Master Thesis Data Science and Society

Representational Similarity Analysis of Smartphone Use and Mood

By:
M.H.P. Roost
(2017225, U759603)

Thesis committee:
dr. A.T. Hendrickson
dr. D.J. Schad

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Department of Cognitive Science and Artificial Intelligence
School of Humanities and Digital Sciences
Tilburg University

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Abstract

People seem to use their smartphone more intensively every year. Excessive use of smartphones influences people's mood, mental health, and well-being in a negative way. This excessive use is becoming a big problem as people are experiencing difficulties because of this in daily life. Previous research has studied the relationship between mood and smartphone use by analyzing one or a few negative emotions. This present research uses a representational similarity analysis, a multivariate analysis method, to study this relationship with a broader range of moods and smartphone behavior features. The results of this research show weak correlations between similarity in smartphone use and similarity in mood in general with this analysis method and data. Furthermore, a small difference is found between positive and negative moods for smartphone behavior. Also, this study shows that the duration of smartphone use and the frequency of smartphone use are both useful measures to explain smartphone use. The results suggest that this present research might not provide enough information to state that there is a strong relationship between smartphone use and mood using RSA and this type of data.

Keywords: smartphone usage, mood, representational similarity analysis

Contents

1 Introduction

Nowadays, people spend much time on their phones, especially since smartphones are so intertwined with people's daily activities. The amount of time people spend on average on their smartphone is rising every year (SIDN, 2019). Several studies show that smartphone behavior influences people's moods in different ways (Elhai et al., 2016; LiKamWa et al., 2013). This influence has a significant downside since anxiety, stress, and depression are examples of typical mental health stages connected to excessive smartphone use (Shapka, 2019).

Another downside of the rising number of smartphone use is that many people are distracted by their smartphone when working or studying (Gracová et al., 2019; Zarandona et al., 2019). This distraction has an impact on the work and study performance of people. When people feel stressed over a more extended period, their life expectancy can be shortened (Zenonos et al., 2016). All these downsides can impact the mental health and productivity at work of people, especially when these problems persist for a longer time (Zenonos et al., 2016). The problem of people not being able to function optimally due to excessive smartphone use affects the performance of companies and other institutions that run on human resources. Therefore, this problem is not only a problem of society but also a problem in the business world. The well-being of people and the influence on companies has been studied in a wide range before (Bassi et al., 2013; Dar et al., 2011; Lee et al., 2014). These studies shows how high the importance of people's mood and well-being is for society and the productivity of businesses.

Because of the importance of this public health challenge, much research is done in this field. Studies have focused on the relationship between smartphone use and one specific negative emotion (Arnavut & Nuri, 2018; Demirci et al., 2015; Van Deursen et al., 2015; Wolniewicz et al., 2020). However, it is not clear if this relationship also exists for a broader range of moods. To be able to do a more extensive study that looks at the relationship between smartphone use and several moods at the same time, an analysis method that can handle many features at the same time is needed. A multivariate study like Representational Similarity Analysis (RSA) is an analysis method that can use many features and can compare across multiple dimensions (Popal et al., 2019). This present research focuses on analyzing this relationship between mood and smartphone use with another analysis method than what is done before to include more features. This is to see if the relationship that is stated in the literature still exists when taking into account all these different features and by using RSA.

1.1 Research questions

To investigate if it is possible to study this relationship with the representational similarity analysis method, the research question of this thesis is as follows:

To what extent can representational similarity analysis be used to identify similarities across mood and the intensity of smartphone application use?

For this study, research involving smartphone use behavior and the corresponding moods of people are used. With the use of this dataset, the following sub-questions contribute to answering the main research question:

1. *Which mood measure is most similar to smartphone use?*

All the similarities of different mood measures individually are compared to the similarity of smartphone use. This comparison is made to show which mood measurement shows the strongest similarity with smartphone use.

2. *How dissimilar are positive and negative moods for duration and frequency smartphone use?*

The theory in literature states that negative moods are more strongly connected to the increase of duration and frequency smartphone use (Arnavut & Nuri, 2018; Demirci et al., 2015; Van Deursen et al., 2015; Elhai et al., 2017; Extremera et al., 2019). For this question, similarity in negative and positive mood measures are compared individually to the similarity in duration and frequency of smartphone use. These comparisons test the difference in the similarity between positive and negative moods for an increased similarity in duration and frequency smartphone use.

3. *How similar are duration and frequency smartphone use for mood?*

Duration and frequency smartphone use are both defined as predictors to predict smartphone addiction (Haug et al., 2015; Lin et al., 2015). Therefore this question tests the similarity between duration smartphone use and frequency smartphone use for every mood measure. This, in turn, could show if similarity in duration smartphone use or frequency smartphone use are different and so their performance to predict smartphone addiction as literature states (Arnavut & Nuri, 2018; Bae, 2017; Lee et al., 2014; Lin et al., 2015). But also if similarity in these two measurements are different for similarity in different kind of moods.

4. *Is smartphone use more similar to itself than to any mood measure?*

For this question, similarity in duration and frequency smartphone use, two different smartphone use measurements, are compared to each other. This sub-question checks for the use of the methodology and data in this study as this has never been done before.

The first three sub-questions test for the features stated in literature as characteristics of the relationship between smartphone use and mood. By answering these questions, it could provide insight into the usefulness of using RSA to study this relationship. If this study can also confirm the use of the features, that are stated in the literature, to explain this relationship, RSA could be defined as a useful analysis method. This eventual confirmation supports the possibility of using RSA for a broader spectrum of studies than what is done before. The last sub-question is a methodological question. This sub-question is included to do a methodological check as it is straightforward that smartphone use is more similar to itself than to another mood measure.

1.2 Findings

The research shows that there is a small difference in similarity between positive and negative moods for the intensity of smartphone use. More similarity in excessive use of smartphones shows a positive correlation with similarity in negative moods, and the correlation with similarity in positive moods leans towards a negative correlation. Both frequency and duration are useful measurements to explain smartphone use. Also, the frequency and duration of smartphone use are strongly correlated, which means that as similarity in one increases, the similarity in the other increases. Overall, the correlations are not strong and do not direct convincingly towards a direction. This result suggests that RSA could not be used to identify similarities across mood and smartphone use.

1.3 Outline

First, the related work describes the underlying relationship for this study and highlights relevant literature in section 2.1. Next, in section 2.2 the analysis method that is used is explained broadly with literature and method examples. The next section shares the specifics of the data that is used in 3.1 and describes all the cleaning steps, preprocessing steps and implementation of the analysis method in 3.2, 3.3 and 3.4. Afterward, the results of the analysis are presented in 4 and discussed with the use of literature, limitations, and suggestions for further research in 5. In the end, in section 6, the research questions are answered, and a conclusion for this research is given.

2 Related Work

This section describes the relationship between smartphone use and mood further with literature and previous research in section 2.1. Following, a description of the literature that is relevant to another analysis method to study the relationship between smartphone use and mood in 2.2.

2.1 Smartphone usage and mood

This section covers the literature background of the relationship between smartphone use and mood and is divided into four sections. The first section 2.1.1 describes the literature that shows the impact of rising smartphone use. Next, section 2.1.2 covers the development of smartphone addiction and the consequences of that. In 2.1.3 the problems for mental health are covered and 2.1.4 shows the addition of this present research.

