Measuring loneliness using passive sensing data from the mobile application BEHAPP

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Abstract

Loneliness is a subjective experience of a lack of satisfying social relationships and networks, which can cause significant distress in individuals. Loneliness has numerous implications for health and society. Loneliness can be assessed with help of surveys, but these have several limitations. This could be overcome with the use of passive sensing, which is the measurement of behaviour without active intervention by the subject. Here we investigate whether passive sensing data from the mobile application BEHAPP correlate with survey-based measurements of loneliness. We also study whether scales could be formed from the BEHAPP data and correlate these with scores of loneliness using a principal components analysis. A dataset originating from the PRISM study was used for this. The dataset contains data of 68 individuals with a wide range in age and (psychiatric) diseases (Alzheimer's disease and schizophrenia) and has BEHAPP data for several sensor features that belong to multiple smartphone sensors. We found that the total number of calls, number of people who called or were called by a subject, number of missed calls and duration of all app and call events correlated significantly and positively with survey scores of loneliness. Four components, *phone addiction, calling behaviour, location* and *missing calls* were formed. None of the scales correlated significantly with loneliness. The literature suggests that age and state of disease may interact with some scales and influence the correlation between loneliness and them. We argue that the significance of the correlation between a feature and loneliness may depend upon the specificity of the feature and the diversity in age and disease in the relatively small sample that we used. A bigger sample is needed in order to detect possible correlations between loneliness and other, more specific features. We suggest that not yet existing features could be correlated to loneliness in future research.

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Introduction

Definition of loneliness and related concepts

Over the last decades, a lot of investigations have been performed on loneliness by researchers. It is commonly recognized that loneliness forms a major burden for society with many health implications (Holt-Lunstad, Smith, Baker, Harris & Stephenson, 2015; M. Lim, Eres, & Vasan, 2020). From an evolutionary perspective, loneliness is seen as an aversive signal indicating that essential social connections are lacking and may thus act as a motivating force to seek contact with conspecifics in order to enhance chances of survival (Goossens et al., 2015). One important concept that has frequently been associated with loneliness is social isolation. Compared to the subjective nature of loneliness, social isolation is defined as the objective absence of social relationships and networks on an individual level and society (Griffin, 2010). Although loneliness and social isolation are sometimes mistakenly seen as equal concepts, studies indicate they are distinct (Cacioppo, Hawkley & Thisted, 2010; Savikko, Routasalo, Tilvis, Strandberg & Pitkälä, 2005). Social isolation is the objective absence of social relationships and networks on an individual level and society (Griffin, 2010). Loneliness, on the other hand, is seen as a subjective experience of an individual about a lack of satisfying social relationships and networks, accompanied by significant distress (Perissinotto, Cenzer & Covinsky, 2012; Savikko et al., 2005). Other indications of this distinction come from correlational studies, where on average the correlation coefficient between social isolation and loneliness reached approximately 0.3, which is relatively low (Cornwell & Waite, 2009; Coyle & Dugan, 2012; Matthews et al., 2016). Based on this, loneliness may be seen as an independent concept.

Aetiology of loneliness

To date, a substantial body of literature has accrued on the investigation of loneliness, its epidemiology and its relations to other health factors. For example, the prevalence of loneliness among humans is estimated between 10 and 30%, varying by age (Beutel et al., 2017; Nicolaisen & Thorsen, 2014; Nyqvist, C.R. Victor, Forsman & Cattan, 2016; C.R. Victor & Yang, 2012). However, evidence on the direction of the relation between age and loneliness is conflicting as some researchers report an increase of loneliness with older age (Nicolaisen & Thorsen, 2014), whereas others observe a decline in loneliness rate with age (Beutel et al., 2017; Nyqvist et al., 2016). Other studies report even more complex, non-linear relationships between loneliness and age (Hawkley, Buecker, Kaiser & Luhmann, 2020; Luhmann & Hawkley, 2016; C.R. Victor & Yang, 2012).

From both cross-sectional and longitudinal studies, it is seen that loneliness has associations with more factors. For instance, factors that are negatively associated with loneliness are marital status, household income, (self-rated, psychological) health and frequency of social contact (Franssen, Stijnen, Hamers & Schneider, 2020; Hawkley et al., 2020; Rico-Uribe et al., 2016). On the other hand, some factors that are related to higher levels of loneliness include depressive symptoms (Lasgaard, Goossens & Elklit, 2011; Liu et al., 2020), health risk taking – e.g. substance use – among adolescents (Stickley, Koyanagi, Koposov, Schwab-Stone & Ruchkin, 2014) and internet and smartphone addiction (Bian & Leung, 2015;

Bozoglan, Demirer & Sahin, 2013). Also, quite a wide range of psychiatric disorders, including depression, panic disorder, anxiety disorder, obsessive-compulsive disorder and psychosis are associated with relatively high levels of loneliness (Alasmawi et al., 2020; Meltzer et al., 2013).

These are just a few of the numerous cross-sectional studies on associations with loneliness that have been done already. However, a major limitation of cross-sectional studies on loneliness is that they are unable to pinpoint causal relationships. Therefore, a growing number of longitudinal studies are also being done on loneliness as to elucidate these causal relationships. These studies have discovered several antecedents to loneliness. First, a well-known predictor of loneliness is the loss of a partner, especially among the elderly (Aartsen & Jylhä, 2011; Dykstra, Van Tilburg & Gierveld, 2005; Savikko et al., 2005; Theeke, 2009). Other factors, such as shrinkage of social network and reduced social activity tend to predict loneliness (Aartsen & Jylhä, 2011; Dahlberg, Andersson, McKee & Lennartsson, 2015; C.R. Victor & Bowling, 2012) as well as depressive symptoms (Aartsen & Jylhä, 2011; Cacioppo, Hughes, Waite, Hawkley & Thisted, 2006; Dahlberg et al., 2015) and physical impairments (Dahlberg et al., 2015; Theeke, 2009).

Loneliness as predictive factor for health outcomes

Also important are the many aversive health outcomes that are predicted by loneliness. These detrimental outcomes might be averted by regularly assessing loneliness for those at risk. This could in turn lead to better health outcomes. According to current literature, there are numerous negative health outcomes that are predicted by loneliness. For example, higher loneliness predicted reduced sleep quality (Harris, Qualter & Robinson, 2013), increased blood pressure (Hawkley, Thisted, Masi & Cacioppo, 2010), reduced physical activity (Hawkley, Thisted & Cacioppo, 2009), work disability among the middle aged (Morris, 2020), more frequent use of health care agencies (Geller, Janson, McGovern & Valdini, 1999; Gerst-Emerson & Jayawardhana, 2015) and depressive and affective symptoms in children (Qualter, Brown & Rotenberg, 2010), adults (Cacioppo et al., 2006, 2010) and the elderly (Domènech-Abella, Mundó, Haro & Rubio-Valera, 2019; Holvast et al., 2015; Luo, Hawkley, Waite & Cacioppo, 2012). In the latter group, odds of remission were lower among lonely individuals (Holvast et al., 2015). Moreover, a recent study indicated the existence of a bidirectional, causal relationship between loneliness and depression, meaning that loneliness can cause depression and vice versa, which may imply that loneliness and depression enhance each other (Hsueh, Chen, Hsiao & Lin, 2019). Furthermore, cognitive decline and Alzheimer's disease in elderly seems to be predicted by loneliness and vice versa, indicating a second 'vicious circle' (Holwerda et al., 2014; Zhong, Chen, Tu & Conwell, 2017). Another outcome of high loneliness is mortality (Herlitz et al., 1998; Luo et al., 2012; Tabue Teguo et al., 2016). According to a recent review, there is a 26% increase in likelihood of mortality in people who feel lonely in comparison to those who do not feel so (Holt-Lunstad et al., 2015). Lastly, attempts to estimate economic costs as a consequence of loneliness have also been made. It is estimated that, in a period of some 10 to 15 years, the costs of loneliness could rise in the order of thousands of dollars per person (Mihalopoulos et al., 2020). All of the above indicate that loneliness has a broad and far-reaching impact on human health, economics and thus society.

