily.

Very Inaccurate ◯ ◯ ◯ ◯ ◯ Very Accurate

42) I serve others.

Very Inaccurate ◯ ◯ ◯ ◯ ◯ Very Accurate

43) I put others first.

Very Inaccurate ◯ ◯ ◯ ◯ ◯ Very Accurate

44) I am highly theoretical.

Very Inaccurate ◯ ◯ ◯ ◯ ◯ Very Accurate

45) I like order.

Very Inaccurate ◯ ◯ ◯ ◯ ◯ Very Accurate

46) I am more calm than worrying.

Very Inaccurate ◯ ◯ ◯ ◯ ◯ Very Accurate

47) I seek out the patterns of the universe.

Very Inaccurate ◯ ◯ ◯ ◯ ◯ Very Accurate

48) I follow a schedule.

Very Inaccurate ◯ ◯ ◯ ◯ ◯ Very Accurate

49) I put myself first.

Very Inaccurate ◯ ◯ ◯ ◯ ◯ Very Accurate

50) I am quiet.

Very Inaccurate ◯ ◯ ◯ ◯ ◯ Very Accurate

51) I am outgoing.

Very Inaccurate ◯ ◯ ◯ ◯ ◯ Very Accurate

52) I detach to analyze factors from multiple perspectives.

Very Inaccurate ◯ ◯ ◯ ◯ ◯ Very Accurate

53) I am always worried about something.

Very Inaccurate ○ ○ ○ ○ ○ Very Accurate

54) I am more controlled than random.

Very Inaccurate ○ ○ ○ ○ ○ Very Accurate

55) I talk out loud to myself.

Very Inaccurate ○ ○ ○ ○ ○ Very Accurate