2.1.1 The impact of rising smartphone use

According to a study of SIDN (2019), Dutch people spent, on average, 61 hours per month on their smartphones. This number means that, on average, Dutch people spent more than two hours per day on their smartphones. Two years before, in 2016, it was only 40 hours per month (SIDN, 2019). People seem aware of their increasing smartphone use. This awareness is evident from the study of the Pew Research Center. This study shows that in general, 54% of the teens who participated in the study felt like they spent too much time on their smartphone. Besides, also 36% of their parents admitted doing this too much (Gracová et al., 2019). Besides, 15% of these parents stated that their phone was a real distraction when they tried to focus on work (Gracová et al., 2019). Also, a study of Zarandona et al. (2019), shows 23.3% of the students admitted their smartphone was a distraction during lectures and used it at least once during that lecture for personal ends. These numbers tell that using smartphones intensively impacts people's daily lives and their work and study performance. The problem of people not being able to function optimally because of rising smartphone use has, in turn, an effect on the performance of companies and other institutions that run on human resources. Therefore, this problem is not only a problem of society but also a problem in the business world.

2.1.2 Smartphone addiction

Spending much time on a smartphone does not only have an impact on the performance of people in their daily lives. Rising usage frequency and usage duration of smartphones are connected to smartphone addiction (Arnavut & Nuri, 2018; Bae, 2017; Lee et al., 2014; Lin et al., 2015). Excessive frequency and excessive time used both showed a strong association with smartphone addiction (Haug et al., 2015; Lin et al., 2015). However, different studies showed different outcomes of which measurement, frequency, or duration, is more strongly connected to smartphone addiction.

In the studies of Lee et al. (2014) and Lin et al. (2015), frequency predicted smartphone addiction better. But according to Fischer-Grote et al. (2019) and Haug et al. (2015), the time used on smartphones is a better indicator for smartphone addiction. This statement implies that frequency and duration are both useful measures for smartphone addiction. A different way of measuring frequency and duration shows different outcomes for a strong association with smartphone addiction.

There are several characteristics that people struggle with when they are addicted to using smartphones. Griffiths' component model of addiction measures seven core components that define a behavioral addiction (Griffiths, 2005). When all these seven symptoms, salience, mood modification, tolerance, withdrawal, conflict, problems, and relapse can be detected in the behavior, one can speak of addiction according to Griffiths (2005). One of the most prominent symptoms of addiction is mood modification (Lee et al., 2014). Long-lasting mood modifications could lead to lasting adverse mental health outcomes. Besides, young people have the highest risk of experiencing these negative mental health outcomes (Shapka, 2019). These mood modifications and negative mental health outcomes could express sleep disruption, moods like anxiety, stress, depression, loneliness, or even self-harm or suicide tendencies (Shapka, 2019). Also, 56% of the teens who participated in a study of Gracová et al. (2019) say that when they did not have their smartphone within reach, they felt lonely, upset, or anxious. In summary, excessive smartphone use is a critical public health challenge and connected to negative moods and mental health issues (Elhai et al., 2016).

2.1.3 Mental health problems from smartphone use

Previous research has reported several dimensions of how excessive phone usage affects the long emotional state, also known as mood. These studies focused on the relationship between problematic smartphone use, smartphone addiction and specifically anxiety (Arnavut & Nuri, 2018; Demirci et al., 2015), depression (Demirci et al., 2015; Wolniewicz et al., 2020) or general stress (Van Deursen et al., 2015). These studies showed how excessive smartphone use and smartphone addiction was strongly connected to these negative mental health outcomes. The method that was used to conduct these studies was divergent. For example, Arnavut & Nuri (2018) used multiple regression analysis with data from surveys and self-estimated smartphone behavior. Demirci et al. (2015) used linear regression analysis to explore the association between phone use and depression and anxiety. Other studies that used phone use data developed smartphone applications that enhanced public mental health (Bakker et al., 2018, 2016). Others identified mood from smartphone usage (LiKamWa et al., 2013) or tried to predict emotional state based on smartphone data (Fukazawa et al., 2019). This last study of Fukazawa et al. (2019) used a classification task to predict anxiety changes by using smartphone log data. Considering all the above, the research methods and input data of studies investigating the relationship between smartphone use and mood were different and extensive. However, these studies did not include a wide range of features for mood or smartphone behavior.

This connection between smartphone use and mental health also works the other way around according to other studies. Individuals were inclined to start using smartphones excessively to manage negative feelings or moods (Elhai et al., 2017, 2018; Extremera et al., 2019). This behavior showed that these people, mostly adolescents, wanted to avoid coping with these negative emotions and were looking for a distraction. They found this distraction by using their smartphone (Hoffner & Lee, 2015). This information states that not only smartphone usage has an influence on mood and influences people's emotional state negatively. However,it also states that negative emotions, like stress or depression, make people use smartphones more to handle that emotional state. All these studies showed that this relationship exists for both ways. Besides, all these studies showed how the relationship worked for smartphone use and negative moods in general. However, these studies were based on only one or a few (negative) moods to support the relationship between smartphone use and mood.

2.1.4 The connection with this present research

There seems to be a strong connection between smartphone behavior and emotional state. However, only a few moods were already highlighted, so it is interesting to analyze this brain-behavior relationship with a wider variety of several moods that people experience during the day. So the present research aims at analyzing a dataset that includes a broader range of different emotional states. Also, this study analyzes smartphone behavior patterns for multiple smartphone applications that are gathered via smartphone log data. To be able to handle this large number of features, a multivariate analysis method is used. A multivariate analysis method can find the relationship or pattern between several variables together (Hair et al., 1998). As a result, this analysis method can predict how the change in one variable affects the change in other variables. Representational similarity analysis is a multivariate method that can analyze across multiple dimensions and include a large number of features (Popal et al., 2019). This analysis method, frequently used in neuroscience, has never been used before to analyze the brain-behavior relationship between smartphone use and mood. Therefore it is exciting and beneficial to analyze this relationship with RSA.

2.2 Representational Similarity Analysis

Representational similarity analysis is a multivariate analysis method that has been used to analyze parts of patterns of brain-activity measurement, computational modeling, and behavioral measurement (Dimsdale-Zucker & Ranganath, 2018). Most studies that used the RSA analysis method before had brain activity data patterns (fMRI) as input for the study (Anderson et al., 2016; Tucciarelli et al., 2019). However, this analysis method is not exclusive for fMRI data Popal et al. (2019) and can also be used to analyze behavioral measurements connected to the brain. This is the case with the connection between smartphone usage and people's mood. So, it is an opportunity to use this analysis method for this present research.

In previous studies, RSA was mostly used for studies within neuroscience (Kriegeskorte et al., 2008; Nili et al., 2014). With this method, it is possible to compare two groups of stimuli and see how representations differ between groups by creating a contrast that takes the average response of stimuli within a group (Popal et al., 2019). RSA can be used to look at higher-order representational space, compare across multiple dimensions, or test several models of cognition (Kriegeskorte et al., 2008). Another unique benefit of RSA is that comparison can be made between different data sources (Popal et al., 2019), which means comparing behavioral data to neural response data. Besides, RSA uses distance measures to identify the representational space and can define all features of the domains instead of a subset of features like with other multivariate methods (Popal et al., 2019).