Measurement of loneliness using surveys

In the previously discussed studies, several methods for measuring loneliness have been employed. For instance, some studies used one question – *'Do you feel lonely?'* – to assess scores of loneliness (Herlitz et al., 1998; Holwerda et al., 2014; Nyqvist et al., 2016). One study found that a single question seems suitable to use in a sample with mainly elderly people (C. Victor, Grenade & Boldy, 2005). The one-question method readily allows for a dichotomous distribution of loneliness scores such that it can be used in logistic regression models with other variables that are relevant to loneliness (Nyqvist et al., 2016). However, some researchers claim that this 'simplicity' also has some disadvantages. By way of example, it was observed that loneliness is a multifactorial phenomenon (de Jong-Gierveld & Kamphuls, 1985; de Jong-Gierveld & Van Tilburg, 2008; McHugh & Lawlor, 2013). It might thus be risky to summarize this in a single question. An appropriate answer to this question also requires knowledge about the definition of loneliness, which may in turn vary depending on one's personal background (C. Victor et al., 2005). A single question more or less forces people to directly 'label' themselves lonely, which is seen as stigmatizing (Austin et al., 2016; C. Victor et al., 2005).

To overcome these limitations, surveys specified to loneliness are used that more implicitly and extensively ask about feelings of loneliness. Two commonly used surveys to assess loneliness are the University of California Los Angeles (UCLA) (Russell, Peplau & Ferguson, 1978) and the de Jong-Gierveld loneliness scale (dJG) (de Jong-Gierveld & Kamphuls, 1985). With this, researchers hoped to develop an instrument to measure loneliness on a more continuous scale (de Jong-Gierveld & Kamphuls, 1985). For a detailed overview of the questions posed in these surveys, see (de Jong-Gierveld & Kamphuls, 1985; D. Russell et al., 1978). For both surveys, it is recognized that they are reliable and valid instruments to measure loneliness with (Neto, 2014; Penning, Liu & Chou, 2014; Russell, 1996; Vassar & Crosby, 2008).

Unfortunately, the UCLA and the dJG scales do not seem to be free of pitfalls. One commonly known problem of surveys is that they are subject to wording effects. Here, two types of wording are distinguished: negative and positive wording. The first refers to sentences that include a negative such as 'not', whereas this is not the case for the latter. Research points out that wording effects are present for both loneliness scales (Dodeen, 2015; Penning et al., 2014). For example, for the UCLA-scale it is found that there are as well negative as positive wording effects (Dodeen, 2015). Therefore, scientists claim to be cautious with handling this scale, as these effects may negatively affect a subject's outcome score and thus obscure relevant patterns in the data (Dodeen, 2015).

Besides these method effects, the usage of such surveys requires a strict routine application, which is considered troublesome (Sanchez, Martinez, Campos, Estrada, & Pelechano, 2015). Answers on questionnaires are also subject to memory problems of participants (Eagle, Pentland & Lazer, 2009; Petersen, Austin, Kaye, Pavel & Hayes, 2013) and over- or underestimation of the metric that is questioned (Austin et al., 2016; Salthouse, Berish & Miles, 2002). Recent research has found that there might be a disease-related bias as well in responses on surveys. In particular, it was observed that patients with AD and

schizophrenia seemed to have a greater response bias as the severity of the disease increased (Jongs et al., 2020).

Finally, some subjects who were initially classified as lonely by the direct question were classified as non-lonely on either of the continuous scales, thereby denoting a substantial difference between the explicit one-question method and the more implicit aforementioned questionnaires (Shiovitz-Ezra & Ayalon, 2012). Although an elaborate analysis of the differences between the methods lies beyond the scope of this report, it should be remarked that eventual inconsistencies between results of studies are possibly due to the use of these two separate assessment methods (Shiovitz-Ezra & Ayalon, 2012).

Measurement of loneliness using passive sensing

As a consequence of these caveats of survey-based measurement of loneliness, scientists have developed a wide variety of technologies to measure loneliness using passive sensing. Passive sensing is the use of technologies that register behaviours without active involvement of the user. Examples of methods used for passive sensing are smartphone apps and bodily mounted devices, such as accelerometers. Sensor types include: light sensors, global positioning system (GPS), accelerometer, call and text logs. By means of these sensors, multiple (behavioural) outcomes can be detected. For instance, in a study by Petersen et al. (2013), the researchers used contact sensors and motion activated video cameras to measure in-home behaviours possibly related to loneliness. Results showed that time out of home negatively correlated with UCLA loneliness scores (Petersen et al., 2013). However, limitations of this method are that it requires installation of sensors at home, which only collects data when individuals are at home (Sanchez et al., 2015). To overcome this limitation, smartphone-based sensing methods to measure loneliness have been worked on recently.

One of the first studies to assess mobile passive sensing in relation to loneliness was that of Ben-Zeev, Scherer, Wang, Xie and Campbell (2015). A total of 47 participants enrolled in the 10-week lasting study. Several psychological behaviours – including loneliness – were correlated to measurements on geospatial and kinaesthetic activity, sleep duration and others with help of passive sensing. A major finding with regard to loneliness was that higher physical activity was related to a decrease in loneliness scores afterwards (Ben-Zeev et al., 2015). Also, W. Sanchez and colleagues (2015) found that UCLA scores of loneliness were associated with outgoing and incoming calls and time spent out of home (W. Sanchez et al., 2015). Another example comes from a study with college students. It was found that loneliness negatively correlated with the number of incoming and outgoing calls and moving and travelling from home (Pulekar & Agu, 2016). However, it is hard to generalize these results to the general population due to the small sample size (9 students). A study with a larger sample was carried out by Gao, Zhu, Liu and Liu (2016). In this study, 127 volunteers in possession of a smartphone were recruited to collect data from, with the smartphone application *MobileSens*. Consistent with previously mentioned studies, the number of phone calls was negatively correlated with loneliness. In addition, some types of applications were positively correlated with loneliness, such as health & fitness and social media. These findings imply that smartphone data could help in recognizing elevated levels of loneliness and subsequently

anticipate on this by improving social interactions (Gao et al., 2016). The discussed and additional research is summarized in ***Table 1***.

More generally, some researchers have not merely looked at correlations between single smartphone features and social behaviours. In recent studies, principal components analysis (PCA) has been used as an alternative method in order to understand how passive sensing data are related to survey-based measurements (R. Wang et al., 2020; W. Wang et al., 2020). The advantage of using PCA is that the number of features can be drastically reduced without losing too much information, which helps simplifying the dataset. The goal of PCA is dimension reduction, to combine a larger of features into a smaller number of principal components (PCs) which adequately describes the variation in the data. In the context of social sciences, PCA offers the possibility to reveal PCs that actually represent distinct behavioural patterns that can in turn be correlated to measurements with surveys (R. Wang et al., 2020; W. Wang et al., 2020). W. Wang and colleagues (2020) observed a high frequency of incoming and outgoing SMS together with less environmental voice duration and more time using apps related to social media. This then translates into the behavioural pattern of *texting and chatting on the phone without others around* (W. Wang et al., 2020). It was also found that making and receiving more calls cohered with having less conversation and visiting more places during certain parts of the day (R. Wang et al., 2020).

Furthermore, the features in the principal components may cluster with each other based on what type of feature they belong to. In general, it seemed that sensor *scales* or *dimensions* could be formed based on real data. For example, two distinct call features - incoming and outgoing – seemed to cluster with each other quite frequently (R. Wang et al., 2020; W. Wang et al., 2020). Circadian features that are related to sleep patterns clustered as did features related to app use (W. Wang et al., 2020). Mobility features such as the relative amount of time spent at home and the number of locations visited were also paired in a component (M. Sanchez et al., 2017).

Current study

In the present study, one of the questions we try to answer is to what extent scores of loneliness correlate with smartphone features of the smartphone application BEHAPP. This is an application with the capability of gathering data objectively from a participant's smartphone, with the purpose of measuring communication and exploration behaviours (*BeHapp*, n.d.). The dataset that is used in this study originates from the PRISM (**P**sychiatric **R**atings using **I**ntermediate **S**tratified **M**arkers) project (Kas et al., 2019) and contains data that was extracted from the mobile phone of the participants, during a period of 6 weeks. The data used represents a sample that consists of healthy people and people with either schizophrenia or Alzheimer's disease (AD) (Bilderbeck et al., 2019). Since several psychiatric illnesses are also associated with elevated levels of loneliness, such as schizophrenia (Trémeau, Antonius, Malaspina, Goff & Javitt, 2016) and AD or dementia (Holwerda et al., 2014; Wilson et al., 2007), we expect to have a broad range of loneliness scores. We presume that the results of our correlation analysis of features with loneliness will resemble the results given in ***Table 1***.

Secondly, we conduct a PCA subsequent to the correlation analysis to investigate whether certain groups of features form distinct scales based on the variation between individuals. If

so, we presume that three scales will be formed based on prior research. These are components that will separately encompass: call, app usage and mobility features (M. Sanchez et al., 2017; R. Wang et al., 2020; W. Wang et al., 2020). We expect the resulting components (i.e. scales) to be correlated with one another, as it is considered usual that social behaviours correlate with each other in these sciences (Chung et al., 2018; De Nadai, Cardoso, Lima, Lepri & Oliver, 2019; S. Kim, J. Kim & Jee, 2015; Meehl, 1990). Here, we briefly present some works that indicate that different (smartphone) behaviours correlated with each other. It was found that smartphone or app usage was inversely associated with physical activity (Kim et al., 2015) but correlated positively with mobility (De Nadai et al., 2019). In another study, it was observed that the smartphone addiction correlated with later self-reported onset of sleep time and shorter sleep duration (Chung et al., 2018). Based on these studies, we may thus hypothesize that the scale of *app usage* correlates with the *mobility* scale. We also correlate each of these components to the loneliness scores of participants to find out if BEHAPP components are able to indicate the presence of loneliness. According to ***Table 1***, we think that the *call* and *mobility* scale correlate negatively with loneliness and the *app usage* scale correlates positively with loneliness. To date, the only research that utilized PCA in combination with passive sensing was related to schizophrenia or peri-urban and rural movement [see (M. Sanchez et al., 2017; R. Wang et al., 2020; W. Wang et al., 2020)]. Hence, we believe that this is the first study in which PCA is applied to passive sensing data together with loneliness.

Table 1. Overview of smartphone features that correlate with loneliness and our hypotheses

Behavioural outcome	**Correlation with loneliness**	**References**	**Hypothesis**
No. call logs (general)	**-**	Gao et al., 2016; Petersen, Thielke, Austin & Kaye, 2016; Pulekar & Agu, 2016	**-**
No. incoming calls	**-**	Gao et al., 2016; Petersen, Thielke, Austin & Kaye, 2016; Pulekar & Agu, 2016	**-**
No. outgoing calls	**-**	Gao et al., 2016; Pulekar & Agu, 2016	**-**
No. contacts	**-**	Pulekar & Agu, 2016	**N/A**
% of calls missed	**+**	Pulekar & Agu, 2016	**+**
Text logs	**+**	Pulekar & Agu, 2016	**N/A**

System app use*	**+**	Gao et al., 2016	**N/A**
Health app use*	**+**	Gao et al., 2016	**+**
No. browser app opened	**+**	Gao et al., 2016; Pulekar & Agu, 2016	**N/A**
No. Wi-Fi-points connected to	**+**	Pulekar & Agu, 2016	**N/A**
Time out of home	**-**	Austin et al., 2016; Petersen et al., 2014	**-**
Time in places for social events	**-**	Doryab et al., 2019	**-**
Length of sedentary bouts** Physical activity***	**+** **-**	Doryab et al., 2019; Ben-Zeev et al., 2015	**N/A** **N/A**

*Denotes the frequency with which the apps were used. **at least 5-min < 10 steps of movement. *** Participant was active if there was movement for at least 5 min within a 10-min epoch. In the ***Correlation with loneliness*** column, '**+**' indicates a positive correlation, whereas '**-**' indicates a negative correlation with loneliness. **N/A** means that the feature is not in our data.

Materials and Methods

Data collection

Smartphone usage data - BEHAPP

Smartphone data was collected from the participants during an assessment period of 6 weeks for each participant over a period between August of 2017 and March 2019 using the previously mentioned app BEHAPP. For more technical details of the usage of the app, app features and data collection procedures see (Bilderbeck et al., 2019; Jagesar, 2016; Jongs et al., 2020; van der Wee et al., 2019). Procedures of data protection were adhered to as best as possible during the phase of data collection (Mulder, Jagesar, Klingenberg, Bonnici & Kas, 2018; van der Wee et al., 2019). After the period of raw data collection, variables or *features* were created to describe the behaviours in our data. These features are used for the analysis of our data in relation to loneliness. To initialize the process of feature creation, the raw data was subdivided into four subdomains: *Call logs, Global Positioning System (GPS)*, *app usage* and *phone usage*. App features are summarized in ***Table 2***.

The dataset

The dataset consists of data originating from a part of 168 participants who participated on and finished the PRISM project. For more details on the regulation of the project and sample characteristics, an overview can be found in the paper by Bilderbeck et al. (2019). Eventually, 83 subjects chose to also participate on the part of the project related to the BEHAPP application. Further attrition of the sample was due to the fact that people did not activate the BEHAPP application or had too few data to estimate feature values. Participants who had data for a minimum of 14 unique days were included in the dataset. In this way, data from 68 participants could be retrieved from the original sample. The dataset contains 35 variables, of which 28 were BEHAPP variables and 7 were non-BEHAPP variables. The variables in the former group are also stated in ***Table 2*** and the latter group is explained here. The 6 non-BEHAPP variables include: disease

label (healthy control, Alzheimer's disease and schizophrenia), sex (male, female), country (Spain and the Netherlands), age, years of education and loneliness. Each participant was assigned a unique BEHAPP-ID. Regarding the BEHAPP features, the quantities in each entry of the dataset were expressed as count-based behavioural phenotypes or duration-based behavioural phenotypes, depending on the variable measured. The quantities were then averaged over the number of days on which there was data for that variable.

Table 2. Sensor types and their extracted features

Sensor type	Extracted feature	Feature label
Call	Duration* of outgoing calls;	OutCalls
	Duration of incoming calls;	InCalls
	No. calls;	N_CALLS
	No. unique contacts that (was) called;	N_CONTACTS
	No. missed calls;	N_MISSED_CALLS
	Percentage of missed calls	MISSED_CALLS_(%)
Phone usage	Duration of call and app events;	PHONE_USAGE
	No. call and app events;	N_PHONE_USAGE
	No. call and app events between 0:00 and 5:00	PHONE_USAGE_NIGHT
	Duration of call and app events between 0:00 and 5:00	N_PHONE_USAGE_NIGHT
	Duration (hours) without call and app logs (sleep);	SLEEP
	Standard deviation of above;	SLEEP_STDEV
	The average* moment of waking up based on amount of app and call data;	WAKE_TIME
	Standard deviation of above;	WAKE_TIME_STDEV
	The average moment of going to sleep based on the amount of app and call data;	BED_TIME
	Standard deviation of above	BED_TIME_STDEV
	The daily average of the proportion of 20 minutes intervals that an application is opened	ADDICTION_20m
App usage	Duration of *communication* apps opened;	CommApps
	Duration of *social* apps opened;	SocialApps
	Duration of *health* apps opened	HealthApps
Location, GPS	Duration of traveling events;	Traveling
	Duration of stay points;	Stationary
	Duration of stay points annotated 'HOME';	Home
	Duration of stay points other than home visited between 19:00 and 00:00;	LeisureStaypoints
	Percentage of which an individual is at home;	Home_(%)
	Average distance from home for all stay points excluding home;	DISTANCE_FROM_HOME_AVG
	Max distance from home for all stay points excluding home;	DISTANCE_FROM_HOME_MAX
	No. unique stay points	N_UNIQUE_STAYPOINTS

* Durations were summed up and averaged over the number of days with data, resulting in the average duration per day. ** This was also averaged over the number of days with data.

Loneliness

The de Jong-Gierveld 11-item loneliness scale was used to assess levels of loneliness among the participants on a 5-point Likert scale. After processing the raw scores, the scores per item were reencoded to 0 for low loneliness and 1 for high loneliness. Hence, the total score could fall between 0 and 11. For additional information on the coding of the scores, and the survey itself see (De Jong-Gierveld & Kamphuls, 1985; De Jong-Gierveld & Van Tilburg, 1999).