The focus of previous studies that analyzed brain-behavior relationships by using the RSA analysis method is divergent. An example is the study of Pegors et al. (2017) that analyzed how the content of messages that show anti-messages was related to change in behavior. The input features for this study were the different visual anti-smoking messages and ratings of the participants on the question if they wanted to quit after seeing the ad. The response was measured with a 5 point Likert scale. On top of that, they also measured the neural response of the participant with an MRI scanner. Another study of Blair et al. (2012) analyzed how people react, in terms of brain response, and what their reaction time was for comparing and translating positive and negative numbers. Input features were the comparisons of the negative and positive numbers, people's reaction time, and also a neural response with fMRI. These studies investigated the relationship between different domains that included behavior data and also neural data. However, as mentioned before, RSA is not exclusive for neural brain data studies. This is supported by the studies of Brooks & Freeman (2018) and Stolier et al. (2018) that did not use brain activity data. Instead, input data for Brooks & Freeman (2018) was mouse tracking activity data, and participants responded to the emotion category they identified pictures with. These studies show the wide capacity of using RSA for studies with different ranges of features, data patterns, and research domains. Also, the studies show how the use of RSA works for studies with brain-behavior relationships and studies that do not use brain activity data. This is important as this present research investigates a brain-behavior relationship with the use of data that does not include brain activity patterns.

For this present research, the data patterns represent the participants' mood and simultaneous activity patterns of the smartphone behavior of those same participants. Emotional responses are measured combined with the measurement of participants their smartphone use categorized for smartphone applications. In this way, the analysis measures if the information from every participant is represented in the features of these domains, and if there is a match or not. Meaning, the degree of (dis)similarity between the mood and smartphone usage of the participants can be assessed. One of the advantages of RSA is that it can handle a large number of features. So all the moods of participants and smartphone application categories use measured in different ways can be included in this study.

3 Experimental Setup

The following section describes a detailed description of the experimental procedure of this study. It is divided into four sections. Firstly, the description of the datasets in section 3.1. Secondly, all the preprocessing steps in section 3.2. Thirdly, section 3.3 shows the steps for creating the models. Lastly, the evaluation methods of the models are described in section 3.4.

3.1 Datasets

For this research, a combination of three datasets was used. The mood dataset, phone use dataset, and application dataset. These three datasets were used as they gave an overview of what people did on their smartphone all day long, very precisely, and how they felt during a specific day. The data was gathered from students who studied at Tilburg University and participated in the study of Hendrickson et al. (2019). The smartphone behavior data was gathered with log smartphone techniques between the 21st of February and the 26th of March 2019. Surveys were sent out to the participants between the 21st of February and due to an error, the 4th of June 2019.

The mood dataset consisted of 16016 rows of data that included insight into the participants' answers on a survey. This survey was sent four times randomly between 09:00h and 22:30h during the day. The mood dataset contained information about: user id, at what time the survey was sent, how much time was used to complete the survey, with which moods the participants identified themselves the last few hours, what their main activity and the social setting was the last few hours and if the participants enjoyed that situation.

The phone use dataset consisted of 586792 rows of data that included information on the smartphone usage of 124 participants. It contained information about: the category of the application used, battery percentage of the phone, end and start time of their use, notification information, session number, and user id.

The application dataset consisted of 1748 rows representing smartphone applications that were categorized into 59 unique smartphone application categories. This application dataset was an extension of the application information from the phone use dataset.

3.2 Preprocessing

All code for this research was written in the programming language Python (Van Rossum & Drake Jr, 1995) and can be found in Appendix A. The following section 3.2.1 describes how the mood features from the mood dataset are created. Also, section 3.2.2 describes how the smartphone application features from the phone use dataset and application dataset are created.

3.2.1 Mood features

There were a few rows in the mood dataset that were duplicate. Also, a few unique users in the phone use dataset were not present in the mood dataset. The lack of these users did not give a good representation of the participants and their mood indications. So, 14 duplicate rows and 23 error user IDs representing 1804 rows were excluded from the dataset. Furthermore, the participants needed to fill out the survey in two hours after it was sent. When the participant did not manage to do this, the survey expired. Also, some surveys were canceled by the participant, or due to an error, the survey was blocked. All these surveys did not have any or not enough information about the participants' mood and social setting. Therefore, all these 6398 rows were excluded from the mood dataset. As mentioned in section 3.1, the mood data continued for a more extended period than the phone use data. After the 26th of March, the data were excluded from the mood dataset because there was no registration of phone use for this last period. This data accounted for 138 rows, so eventually, the cleaned mood dataset contained 8390 rows of data.

Table 1 shows all the mood features that are used for modelling. The possible values for the moods varied between 'not at all' (value = 0) to 'extremely' (value = 5).

Variable name	Possible values	Explanation
Anxious	[0-5], ordinal	If the participant
Bored	[0-5], ordinal	felt like this mood
Gloomy	[0-5], ordinal	
Calm	[0-5], ordinal	
Stressed	[0-5], ordinal	
Content	[0-5], ordinal	
Cheerful	[0-5], ordinal	
Tired	[0-5], ordinal	
Energetic	[0-5], ordinal	
Upset	[0-5], ordinal	
Envious	[0-5], ordinal	

Table 1: Overview mood features

3.2.2 Smartphone Application features

A few cleaning steps that accounted for the mood dataset were also done in the phone use dataset. These steps were done in both datasets so they could be compared when using RSA. Equal length of datasets is useful for RSA when mood and smartphone use are compared for the same number of users. So, duplicate rows and error user IDs were excluded from the data.

In the application dataset, 14 applications were not assigned to a category. Therefore, these applications were manually assigned to an already existing category. The categorization of these applications can be found in Appendix B. For most of these applications, the application name was missing as well. So, the names of these applications were replaced based on the category names.

Then, the phone usage data was merged with the application dataset based on the shared variable *app_id*. This merge was done with the pandas package (McKinney et al., 2010) and in a way that no column or row got lost, but only the columns from the application data were added after the last column of the phone use data. The combination of the two datasets resulted in a new dataset smartphone application use.

Next, two new columns were made for this new combined dataset. The first column, *duration_app*, is the time a user uses an application. This variable was created by subtracting *startTimeMillis* and *endTimeMillis*. The second column *frequency_app*, was the number of times an application was used. The values of all rows in the phone use dataset were marked with 1.0 and summed per application category. Afterward, the higher-level feature for smartphone usage was computed. This feature was the time spent per use, computed by dividing duration by frequency for every application category.

As mentioned in section 3.1, all applications were categorized into 59 unique categories. Figure 1 shows how the usage of all these applications was divided. Due to formatting reasons, the bar plot shows the 40 most used applications. The Figures for the preprocessing part were made with the package matplotlib in python (Hunter, 2007). Figure 1 shows that the first eight applications accounted for the highest usage of smartphone applications.

These applications had a high impact on the category they were in because of this application's high-frequency usage. Therefore, the applications used more than 10,000 times were not assigned to a joined category of several applications but were a self-contained category. That applied to Facebook Messenger, Spotify, Whatsapp Messenger, Instagram, Snapchat, Facebook, Google Chrome, and Youtube. Also, not all application categories were used as much as other categories. By creating new categories, the frequency used per category was better distributed over all the application categories, as Figure 2 shows. So, categories that were of the same nature were combined, as was seen in other studies (Ferdous et al., 2015).