Data pre-processing

Data cleaning and tidying

Data cleaning was done in order to facilitate further analysis on the data. Missingness of the data was handled as follows. When data were absent in call-related features, it most likely indicated that participants did not make or receive any calls during the period because calls are rare events in the data. For this reason, missing entries were converted to zeros for these features. Features were also screened for appropriateness of the occurring scores and discarded from subsequent analyses when values were systematically inappropriate. Data were screened for outliers to run the Pearson correlation analysis correctly. This is important, because the Pearson correlation coefficient is sensitive to outliers in the data (Schober, Boer & Schwarte, 2018). Outlier detection is done with help of a robust outlier method that is called *adjusted outlyingness* (AO). This method is described as robust against deviations from normality of higher dimensional data and is described the paper of Hubert and van der Veeken (2008). This method is particularly useful for passive sensing data, as it tends to have many dimensions and tends to be significantly skewed for several features (Gao et al., 2016). For the PCA, missing entries were deleted with help of listwise deletion.

Factorability of the data

A factorability test is run for the data in order to determine whether the data is feasible for further analysis with help of PCA. The test comprises the following, based on a schematic procedure provided by Pett, Lackey and Sullivan (2003). The correlation matrix of the BEHAPP-features is also inspected, its determinant included. If the latter lies between 0 and 1 and exceeds 0.00001, then items or features correlate strong enough to each other but not too strong. Either of two features or both should be removed if these have a (Pearson) correlation coefficient of > 0.8 with each other (Fellnhofer & Puumalainen, 2017; Shrestha, 2021). Next, Bartlett's test of sphericity is conducted to assess whether items are correlated to each other well enough. If this is the case, it confirms that linear combinations of items exist (Beavers et al., 2013). A Kaiser-Meyer-Olkin (KMO) test of sampling adequacy is done to test whether shared variance in items exists. If the Bartlett's test is significant (i.e. $p < 0.05$) and if the KMO-value ≥ 0.5, then it is considered appropriate to conduct a PCA (Kaiser & Rice, 1974).

Data analysis

Association analysis

For the demographic variables, it is assessed whether disease label matters for the loneliness scores as well as for age. We expected that loneliness scores would be elevated in AD and SZ patients. It is also expected that it is AD that contributes to a broader range in age. For this, a one-way ANOVA is conducted if the data is distributed normally and if there is homogeneity of variance. For non-normal data with homogeneity of variance between the groups, a Welch's ANOVA is conducted. Otherwise, a Kruskal-Wallis test is done. A Bonferroni correction is applied for multiple comparisons.

Correlation analysis

For all feature variables, the correlation with loneliness is calculated by means of simple correlation analysis. If necessary, mathematical transformations are performed to construct a monotonic and linear relationship between the two variables. Bivariate outliers are calculated for loneliness in relation to one feature for all features. These are then filtered out with help of the AO method described earlier and converted to non-numerical values. Only observations that have a non-missing loneliness AND non-missing feature value are included. Afterwards, the Pearson product-moment correlation coefficient is calculated.

Principle component analysis (PCA)

Principle component analysis (PCA) is performed to assess to what extent scales form based on the available data. In our case, oblique rotation techniques are used because we expect the scales to be correlated with each other. The oblique rotation technique *Promax* is used in the workflow. We choose for this method, as it can be used quickly and seems to generate solutions that are more replicable than those seen with the *Direct Oblimin* method of rotation (Hendrickson & White, 1964; Kieffer, 1998). The workflow of the PCA is based on the one provided by Furr and Bacharach (2007) and is described below. After the PCA is conducted, the number of components is extracted based on **1)** the point of flattening in the scree plot and **2)** the absolute magnitude of the eigenvalue that are a measure of the proportion of variation explained by a component and the strength of a component, respectively. Eigenvalues that exceed the (absolute) value of 1 [Kaiser criterion (Kaiser, 1960)] could be included in a follow-up examination of component-component associations (Furr & Bacharach, 2007). The Promax rotation technique is used accordingly to achieve a component structure that is as simple and interpretable as possible. After that, the item-component associations per component are examined. This is done by looking at the *pattern matrix* that comes out of the PCA. The entries of this matrix contain a loading of an item on a component (*pattern coefficient)* after correcting for possible correlations between components (Furr & Bacharach, 2007). If a simple structure arises with clear-cut item-component associations, then these associations are studied in more detail. This is done to investigate how the components themselves are determined by the items.

There is also the case in which a simple structure does not arise (i.e. *ambiguous* structure) after component-extraction and rotation. If an ambiguous structure occurs, at least one of the following rules is violated. In a component loading matrix, each row should contain at least one zero (i.e. none of the items load on all components) (Kieffer, 1998). Also, items should have component-loadings near zero on all components but one. That is, an item should only have a substantial component loading on no more than one component (UCLA: Statistical Consulting Group, n.d.). This item-component loading is considered substantial if and only if it is equal to or larger than 0.32 (Tabachnick & Fidell, 2007). Components should also contain at least three items that strongly load on it to speak of a solid component (Costello & Osborne, 2005). In this study, the 'item' is considered a BEHAPP-*feature*. If the component structure is ambiguous, the step of component extraction is re-evaluated and the number of components that are extracted is adjusted. This is done whilst keeping the three aforementioned criteria of component extraction in mind. The steps of component rotation and *feature*-component examination are also performed again to still assess if a simple structure arises.

The analysis does *not converge* if a simple structure does not appear despite repeated variation of the number of components extracted. A solution to this is to drop the feature(s) that hinder(s) the formation of a simple component structure. These are the features that either do not have a loading on any component or load on all components with 0.32 or higher. After that, the PCA is reconducted and the whole process of rotation and component examination starts over. Above described processes are repeated until a clear component structure arises from the data (Furr & Bacharach, 2007) (**Figure 1**). If, eventually, a simple structure arises, the component-component associations are examined in more detail by looking at the *component correlation matrix*. This matrix indicates if and how components are correlated to one another. If none of the components is related to another component an orthogonal PCA is conducted. The preferred method for doing this is *Varimax*. This is considered a preferable method because other methods such as

Quartimax tend to have more methodological drawbacks (Kaiser, 1958). Eventually, it is asserted that the variance explained by the remaining components should be at least 60% (Hair, 2014). If we do not reach this threshold according to the three criteria mentioned above, then it might mean that we have a (too) small sample or that there is too much variation in the feature values (noisiness) to capture as much variation as possible in a small number of components.

Software use

The data is pre-processed with the programming languages Python (Python 3.8) and RStudio (R version 4.0.2). Data cleaning and correcting is done in Python as well as the association and correlation analysis. R is used to find outliers in the data for the correlation analysis and to do the PCA.

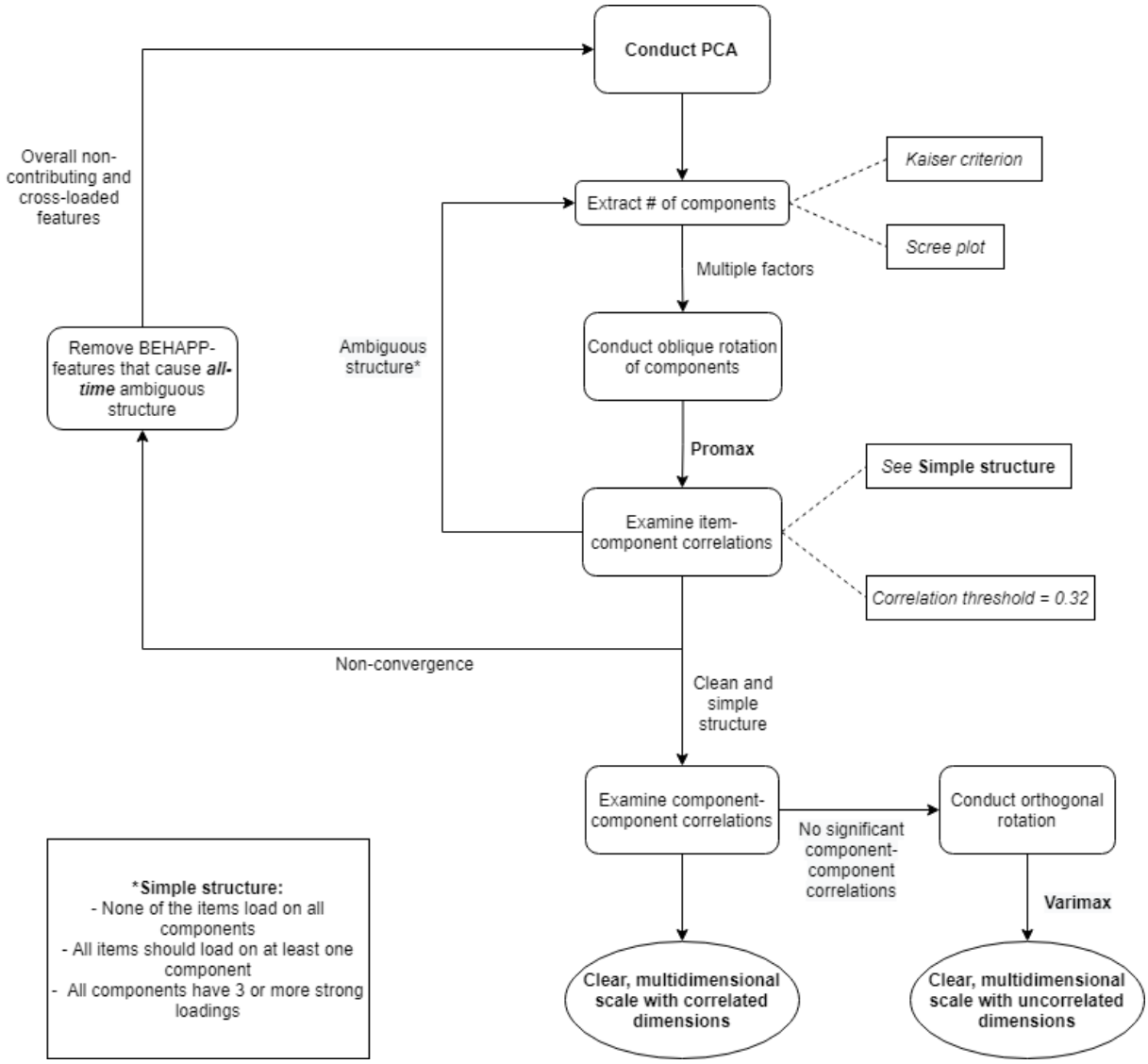

Figure 1. Schematic of the workflow for the PCA based on work of Furr and Bacharach (2007).

Results

Data cleaning

The data was successfully cleaned. Missing values of phone call features were converted to zero values.

Descriptive statistics of the study sample

The dataset contained data of 68 participants. The sample consisted of healthy controls (n = 29), subjects with schizophrenia (SZ, n = 18) and subjects with Alzheimer's disease (AD, n = 21). The sample consisted of both males (n = 44) and females (n = 24). Participants originated from the Netherlands (n = 39) or Spain (n = 29). The mean age of the participants was 48.9 ± 20.0 years and the mean number of years of education was 16.1 ± 4.6 years. Mean loneliness score was 2.6 ± 3.1 (***Table 3***). ***Figure 2*** shows the distribution of loneliness scores among the 68 participants.

Table 3. Demographic characteristics of the study sample

Quantitative variables	**Mean (standard deviation)**
Age	48.9 (20.0)
Education years	16.1 (4.6)
Loneliness	2.6 (3.1)
Categorical variables	**Count (%)**
Sex	
Male	44 (64.7%)
Female	24 (35.3%)
Disease label	
HC	29 (42.6%)
AD	21 (30.9%)
SZ	18 (26.5%)
Nationality	
NL	39 (57.4%)
ES	29 (42.6%)

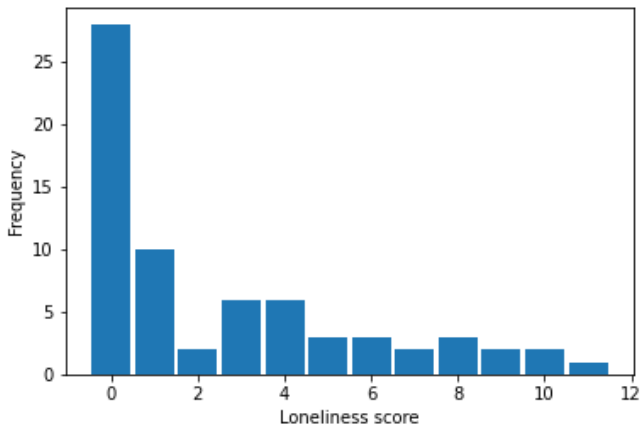

Figure 2. Distribution of loneliness scores among the 68 BEHAPP participants.

Descriptive statistics of features

Features were examined with respect to their distributions. It turned out that the distribution of feature values was significantly skewed for all features. Also, all features had a significantly skewed bivariate distribution when paired with loneliness (***Table 4***). All features, except circadian features, had zero implausible values. For instance, it was seen that bed times were spread over the day, with roughly half of the values indicating a bedtime in the middle of the day (***Table S1***). Thus, circadian features and their standard deviation were removed from the dataset and not included in the subsequent correlation analysis and PCA. As a consequence, 22 features were left to conduct further analyses on.

Table 4. Inferential properties of feature scores among participants.

Feature (label)	# of participants	Z-score univ.	p-value univ.	Univ. normal	Zirkler score biv.	p-value biv.	Biv. normal
OutCalls	68	5.01	< 0.001	No	5.30	< 0.001	No
InCalls	68	5.01	< 0.001	No	5.22	< 0.001	No
N_CALLS	68	4.48	< 0.001	No	4.18	< 0.001	No
N_CONTACTS	68	3.01	< 0.01	No	3.24	< 0.001	No
N_MISSED_CALLS	68	6.72	< 0.001	No	4.25	< 0.001	No
MISSED_CALLS_(%)	68	3.82	< 0.001	No	3.41	< 0.001	No
PHONE_USAGE	68	3.99	< 0.001	No	3.38	< 0.001	No
N_PHONE_USAGE	68	4.61	< 0.001	No	4.04	< 0.001	No
PHONE_USAGE_NIGHT	68	7.71	< 0.001	No	7.66	< 0.001	No
N_PHONE_USAGE_NIGHT	68	5.85	< 0.001	No	5.28	< 0.001	No
CommApps	68	6.53	< 0.001	No	4.49	< 0.001	No
SocialApps	68	5.91	< 0.001	No	5.42	< 0.001	No
HealthApps	68	7.71	< 0.001	No	7.58	< 0.001	No
Traveling	63	4.38	< 0.001	No	2.74	< 0.001	No
Stationary	65	5.87	< 0.001	No	5.06	< 0.001	No

Home	65	7.67	< 0.001	No	4.71	< 0.001	No
LeisureStaypoints	65	3.79	< 0.001	No	3.78	< 0.001	No
Home_(%)	65	-2.90	< 0.01	No	3.14	< 0.001	No
DISTANCE_FROM_HOME_AVG	65	9.20	< 0.001	No	10.22	< 0.001	No
DISTANCE_FROM_HOME_MAX	65	8.59	< 0.001	No	8.37	< 0.001	No
N_UNIQUE_STAYPOINTS	65	2.68	< 0.01	No	2.77	< 0.001	No
ADDICTION_20m	68	2.70	< 0.01	No	3.09	< 0.001	No
SLEEP	64	2.74	< 0.01	No	2.83	< 0.001	No
SLEEP_STDEV	61	2.28	< 0.05	No	2.36	< 0.001	No
WAKE_TIME	68	2.90	< 0.01	No	2.86	< 0.001	No
BED_TIME	68	-1.99	< 0.05	No	3.07	< 0.001	No
WAKE_TIME_STDEV	67	4.36	< 0.001	No	3.05	< 0.001	No
BED_TIME_STDEV	67	-3.10	< 0.01	No	2.98	< 0.001	No

Abbreviations: IQR; the interquartile range of the feature scores. **Z-score univ.**; the Z-score for the univariate distribution. Higher scores indicate more skewness. **p-value univ.**; the p-value for the univariate distribution. A p-value of < 0.05 indicates that the distribution of feature scores for a feature is significantly skewed. **Univ. normal**; Indicates whether the distribution of feature scores for a feature is normal: 'Yes' if it is, else 'No'. **Zirkler score biv.**; Is the Zirkler score for the bivariate distribution of a feature with loneliness. Higher scores indicate more skewness. **p-value biv.**; the p-value for the bivariate distribution of a feature with loneliness. A p-value of < 0.05 indicates that the distribution of a feature with loneliness is significantly skewed. **Biv. normal**; Indicates whether the bivariate distribution of a feature with loneliness is normal: 'Yes' if it is, else 'No'.