A better distribution over all the application categories was useful when computing dissimilarity for smartphone use between participants. This distribution improvement prevented that many categories were not used at all by many participants and therefore did not represent smartphone use well. Table 5 in Appendix C shows an overview of the new categories with application examples for this research.

Table 2 shows all the phone use application features that are used for modeling.

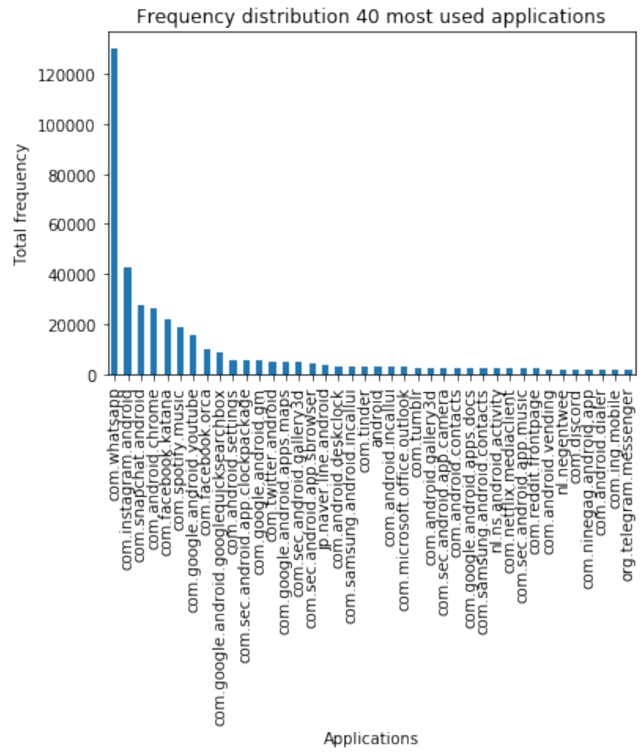

Figure 1: The frequency distribution of the 40 most used applications

Variable name	Possible values	Explanation
Duration, for every application category	$[0 - \infty]$, integer	18 features that measure the total time spent in an application from that specific category
Frequency, for every application category	$[0 - \infty]$, ordinal	18 features that measure the total number of times an application from that specific category is used
Duration per frequency/use, for every application category	$[0 - \infty]$, integer	18 features that measure the time spent per use of an application from that specific category

Table 2: Overview phone use application features

3.3 Modeling

This section describes theoretically the analysis method used for modelling in 3.3.1, followed by a description of how the models are created for smartphone use in 3.3.2 and for mood in 3.3.3.

As explained in section 2, Representational Similarity Analysis was used to

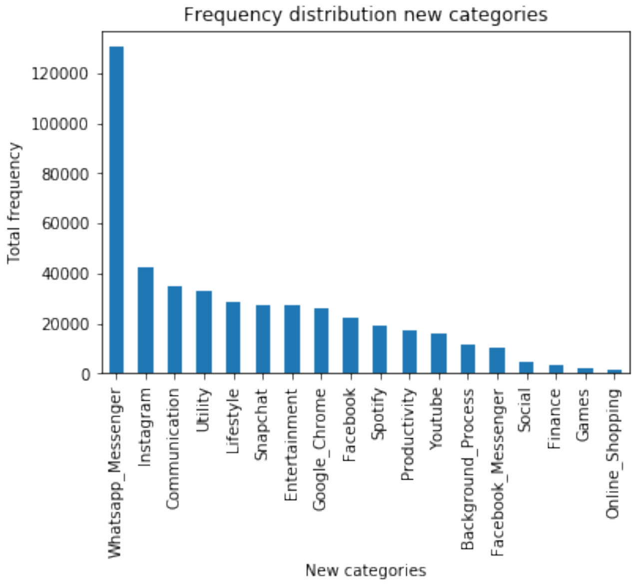

Figure 2: The frequency distribution of new smartphone application categories used

analyze the relationship, stated by literature, between smartphone usage and people's mood. In this section, there is first a theoretical explanation of the analysis method in 3.3.1, followed by details about the modeling part in Python in sections 3.3.2 and 3.3.3. In section 3.4, details about the evaluation of the models are described. For modeling and evaluation, the packages NumPy and Scikit-Learn were used. These were used as NumPy is useful for adapting matrices (Bauckhage, 2014), and Scikit-Learn offers hands-on functions to compute distance measures (Siless et al., 2013).

3.3.1 Theoretical description RSA

RSA is a multivariate method that has been used to extract parts of patterns of brain-activity measurement, computational modeling, and behavioral measurement (Dimsdale-Zucker & Ranganath, 2018; Kriegeskorte et al., 2008). For this present research, RSA was used to compare participant's mood across multiple dimensions (e.g. mentally tired *vs* stress *vs* anxious *vs* gloomy). RSA was also used to compare people's smartphone category use across multiple dimensions (e.g. duration use of communication apps *vs* entertainment apps *vs* social apps *vs* productivity apps).

In this present research, participants' moods and the smartphone application use were the two domains that were analyzed. Eventually, all domains were individually compared to each other, which resulted in a matrix called a representational dissimilarity matrix (RDM). This process is called the first-order RSA. First-order RSA showed how similar or dissimilar people were across that domain. So, the models in this study were constructed by an RDM that summarized the pairwise similarities between the smartphone users (Pegors et al., 2017). The models showed how similar people were across the use of application categories and mood. Given that there were 124 unique participants in this study, the matrices for smartphone use and mood contained 124 rows and 124 columns. So, the pairwise relationship between the different participants was represented. A big advantage of the matrices is that one can get a good understanding of the results. Also, RSA's valuable benefit is comparing RDM's with each other to see how well the information from one RDM was represented in the other RDM (Popal et al., 2019). RDM's were correlated to get a quantitative sense of the representations in both RDM's. This process is called the second-order RSA. The next sections 3.3.2 and 3.3.3 show how this is implemented for both the domains.

3.3.2 Models for smartphone application category use

Three models were constructed to investigate how similar people were across the use of application categories. A model in this study is a representational dissimilarity matrix (RDM). The first model, 'model smartphone use 1 time per use', was the higher-level model for smartphone application category usage as it represented a summarized value of duration divided by frequency. This model represented the duration per usage or session for an application category. The second model, 'model smartphone use 2 - frequency', calculated the similarity based on the frequency people spent on all smartphone categories. For this model, the feature *frequency_app* was used. The occurrence of a specific application category was summed per unique participant, which gave the total frequency of an application category used per participant. The third model, 'model smartphone use 3 - duration', calculated the similarity based on the duration people spent on all smartphone categories. These models were constructed so that the intensity of the use of applications was measured in different ways. The Euclidean distance was used as a similarity distance measure as it was used often in other studies (Guggenmos et al., 2018). Also, as it is reliable for behavioral data patterns, and accounts for variability across space (Kriegeskorte et al., 2008; Popal et al., 2019). For all of these three models, each cell contained the Euclidean distance between the total of duration, frequency use, or time per use of the application categories per participant. Formula 1 shows the formula where p is a data point that represents, e.g., the duration of smartphone use per application category and participant and v is the number of data points.

$$d = \sqrt{\sum_{i=1}^{v} (p_{1i} - p_{2i})^2} \tag{1}$$

This Euclidean distance for dissimilarity was computed by taking the difference between two points and square this distance. All these squared differences were summed for the number of points.