Kruskal-Wallis test

Loneliness scores were compared between healthy controls (HC), subjects with Alzheimer's disease (AD) and subjects with schizophrenia (SZ). A Kruskal-Wallis test indicated that there were differences between loneliness scores among the three disease groups ($H = 11.33, p = 0.003$). A pairwise post-hoc Dunn test with Bonferroni correction showed that loneliness scores of SZ subjects were significantly different (higher) compared to HC ($p = 0.006$) and AD subjects ($p = 0.012$) (***Figure 3***).

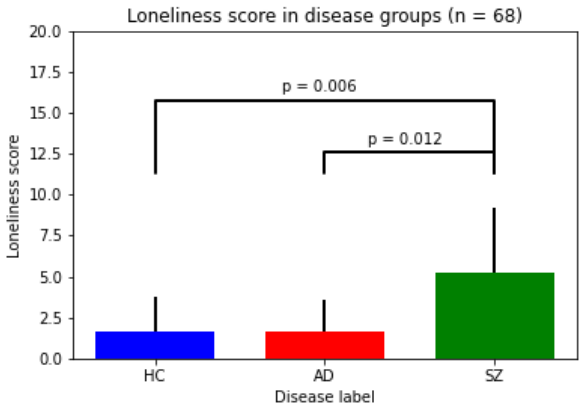

Figure 3. Loneliness and age among disease groups. Plotted are the mean and standard deviation of the loneliness scores. A Kruskall-Wallis test showed that the means of loneliness score were significantly

different among the three disease groups ($H = 11.33, p = 0.003$). A Dunn's post-hoc test showed significant differences for SZ vs HC, ($p = 0.006$) and SZ vs AD ($p = 0.012$), where subjects with schizophrenia had an elevated loneliness score. Note that the total number of participants here is 68. The number of participants for each group are: HC: n = 29; AD: n = 21; SZ: n = 18.

Correlation analysis

In ***Table 5*** the Pearson correlation coefficient for each feature in relation to loneliness is given for the 22 features that were left after filtering for features with inappropriate scores. In the leftmost column, the abbreviations of the features are indicated with the aforementioned feature labels. For each correlation analysis, the sample size is provided excluding missing values for either the feature or loneliness. As the p-values in Table 4 indicate, four out of the 22 features significantly correlated with loneliness. Three of them are features related to the *call* sensor (*N_CONTACTS, N_CALLS* and *N_MISSED_CALLS*), whereas the remaining feature belongs to the *phone usage* sensor (*PHONE_USAGE*).

Table 5. Correlation analysis of feature scores with loneliness scores in BEHAPP participants

Feature (label)	Sample size	Correlation with loneliness	p-value
ADDICTION_20m	62	-0.03498	0.787255
CommApps	57	0.193209	0.149872
DISTANCE_FROM_HOME_AVG	63	-0.13525	0.29058
DISTANCE_FROM_HOME_MAX	65	-0.02281	0.856879
HealthApps	68	0.08249	0.503648
Home	59	-0.02098	0.874652
Home_(%)	65	0.132053	0.294368
InCalls	68	-0.03727	0.762824
LeisureStaypoints	61	0.044359	0.73427
MISSED_CALLS_(%)	66	0.062737	0.616767
N_CALLS	62	0.317435	0.011937*
N_CONTACTS	62	0.404617	0.001107*
N_MISSED_CALLS	62	0.257774	0.043101*
N_PHONE_USAGE	66	0.10321	0.40956
N_PHONE_USAGE_NIGHT	68	-0.12493	0.310058
N_UNIQUE_STAYPOINTS	59	0.207755	0.114352
OutCalls	67	-0.04301	0.729628
PHONE_USAGE	63	0.280343	0.026053*
PHONE_USAGE_NIGHT	68	-0.16375	0.182109
SocialApps	67	-0.05518	0.65742
Stationary	65	-0.02325	0.854121
Traveling	63	0.128236	0.316537

Note: '*' indicates significance

Factorability of the data

The procedure of listwise deletion caused data of 5 participants to be removed from the dataset (after discarding features with inappropriate values, see ***Appendix II – Supplementary tables and figures***). As a result, data of 63 participants were still left to perform the PCA on. This dataset initially had 4 pairs of features that were too highly correlated to each other. At least either of the 2 features of each pair could be removed from the initial dataset, leaving us with a dataset that had a determinant of > 0.00001, passed Bartlett's test of sphericity and had a near-adequate KMO-value of 0.556. This dataset was also selected with help of the procedure for factor structure simplification shown in work of Furr and Bacharach (2007). This final dataset has 63 observations on 17 BEHAPP features.

Principal component analysis

We successfully obtained a component structure of a dataset with 63 observations (participants) on 17 BEHAPP features as mentioned earlier. 4 components were extracted that explained 63% of the total variation between subjects (***Figure 4***).

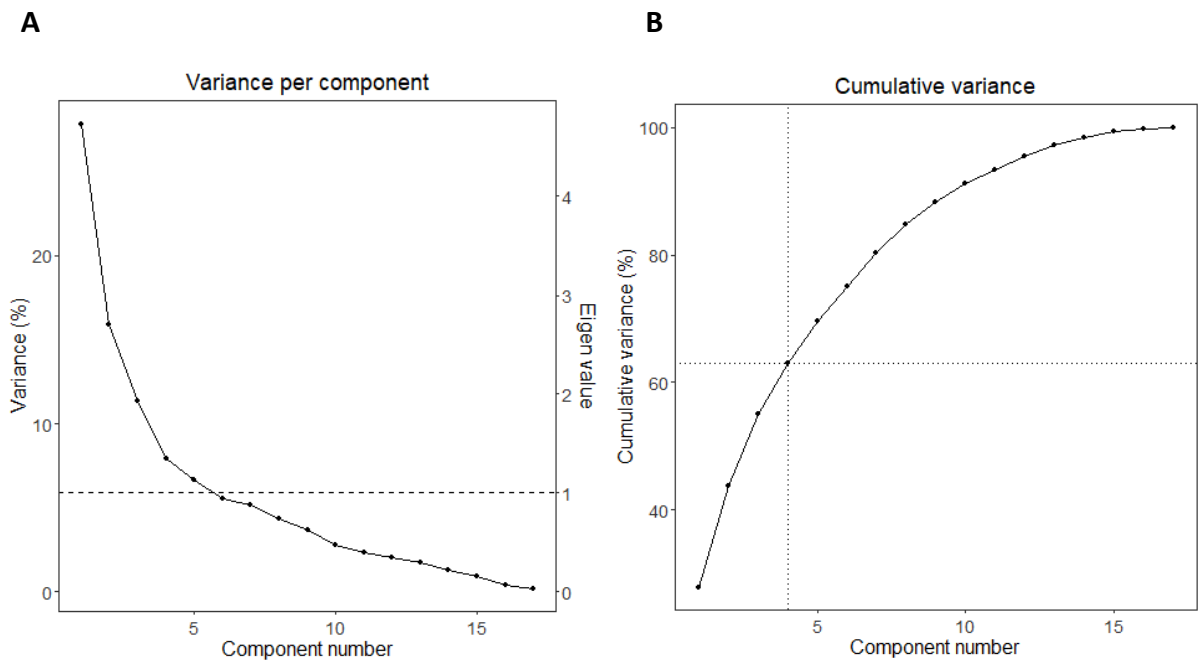

Figure 4. Variances of components. **A)** Variance per component for the 17 components shown. The number of components extracted was mainly based on the location of the elbow in the plot and the Kaiser criterion (dashed line at eigenvalue = 1). **B)** Cumulative variance shown for each component. The point at which 4 extracted components explain 63% of the variance is marked.

Table 6 contains an overview of how the BEHAPP features load on the four components. The components are named based upon the loadings that occur on particular BEHAPP features. For example, the component *Phone addiction* is named so, as predominantly phone usage features load on this component. Loadings that were lower than the threshold of 0.32 were omitted from the table for the sake of clarity. The loadings also indicate how strong each

feature loads on each component and in what direction. Subjects who score high on one component will score high on features that are positively associated with that component (i.e. have a positive loading on that component) and score low on features that have a substantial and negative loading on a component. Participants scoring high on the *Phone addiction* scale may use their phone more extensively, even in the night, as can be inferred from the relatively high loadings on *PHONE_USAGE_NIGHT* and *N_PHONE_USAGE_NIGHT*. High scores on the second component, *Calling behaviour* is associated with a longer duration of incoming and outgoing calls and more frequent calling, whereas traveling behaviour tends to occur less. Participants who are frequently out of home (*Location*) use their phone more scarcely in the night and spend more time in other locations than home.

Table 6. Principal component analysis item loadings

	Phone addiction	**Calling behaviour**	**Location**	**Missing calls**
Variation explained	*21.2%*	*17.5%*	*15.8%*	*8.5%*
OutCalls		0.821		
InCalls		0.827		
N_CALLS		0.928		
N_MISSED_CALLS		0.524		0.641
MISSED_CALLS_(%)				0.873
PHONE_USAGE	0.983			
PHONE_USAGE_NIGHT	0.652		-0.414	
N_PHONE_USAGE_NIGHT	0.645			
CommApps	0.769			
SocialApps	0.639			
HealthApps				-0.33
Traveling		-0.367		
Home			-0.717	
LeisureStaypoints			0.743	
Home_(%)			-0.776	
N_UNIQUE_STAYPOINTS			0.789	
ADDICTION_20m	0.846			

In ***Table 7***, the correlation between one component and another for each component and in ***Table 8*** the correlation between each component and loneliness scores are displayed (on the right). It can be observed that only the correlation between *phone* addiction and *calling behaviour* exceeds the predetermined threshold of 0.32. None of the BEHAPP scales correlated with loneliness significantly.

Table 7. Component intercorrelations

	Phone addiction	Calling behaviour	Location	Missing calls
Phone addiction				
Calling behaviour	0.404			
Location	0.08	0.075		
Missing calls	0.045	0.122	0.142	

Table 8. Correlation of component scores with loneliness

Component	Pearson's r	p-value
Phone addiction	0.009	0.946
Calling behaviour	-0.08	0.535
Location	0.019	0.881
Missing calls	0.021	0.868

Discussion

In this study, we examined the relationship between loneliness and BEHAPP features and tried to answer the question whether informative scales could be formed from the BEHAPP data. To begin with, we found that four out of a total of 22 features showed a significant correlation with loneliness scores. It seemed that in particular the total number of calls, contacts that (were) called and missing calls were positively correlated to loneliness scores. However, we did not find any correlation with loneliness for other call features, such as incoming and outgoing calls. These findings are therefore in contrast with what we hypothesized based upon the literature. Explanations on call behaviour in relation to loneliness are somewhat scarce. Though, an explanation for the opposite found in other studies (Gao et al., 2016; Pulekar & Agu, 2016) is given in the study of Sanchez et al. (2015). They explain that people who maintain contact with other people might be at a lower risk of suffering from loneliness (Sanchez et al., 2015). An increased number of phone calls would thus be associated with lower loneliness scores. However, Petersen and colleagues (2016) found that incoming calls were negatively associated with loneliness, whereas outgoing calls kept constant. They argue that people tend to become lonelier when they receive fewer calls, but make more calls in an attempt to make more connections with other people (Petersen et al., 2016). A possible explanation of the differences between the findings related to calling

behaviour in our study and these studies is that the variability in the discussed studies is lower. Namely, in the study of Petersen et al. (2016) they only recruited older adults, whereas in the research of Gao et al. (2016) and Pulekar and Agu (2016) merely younger people were included in the sample. There are also no indications that (psychiatric) diseases were taken into account in these investigations. Maybe there is an interaction between age, disease and features related to calling behaviour in the sense that the correlation between loneliness and the latter is influenced by age and disease. This could explain why we did not find a significant correlation between loneliness and calling behaviour. After all, we had a broader range for age and disease. Still, the total number of calls did correlate significantly with scores of loneliness. This might be because this feature includes both incoming and outgoing calls. For example, it could be that the number of total calls increases in more lonely people for different reasons. For one person a high number of total calls can be due to relatively many outgoing calls, whereas for the other this can be relatively many incoming calls. In both cases, it means that there is an increase in total calls, which might explain why loneliness scores are significantly correlated with total number of calls but not with incoming and outgoing calls in particular.

The other result was related to phone usage in general. We found a significant and positive correlation between loneliness and general phone usage. It is worth discussing some previous findings, especially because evidence from survey-based measurements on phone usage in relation to loneliness seems conflicting. Sometimes loneliness correlated significantly and negatively with smartphone use (Jafari, Aghaei & Khatony, 2019; Mansourian, Solhi, Adab & Latifi, 2014), but a positive correlation was also regularly found (Bian & Leung, 2015; Enez Darcin et al., 2016). An explanation for the latter is given by Bian and Leung (2015), in which they state that lonely people may more readily use a phone as to enlighten the burden of feeling lonely (Bian & Leung, 2015). The negative correlation between loneliness and phone usage found by Jafari et al. (2019) and Mansourian and colleagues (2014) may imply that individuals who make much use of a smartphone might feel less lonely in the end and thus actually fill out that they are not so lonely (Jafari et al., 2019). Since our finding is a continuation of the conflicting results of other studies regarding phone usage and loneliness, more passive sensing studies in relation to general phone use may be done in order to draw firm conclusions. A possibility to further investigate the relationship between loneliness and phone usage could be with help of longitudinal studies to track the dynamics of phone usage and loneliness.

There were also app usage features that did not correlate significantly with loneliness, whereas the general phone usage feature did so. We present several reasons for this. It might be that the more specific features correlate with loneliness in specific subgroups of the participants tested, but do not so in the whole study population. For example, it might be that loneliness correlates with the duration with which health related apps are opened only in younger people (e.g. students), as was seen in the study of Gao et al. (2016). It might be that this correlation fades away in the older age groups. Since we have quite a large range for age as well as multiple groups of disease, it could be suggested that the correlation of loneliness with more specific features is not significant anymore when it is measured for the whole study population. Another reason may be that our sample size was too small to detect significant

correlations for some features. In a follow-up study, a bigger dataset and more intricate analyses might be used in order to be better able to unravel a possible relationship between loneliness or other social behaviours and a feature.

With regard to the PCA, it should be mentioned that all of these results should be discussed in the light of hypothesis-generating research, as with a KMO of < 0.6 there are indications that the sample size is too small. Major findings include the revelation of BEHAPP *sensor scales* that each separately comprise *call*, *app usage* and *location* features, which was according to our hypothesis. We also found that the *Phone addiction* and *Calling behaviour* scales correlated to each other substantially (r = 0.404). This correlation might exist because both scales contain features of which the measurement depends on direct interactions with a mobile phone. For example, people who can readily handle a phone will not only use it for opening apps but may also be able to make a call more easily. This is in a far lesser extent or even not the case for measurements on behaviours related to mobility, where only the ownership and carrying of a smartphone on one's person is required. According to literature, there indeed seems to be a correlation between addiction to functions of a mobile phone and calling and texting (Warzecha & Pawlak, 2017) that was measured with help of a questionnaire that assessed mobile phone addiction. This interesting similarity may be further investigated in future studies that could assess the relationship between smartphone features and items on an smartphone addiction scale. While there were several significant correlations of BEHAPP features with loneliness, none of the BEHAPP scales had a significant correlation with loneliness. It is also true that each scale consists of multiple features that did not correlate with loneliness. For instance, it might be that a possible correlation between loneliness and these scales is obscured by an interaction between age and the scale *phone addiction*. In particular, in the older age groups or the demented (AD) subjects, participants may not use their phone so much compared with the younger, healthier participants (Alhassan et al., 2018; Benge et al., 2018; Lim, Nordin, Yee & Tan, 2020). In general, if there are lower component or loneliness scores for a specific group, then the correlation coefficient between loneliness and that component drops. This may lead to a possible situation in which there is no correlation between loneliness and phone addiction in the older age group and AD group but still in the younger and healthy age group. It could be that the total correlation between loneliness and phone addiction had become non-significant, because these groups were pooled together in our analysis. The same phenomenon could also apply to the *location* scale, where alterations in behaviours related to this scale may be ascribed to age (Bayam, Liebowitz & Agresti, 2005; Mahlknecht et al., 2013) and state of mental illness as well (Domenech-Cebrían, Martinez-Martinez & Cauli, 2019; Viertiö et al., 2009).