3.3.3 Models for mood

Three models were built as well to analyze how similar people were across mood. The first model, 'model mood 1 - all moods', calculated the similarity across all moods the participants in this study indicated they felt. The second model, 'model mood 2 - negative moods', calculated the similarity across only the negative moods. This model was created to analyze the relationship, stated in the literature, that smartphone use has a negative influence on people's moods (Elhai et al., 2016). A third model was created to ensure the test for that relationship. The third model, 'model mood 3 - positive moods', calculated the similarity across only the positive moods from the participants. The distinction between positive and negative moods was based on how the moods were categorized in other sources (Our English Class, 2018; Reber, 2017). The categorization of the valence of the moods can be found in Table 6 in Appendix D. For all these three mood models, the cells contained the correlation distance between the median of every mood. The correlation distance was used as this distance measure is a preferred distance measure for data patterns like people's emotional state (Aguirre, 2007; Pegors et al., 2017) and normalizes the variability across space (Kriegeskorte et al., 2008). The median was used as a central tendency because it is known for a well-explaining center size for ordinal data. Also, the median is less affected by skewed data and outliers (Wilcox & Keselman, 2003).

Formula 2 shows the formula for the correlation distance where x and y are two centered vectors of, e.g., the anxious values for two different participants.

$$d_{cor}(x, y) = 1 - \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{2}$$

This distance for dissimilarity was computed by calculating one minus the Pearson correlation, as seen in Kriegeskorte et al. (2008) to show how dissimilar participants were in their mood registrations.

3.4 Evaluation

This section describes the methods that are used to evaluate the models. Section 3.4.1 presents a description of how the models can be determined as statistically similar. Next, an explanation of the use of baseline models can be found in 3.4.2 and for cross-validation in 3.4.3.

To measure the relationship, the representational connectivity between the two domains of smartphone use and mood, the RDM's were compared. This representational connectivity could define the connection between the two domains (Kriegeskorte et al., 2008). A visual overview of all the model comparisons for every sub-question can be found in Appendix E. The Spearman Rank Correlation was used to evaluate the comparison between the RDM's and calculate the correlation since there was no assumption that this data follows a specific distribution (Kriegeskorte et al., 2008). A linear relationship between smartphone application use and mood could not be assumed because the values of the two were measured differently. The mood was measured on a 5 point Likert scale, and the smartphone behavior was continuous data. The noise within each RDM could be different as the RDM's were created from different data types. However, Spearman correlation accounts for the difference in noise within each RDM (Popal et al., 2019). Spearman Correlation accounts for people with extreme smartphone behavior or mood swings compared to others as it is robust against outliers (Popal et al., 2019). The correlation was calculated between different RDM's to evaluate the (dis)similarity between the models. The Spearman Rank Correlation assessed the strength and direction of the relationship between the two RDM's and was calculated by the Pearson correlation on the data's ranked values. Formula 3 shows the formula where n is the number of data points, or cells of the matrices and d_i is the difference in the ranks of the i^{th} element of each random cell.

$$r_R = 1 - \frac{6\sum_i d_i^2}{n(n^2-1)} \tag{3}$$

It was essential to diminish the possibility of false-positive correlations when comparing dissimilarity matrices (Ritchie et al., 2017). Diminishing was done by only using the lower or upper triangle of the dissimilarity matrices. Also, the diagonal with only zero's was excluded from the matrix half used to compare.

3.4.1 Statistically similar

A significance test was useful to determine if the RDM's, the so-called models, were statistically similar. When a correlation is statistically significant, it means that the chance that the strength of the relationship between the models happened by chance was less than at least 5% (Akoglu, 2018; Laerd Statistics, 2018). Also, when RDM's were significantly correlated, the conclusion of similarity between two domains is more grounded (Popal et al., 2019). When two RDM's were correlated but the p value was not known, the RDM's could also be correlated by chance (Saenger, 2019). The classical methods for statistical testing assume that two samples have independent measurements. However, according to Kriegeskorte et al. (2008), this cannot be assumed for RDM's. Also, the classical methods are mostly parametric that depend on assumptions like normality (Legendre & Legendre, 2012; Saenger, 2019). But as Figure 2 in section 3.2.2 shows, this cannot be assumed for the data of this research. Because the data does not follow a bell curve shape. Therefore, the standard method of significance testing was not used. A non-parametric alternative was proposed by Holmes et al. (1996) where permutation tests were used for significance testing. The central assumption for using the permutation test is the assumption of exchangeability (Ge et al., 2018). For this research, it is assumed that when randomizing the data values, the data is just as likely as the original data.

The definition of a permutation testing is that "a permutation test is used to determine the statistical significance of a model by computing a test statistic on the dataset and then for many random permutations of that data. If the model is significant, the original test statistic value should lie at one of the tails of the null hypothesis distribution" (Sim et al., 2009, p.2). First, the original correlation between the two original samples was calculated, for example, between all moods and duration for smartphone use. Secondly, a number smaller than N! was chosen as the number of permutations, where N is the number of values in one sample. Thirdly, the first original sample was permuted. This permutation means that a random selection of 5,000 permutations of one sample is used for the randomization test. The selection of 5,000 was chosen for this study as this number was often used in examples (Ge et al., 2018; Legendre & Legendre, 2012), and a large number smaller than 124!. Also, permutation testing is computational heavy, so, due to time constraints, this number was used as larger numbers take more time to run. Fourthly, correlations were calculated between all the 5,000 permutations and the original of the second sample. Finally, the original correlation between the two original samples was included, which resulted in 5,001 correlation values between the two samples. Eventually, the number of correlations larger than or equal to the absolute value of the original correlation was calculated. This number was divided by 5,001, which resulted in the p-value that showed if the correlation was statistically significant.

According to Nichols & Holmes (2002), "this method is conceptually simple, relies only on minimal assumptions, deals with the multiple comparisons issue, and can be applied when the assumptions of a parametric approach are untenable. Further, in some circumstances, the permutation method outperforms parametric approaches" (p.2). Several other studies that used representational similarity analysis used permutation testing for significance testing (Leeds & Shutov, n.d.; Thirion et al., 2015; Zopf et al., 2019). These studies showed that the permutation test is a popular method for the significance analysis of distance matrix correlations, especially when the assumption of a Gaussian distribution is violated.

3.4.2 Baseline models

Baseline models were created for the higher-level models to see how well the model comparisons performed. These baseline models were compared to create a baseline comparison. In this way, a natural way to use a baseline was created to compare the performance of the model comparisons. This baseline creation was done by randomly picking numbers between the minimum and maximum of the original model for the values of the data frames. After that, the same steps were followed. The similarity distance was calculated between every cell. It was assumed that the correlation of model comparison with randomly picked numbers is almost equal to zero. It could be used as a benchmark to compare with the created model comparisons.

3.4.3 Cross-validation

When one creates a model, it is essential to control for stability within the data. Usually, when a machine learning model was built, this was controlled by using cross-validation. The data was split up in several parts to train the model on different parts of the data (Shulga, 2018). However, for representational similarity analysis, there was no model training, and therefore the traditional way of cross-validation was not useful for this analysis method. Therefore, the data of all moods and duration per use were split up differently to control for stability within the data for this analysis. The mood and duration per use data were split up randomly into three parts. Afterward, the performance of the model with the total data was compared with the performance of the three models with every two different parts of the data. By comparing these performances, the stability within the data was tested. When data appeared to be stable, the statistical results of the study were more confident.

4 Results

In this section, the results of the first-order RSA are presented in section 4.1. The results of comparing the models of the second-order RSA are shown in section 4.2.

4.1 Performance of models

As described in section 3, six models were constructed by creating a representational dissimilarity analysis. Model mood 1 - all moods, model mood 2 - negative moods, model mood 3 - positive moods, model smartphone use 1 - time per use, model smartphone use 2 - frequency and model smartphone use 3 - duration. The dissimilarity was measured between all participants in the study for mood and smartphone use to compute these models. All the models for mood and smartphone use were symmetrical along the diagonal as the similarity between a participant, and itself is 100%. The dissimilarity between two participants was measured for each possible pair. To get a visual sense of the dissimilarity across all participants, the six RDM's are visualized in Appendix F, Figures 4 to 11 to see how dissimilar the participants were across each other. All these Figures were created with the Seaborn package in python (Seaborn, 2018).

The three models for mood showed how similar people were across all moods, negative moods, and positive moods. The mood matrices, Figures 4, 5, 6, showed that there were several larger dissimilarities between people across all the moods and negative moods. Participants showing bigger dissimilarities with other participants could be determined as participants with extreme moods. For dissimilarity across positive and negative moods, in Figures 5 and 6, several participants were very similar to other participants. Besides that, the differences in positive moods were extremer than for the other mood measures. The RDM for positive mood, in Figure 5, showed several participants that were very similar but also several that were extremely dissimilar to others. The quantitative comparison results are presented in the next section 4.2.

The three models for smartphone use showed similarity for people across time per use, frequency, and duration. In Appendix F, Figure 7 for time per use, Figure 9 for frequency and Figure 8 for duration visualize the dissimilarity matrices for these three smartphone use models. The dissimilarity matrices showed that for smartphone use in general, several participants showed extreme behavior. For every model, other participants showed very dissimilar behavior compared to all the other participants. Beyond that, it seemed like the participants were overall similar to each other across their smartphone application behavior.

Besides these three smartphone use models and three mood models, also two baseline models were created, as described in section 3.4.2. The matrices that showed the performance of these baseline models are shown in Figures 10 and 11 in Appendix F. These matrices showed that overall the participants were similar for mood. However, the baseline matrix for smartphone use showed several extreme cases of dissimilarity.

4.2 Comparison of models

The statistical comparison between RDM's was made by measuring the Spearman Rank Correlation, as described in section 3.4, between several model combinations. Table 3 shows the correlations for all model comparisons to see if there was an association between the similarity in two domains and to see if the correlation was positive or negative. It also shows the significance level for every correlation. The Figures that show the distribution of the permutation test of all the correlations can be found in Appendix G.

Model comparison	Correlation
All mood - Time per usage	-0.0145
Negative moods - Time per usage	-0.1170 ***
Negative moods - Duration	0.1357 ***
Negative moods - Frequency	0.1524 ***
Positive moods - Time per usage	0.0231 *
Positive moods - Duration	-0.0574 ***
Positive moods - Frequency	0.0192
Duration - All moods	0.2019 ***
Frequency - All moods	0.0932 ***
Frequency - Duration	0.5088 ***
Baseline	0.0134
* significant at p < 0.05 ** significant at p < 0.01 *** significant at p < 0.001	

Table 3: Overview correlation measures comparisons RDM's

As mentioned in section 3.4.3, the performance of the three models with every two different parts of the data was compared with the performance of the model with the total data. For the comparison between all moods and time per use (r_s = -0.0258, $p < 0.001$), the three folds resulted in r_s = -0.0595 for fold 1, r_s = -0.0020 for fold 2 and for fold 3 r_s = -0.0499. The values in the different folds show fairly similar values. This suggests that the data overall is stable, and therefore the results are more confident.

For the baseline performance, Table 3 presents that the comparison between the baseline models showed a very small correlation. However, the correlation was not statistically significant as can be seen in Figure 22 in Appendix G. This result was in line with expectations as the baseline comparison was a correlation of two models with randomly picked numbers between the minimum and maximum of the values for the higher-level models.

4.2.1 Sub-question 1

The first sub-question: Which mood measure is most similar to smartphone use, was answered by comparing the models for every mood measure with the model for time per use smartphone use. All moods model, positive moods model, and negative moods model were individually compared with the time per use model. The Spearman Correlation for the comparison between all moods and time per use was negative (r_s = -0.0145) and Table 3 shows that the correlation is not statistically significant. That implied there was not a statistically significant association between all moods and time per use smartphone use. Figure 12 in Appendix G shows the distribution of the correlations between permuted samples for the comparison between all the moods and time per use. Figure 12 shows that a large fraction of the permuted values is greater than or equal to the original correlation coefficient. Therefore, the p-value is large (p = 0.209) and not statistically significant ($p > 0.05$). Furthermore, the negative and positive moods were also individually compared with time per use. The comparison between negative moods and time per use showed a small negative correlation (r_s = -0.1170) that is statistically significant ($p < 0.001$) shown in Table 3. Figure 13 in Appendix G shows that the original correlation coefficient is outside the tail of the histogram. In contrast to the negative mood measure, positive moods compared with time per use showed a very small positive correlation (r_s = 0.0231) that is statistically significant ($p < 0.05$). The model with the positive moods showed the only positive correlation with time per smartphone use.

4.2.2 Sub-question 2

The second sub-question: How dissimilar are positive and negative moods for duration and frequency smartphone use, was answered by comparing four models individually to each other. The positive and negative mood models were individually compared with the frequency and duration smartphone use models. Comparing negative moods with duration and again negative moods with frequency showed a small positive correlation (r_s = 0.1357, r_s = 0.0.1524) that was statistically significant for both comparisons. This is shown in Table 3. Figures 14 and 15 in Appendix G present the distribution of the permuted samples that show both correlations are statistically significant. This correlation suggested a positive association between similarity in negative moods and similarity in smartphone use in frequency and duration. The comparison between positive moods and duration showed a very small negative correlation (r_s = -0.0574) that was statistically significant. This association implied that as the similarity in duration increases, the similarity in positive moods tends to decrease. The comparison between positive moods and frequency showed a small positive correlation (r_s = 0.0192) as well but not statistically significant, as shown in Figure 18 in Appendix G.

4.2.3 Sub-question 3

The third sub-question: How similar are duration and frequency smartphone use for mood, was answered by comparing duration and frequency individually with all the mood models in this study. So, duration and frequency smartphone use were both individually compared with the all moods model, the positive moods model, and the negative moods model. Table 3 presents that the comparison between both duration and frequency with the all moods model showed a positive correlation that was statistically significant as shown in Figures 19 and 20 in Appendix G. The correlation between duration and all moods ($r_s = 0.2019$) showed a stronger correlation than for the comparison between frequency and all moods ($r_s = 0.0932$). The correlations for negative and positive moods between duration and frequency were already presented before in section 4.2.2. The difference in correlation between frequency and duration for positive moods was the largest. The correlation between duration and positive moods showed a minimal negative correlation, and the correlation between frequency and positive moods did not show a statistically significant correlation. All these correlations for positive and negative moods between duration and frequency presented that frequency and duration smartphone use showed small differences compared to each other for any mood model.