There are also important limitations in this study that can be addressed in future research. Firstly, as explained before, the variability relative to the sample size in the dataset is quite large. This makes it hard to detect possible meaningful effects regarding how loneliness scores correlate to sensor data. Data of more participants may be needed to address this issue. Secondly, there are indications that the sample we used is not representative of the general population. This is because the proportions of subjects with Alzheimer's disease and subjects with schizophrenia were 30.9% and 26.5% respectively, whereas in the general population the diseases have a lower prevalence (Saha, Chant, Welham & McGrath, 2005; Niu, Álvarez-

Álvarez, Guillén-Grima, Aguinaga-Ontoso, 2017). Furthermore, scores of loneliness may have been influenced in subjects with Alzheimer's and subjects with schizophrenia, as it is known that state of disease may bias responses on survey questions (Jongs et al., 2020). This could in turn influence the correlation between feature and loneliness scores. In order to examine the measurement of loneliness using smartphones, future studies could include other features which might be of interest in their research. For example, circadian rhythm features might be interesting, as there are indications that measurements of sleep rhythm can be brought in relation to loneliness. Namely, sleep quality and duration might be related to loneliness (Doane & Thurston, 2014; Harris et al., 2013; McHugh & Lawlor, 2013). A multimodal approach may be used to measure sleep by including inferences on an accelerometer, ambient sound and light if possible (Ben-Zeev et al., 2015, Chen et al., 2013). Light sensors might be included to measure ambient light, as ambient light and changes herein are closely associated with the circadian rhythm of human-beings (Blume, Garbazza & Spitschan, 2019). Thirdly, several features which have been found to be correlated to loneliness were not included in the BEHAPP features. It might be useful to continue on building in new sensors as to create new features. For instance, the number of text messages received or made as well as the number of Wi-Fi-points someone is connected to (Pulekar & Agu, 2016) and physical activity measured with an accelerometer (Ben-Zeev et al., 2015) were found to be correlated with loneliness scores. This indicates that the BEHAPP features may need to be expanded to perform more meaningful measurements on loneliness or other social behaviours. Lastly, the study was not longitudinal in nature, which means no conclusions regarding the predictive value of the feature scores could be made. Longitudinal studies with smartphone-based passive sensing methods are necessary to examine the value of mobile sensing features for the prediction of loneliness. Despite those limitations, this research is a good starting point in discriminating between features in the BEHAPP application that are probably important in relation to loneliness.

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Appendix I – Python and R functions used

Functions used in Python (version 3.8)

Jupyter Notebook is used as the environment to write code in. The necessary packages and specific modules are imported with the **import** statement followed by **package.*module.*** *function*. Function calls related to a module are made with the statement ***module****.function()*. As such, **pandas** (**v1.0.5**) is used to import the data set into the programming environment, to refine and clean the dataset for further analysis and to clarify results into tables. **numpy** (**v1.18.5**) is used to do the necessary element-wise operations on the dataset. **scipy.*stats.*** *skewtest* (**v1.5.0**) and **pingouin.** *multivariate_normality* (**v.0.3.10**) are used to assess the skewness of the univariate distribution of feature scores and the bivariate distribution of feature scores with loneliness scores, respectively. For tests on loneliness scores in the disease groups HC, AD and SZ, the *f_oneway* from function from **scipy.*stats*** is used for normal data, with its matching post-hoc test *pairwise_tukeyhsd* from **statsmodels.*stats.*** *multicomp* (**v0.11.1**). For normal data with unequal variances between the groups, the *welch_anova* function from the package **pingouin** is used, with the same post-hoc test as mentioned previously. Otherwise, the *kruskal* function from **scipy.*stats*** is used, with Dunn's post-hoc test as *posthoc_dunn* from **scikit_posthocs** (**v0.6.7**), with a Bonferroni correction. The *pearsonr* function is applied to calculate the correlation coefficients of interest (see ***Correlation analysis***).

Functions used in R (version 4.0.2)

The detection of outliers is done with help of the function *adjOutlyingness()* from the package ***robustbase*** (**v0.93.7**), which is described in the package documentation of Maechler and colleagues (2021). R is used to calculate bivariate outlying observations. The function *adjOutlyingness()* is used with the following parameter values. The input dataset is a subset of the loneliness variable and one feature each time bivariate outlyingness was calculated. The number of directions (*ndir*) to project the data on was set to 25000 times the number of columns in the subset to assure reliable outlier detection. For the PCA, the function *combinations* from the package ***gtools*** (**v3.8.2**) was used to generate possible datasets based on the removal of combinations of highly correlated features. The function *bart_spher* from ***REdaS*** (**v 0.9.3**) was used to calculate Bartlett's test of sphericity for these datasets. The sample size for finding directions was set to the number of columns (2) in the subset (*p.samp*). The lower constant and upper constant that are related to the tails of the bivariate distribution were set to 3.5 and 4.0 respectively, as was also shown in the paper of Brys, Hubert, & Rousseeuw (2005). *coef* was set to 1.5 as is the usual constant to multiply the IQR with when considering cutoffs for outliers (Hubert & Van der Veeken, 2008). *qr.tol* was set to 1×10^{-7} as was recommended in the package documentation of the package ***robustbase*** by Maechler (2021). Other parameters are held on the default values. The PCA is also done in this environment with help of the function *principal* from the package ***psych*** (**v2.1.3**). The argument 'promax' was set to true to get rotated components in the solution. 'oblique.scores' was set to FALSE to make sure that the component scores are based upon the pattern matrix. Other parameters were held on the default value. For more information on the package see the package documentation from Revelle (2021) (***Appendix III – Supplementary references***). ***comprehenr*** (**v0.6.10**) and ***ggplot*** (**v3.3.3**) were used to do necessary list comprehensions and make plots, respectively.

Appendix II – Supplementary tables and figures

Table S1. Descriptive properties of the feature scores among participants solely related to feature values.

Feature (label)	# of participants*	Min	Max	Median	IQR
OutCalls	68	0	14.48	1.27	0.31 - 3.31
InCalls	68	0	14.24	0.95	0.28 - 3.38
N_CALLS	68	0	10.97	1.69	0.78 - 3.01
N_CONTACTS	68	0	2.16	0.47	0.23 - 0.89
N_MISSED_CALLS	68	0	3.33	0.3	0.12 - 0.58
MISSED_CALLS_(%)	68	0	75	16.45	8.49 - 27.29
PHONE_USAGE	68	0.64	390.92	82.37	27.36 - 135.73
N_PHONE_USAGE	68	8.6	747.37	83.34	47.52 - 211.08
PHONE_USAGE_NIGHT	68	0	162.98	3.14	0.3 - 8.76
N_PHONE_USAGE_NIGHT	68	0	59.93	3.37	0.79 - 11.61
CommApps	68	0	251.16	25.75	7.36 - 39.46
SocialApps	68	0	129.59	0.22	0.0 - 19.45
HealthApps	68	0	8.13	0.16	0.03 - 0.49
Traveling	63	0.03	4.03	0.7	0.22 - 1.37
Stationary	65	0.37	70.53	5.64	2.89 - 11.0
Home	65	2.09	108.08	16.76	11.78 - 19.57
LeisureStaypoints	65	0	0.03	0.01	0.0 - 0.01
Home_(%)	65	7.1	98.86	68.83	56.27 - 85.65
DISTANCE_FROM_HOME_AVG	65	0.99	5557.58	11.82	5.88 - 51.23
DISTANCE_FROM_HOME_MAX	65	1.27	7357.91	51.91	20.03 - 170.38
N_UNIQUE_STAYPOINTS	65	0.15	2.52	0.77	0.5 - 1.2
ADDICTION_20m	68	0	0.72	0.17	0.09 - 0.37
SLEEP	64	4.37	22.91	9.74	8.04 - 12.74
SLEEP_STDEV	61	1.01	8.95	3.47	2.29 - 4.88
WAKE_TIME	68	5.33	17.2	9.25	8.04 - 10.93
BED_TIME	68	1	20.84	13.98	8.98 - 17.0
WAKE_TIME_STDEV	67	1.17	8.68	2.66	1.78 - 3.54
BED_TIME_STDEV	67	0	12.7	8.7	6.69 - 10.12