4.2.4 Sub-question 4

The last sub-question: Is smartphone use more similar to itself than to any mood measure, was answered by comparing duration and frequency to each other and all the mood models individually to duration and frequency. Table 3 presents that the correlation between frequency and duration was a moderate correlation ($r_s = 0.5088$) that was statistically significant and showed the largest correlation of all the model comparisons. The comparisons between the mood models and duration and frequency individually showed a way smaller correlation as already presented in section 4.2.3.

5 Discussion

The goal of this study is to investigate to what extent representational similarity analysis can be used to identify the similarity across mood and the intensity of smartphone use. So this research used this analysis method to study an existing relationship that is stated in the literature with more different features than what has been done before. Section 5.1 discusses the findings of the research and answers the sub-questions. Section 5.2 discusses the limitations of the study and suggestions for further research.

To interpret the results accurately, one should be aware of the differences between a positive correlation, a negative correlation, and no correlation between similarity measures. The correlation does not imply causation, but it indicates the nature of the relationship between people. A positive correlation between two similarity measures indicates that an increase in similarity in one domain has a positive association with the increase of similarity in the other domain. For a negative correlation, this association is negative, so the similarity in the two domains does not move in the same direction. No correlation indicates that there is no association in how the similarity in the two domains changes. The interpretation is different from the standard interpretation of a correlation. For standard interpretation, the correlations indicate a change in the values of the domain itself instead of a change in the similarity.

5.1 Findings

This section is divided into five parts where the first four represent each another sub-question and the last section present the contribution of this study. Section 5.1.1 discusses the findings for sub-question 1, section 5.1.2 for sub-question 2, section 5.1.3 for sub-question 3 and section 5.1.4 for sub-question 4. The final section 5.1.5 discusses what the contribution of this present research is within the existing framework.

5.1.1 Sub-question 1

The first sub-question: Which mood measure is most similar to smartphone use, was answered by comparing the models for every mood with the model for smartphone use. The three mood models all measure a different set of moods: all moods, only positive moods, and only negative moods. These three mood models are compared to the time of a single use of an application category.

The correlation with positive moods and smartphone use shows the only positive association in similarity. This correlation means that people have the most similar rank in these models. So, a change in the similarity of the time of a single-use on smartphones has a positive association with the change in the similarity of positive moods. Unexpectedly, the positive mood measure is most similar, as literature states that the association with negative moods is strong (Elhai et al., 2016). So, the fact that the correlation between the similarity in negative moods and similarity in smartphone use showed a negative association is remarkable as well. The weak correlations with smartphone use, positive or negative, indicate that there is no convincing association between this way of measuring smartphone use and these two mood measurements. An explanation for the lack of association between these models is that this higher level relationship cannot be explained by using RSA. On another note, the weak correlations of all the model comparisons for this sub-question could be explained by the use of behavioral data of people. It is challenging to predict humans, and therefore the correlations of studies that involve human behavior tend to have weaker correlations (Frost, 2018).

5.1.2 Sub-question 2

The second sub-question: How dissimilar are positive and negative moods for duration and frequency smartphone use, was answered by comparing four models individually to each other. The positive and negative mood models were individually compared with the frequency and duration smartphone use models. The small negative correlation between positive moods and duration implied that as people are more similar in positive mood, they are less similar in the duration of smartphone use. This was not the case for frequency, as the correlation between frequency and positive moods did not imply any association. It is remarkable that for positive moods, the association with smartphone use duration is present but not with frequency smartphone use. However, the findings for the negative mood correlations are in line with the literature stating that there is a relationship between increasing smartphone use and increasing problems with human emotional state, for both ways (Arnavut & Nuri, 2018; Demirci et al., 2015; Van Deursen et al., 2015; Elhai et al., 2017; Extremera et al., 2019). Nonetheless, it was expected to show a more strong association for negative moods and a bigger difference between similarity in positive and similarity in negative moods. An explanation for this could be that only one assessment per registration for every mood individually cannot display a great picture of someone's emotional state. In other studies that focused on less different emotional states, more extensive assessments with, on average, 20 items are used to assess one specific emotional state (Demirci et al., 2015; Wolniewicz et al., 2020). A more extensive mood assessment for every mood individually could give a more convincing direction and difference for negative and positive moods.

5.1.3 Sub-question 3

The third sub-question: How similar are duration and frequency smartphone use for mood, was answered by comparing duration and frequency individually with all the mood models in this study. So, duration and frequency smartphone use were both individually compared with the all moods model, the positive moods model, and the negative moods model. The correlations showed overall that similarity in duration and frequency smartphone use was somewhat similar in explaining smartphone use for mood. This finding is in line with the literature stating that frequency and duration are useful measures to explain smartphone usage (Haug et al., 2015). Also, the small difference for the similarity in frequency and duration between the similarity in negative moods is expected as the literature is divided about this relationship. On the one hand, the literature agreed on the relationship between rising frequency and duration usage and smartphone addiction (Arnavut & Nuri, 2018; Bae, 2017; Lee et al., 2014; Lin et al., 2015). On the other hand, the literature also agreed on the relationship between smartphone addiction and negative mental health outcomes (Lee et al., 2014; Shapka, 2019). However, the literature was divided about whether the frequency or duration is more strongly connected to smartphone addiction and, therefore, negative emotional state. The outcome of this sub-question cannot show a direction or difference for either one of these measurements for smartphone use. An explanation for this could be that for this research, frequency and duration are measured with smartphone log data (Hendrickson et al., 2019). However, in the previous studies (Haug et al., 2015; Lin et al., 2015), participants estimated their daily duration and frequency. This self-report may be biased as Haug et al. (2015) already mentions this as an implication of the study. This difference in measurement could explain the difference in the outcome. The outcome of this comparison implies that there is not a big difference between the similarity in frequency or the similarity in duration use. Something that can be taken in this is that the test for stability shows somewhat similar values for the different folds of the data. This finding suggests that the data overall is stable, and therefore this result is more confident.

5.1.4 Sub-question 4

The last part of the study focused if smartphone use was more similar to itself than to any mood measure. Frequency and duration, two models that measure smartphone use differently, were compared to each other. Besides, frequency and duration were compared individually to all the mood models. The results showed that two different smartphone use measurements were a lot more similar than to any of the mood models. In general, the correlation between frequency and duration use is moderate. According to (Frost, 2018), this correlation is strong for a study that includes human behavior data. This strong correlation implies that as people are more similar in frequency smartphone use, they are also more similar in the duration of smartphone use. This association is the strongest correlation, which is in line with expectations as duration and frequency explain similar smartphone use components. It sounds logical that similarity in smartphone frequency and similarity in smartphone duration have a strong association and is something that is also stated in the literature (Ferdous et al., 2015). This strong association also gives a cautious indication that RSA can be used to measure a relationship that includes smartphone use.

5.1.5 Contribution of this research

On a final note, the model comparisons performed below a correlation of r_s = 0.2 or r_s = -0.2. The only model comparison that showed a strong association was the similarity in smartphone use, between frequency and duration. Although all the other correlations in this research are low, this research has still added value. To the best of our knowledge, this is the first research investigating the relationship between smartphone use and mood, by including a wide range of features for mood and smartphone use and by using representational similarity analysis. Further research can build on this and try to improve the correlations. The models can be changed by using other input data for mood features. For example, by including a more extensive mood assessment for every mood individually, as seen in studies of Demirci et al. (2015) and Wolniewicz et al. (2020). Another example that can be followed is adding mood input data of brain activity patterns that represent people's moods. Studies of Blair et al. (2012), Cao et al. (2018), Pegors et al. (2017) and Weiler (2018) can be used for that.

5.2 Limitations and suggestions for further research

The first limitation of this research is regarding computing the first-order similarity distance between data patterns. Euclidean distance for smartphone use and Pearson correlation for mood patterns are used to compute similarity distance. These measurements are chosen based on literature. However, according to Kriegeskorte et al. (2008), a variety of distance measurements can be used to see if there is any difference in the performance of computing similarity distance. An example of another similarity distance that could be useful to try is the cross-validated Euclidean distance measure used in a study of Guggenmos et al. (2018). Therefore, it is a suggestion for further research to try different similarity distances for every domain, compare these, and see if any improvement can be made.

The second limitation of this research is the method of significance testing. In this study, permutation tests are used to test if the correlations are statistically significant. The results show that a correlation of $r_s = 0.0231$ is statistically significant ($p < 0.050$). This would never be when a classical method of significance testing was used for Spearman's Rank correlation (Zar, 1972). However, the standard significance tests would be valid under assumptions that are difficult to meet when using real data (Ge et al., 2018). This indicates that the classical method of significance testing is too conservative, but the permutation tests are too permissive. Therefore, it could be an interesting area of future research to pin down what kind of significance test is more appropriate for this research and similar future studies.

Another drawback of this research is the data that is used. To indicate people's mood, people estimate their mood on a 5 point Likert scale of how likely they felt like that for the past time frame. This is a subjective way of measurement, and one event in the past time frame could overrule the general mood (Van Deursen et al., 2015). As mentioned in section 2.2, RSA has been used a lot with brain-activity patterns as an input feature for behavioral studies (Anderson et al., 2016; Nili et al., 2014; Pegors et al., 2017; Tucciarelli et al., 2019). Therefore it would be interesting for further research to measure the mood, long emotional state, of people with brain activity patterns like in the studies of Blair et al. (2012), Cao et al. (2018) and Pegors et al. (2017). Another interesting study of Weiler (2018) started to understand the neuroscience behind mood. This study looked into the patterns of brain activity for changes in mood. That could be very useful when using brain activity patterns for mood as an input feature. The smartphone behavior data used for this study is already measured extensively and objectively via smartphone logging data (Hendrickson et al., 2019). Using the proposed mood data and smartphone behavior data, the measurements for mood are extensive and objective. It could be exciting to investigate this relationship with RSA further.

6 Conclusion

Several models were computed to measure the relationship between mood and smartphone use. When comparing models with assessing second-order dissimilarity, most comparisons showed very weak Spearman correlations. Some too weak to indicate any association in any direction between the two models. There was a small indication that a difference in the intensity of smartphone use between positive and negative moods could be assumed. This difference implied a positive association between negative moods and smartphone use but a negative association between positive moods and smartphone use. The small dissimilarity between different measurements for smartphone use indicated that frequency and duration use were both useful measurements to explain smartphone use. Furthermore, the only comparison that showed a relatively strong correlation was between frequency and duration smartphone use. This finding implied that as people are more similar in the frequency of smartphone use, they are also more similar in the duration of smartphone use. These results indicate that using RSA to analyze the relationship between smartphone use and mood might not be appropriate for this type of data.

In conclusion, this present research cannot provide enough information to state that there is a strong relationship between smartphone use and mood. This conclusion suggests that RSA could not be used to identify similarities across mood and the intensity of smartphone applications used with this type of data. Further research is needed to support this claim, as some improvements can be made for this study.

7 References

Aguirre, G. K. (2007). Continuous carry-over designs for fmri. *Neuroimage*, *35*(4), 1480–1494.

Akoglu, H. (2018). User's guide to correlation coefficients. *Turkish journal of emergency medicine*, *18*(3), 91–93.

Anderson, A. J., Zinszer, B. D., & Raizada, R. D. (2016). Representational similarity encoding for fmri: Pattern-based synthesis to predict brain activity using stimulus-model-similarities. *NeuroImage*, *128*, 44–53.

Arnavut, A., & Nuri, C. (2018). Examination of the relationship between phone usage and smartphone addiction based on certain variables. *Anales De Psicología/Annals of Psychology*, *34*(3), 446–450.

Bae, S.-M. (2017). The relationship between the type of smartphone use and smartphone dependence of korean adolescents: National survey study. *Children and Youth Services Review*, *81*, 207–211.

Bakker, D., Kazantzis, N., Rickwood, D., & Rickard, N. (2016). Mental health smartphone apps: review and evidence-based recommendations for future developments. *JMIR mental health*, *3*(1), e7.

Bakker, D., Kazantzis, N., Rickwood, D., & Rickard, N. (2018). A randomized controlled trial of three smartphone apps for enhancing public mental health. *Behaviour research and therapy*, *109*, 75–83.

Bassi, M., Bacher, G., Negri, L., & Delle Fave, A. (2013). The contribution of job happiness and job meaning to the well-being of workers from thriving and failing companies. *Applied research in quality of life*, *8*(4), 427–448.

Bauckhage, C. (2014). Numpy/scipy recipes for data science: Squared euclidean distance matrices. *researchgate. net, Oct*.

Blair, K. P., Rosenberg-Lee, M., Tsang, J. M., Schwartz, D. L., & Menon, V. (2012). Beyond natural numbers: negative number representation in parietal cortex. *Frontiers in human neuroscience*, *6*, 7.

Brooks, J. A., & Freeman, J. B. (2018). Conceptual knowledge predicts the representational structure of facial emotion perception. *Nature human behaviour*, *2*(8), 581–591.

Cao, L., Xu, J., Yang, X., Li, X., & Liu, B. (2018). Abstract representations of emotions perceived from the face, body, and whole-person expressions in the left postcentral gyrus. *Frontiers in human neuroscience*, *12*, 419.

Dar, L., Akmal, A., Naseem, M. A., & din Khan, K. U. (2011). Impact of stress on employees job performance in business sector of pakistan. *Global journal of management and business research*, *11*(6).

Demirci, K., Akgönül, M., & Akpinar, A. (2015). Relationship of smartphone use severity with sleep quality, depression, and anxiety in university students. *Journal of behavioral addictions*, *4*(2), 85–92.

Dimsdale-Zucker, H. R., & Ranganath, C. (2018). Representational similarity analyses: A practical guide for functional mri applications. In *Handbook of behavioral neuroscience* (Vol. 28, pp. 509–525). Elsevier.

Elhai, J. D., Dvorak, R. D., Levine, J. C., & Hall, B. J. (2017). Problematic smartphone use: A conceptual overview and systematic review of relations with anxiety and depression psychopathology. *Journal of affective disorders*, *207*, 251–259.

Elhai, J. D., Levine, J. C., Dvorak, R. D., & Hall, B. J. (2016). Fear of missing out, need for touch, anxiety and depression are related to problematic smartphone use. *Computers in Human Behavior*, *63*, 509–516.

Elhai, J. D., Tiamiyu, M. F., Weeks, J. W., Levine, J. C., Picard, K. J., & Hall, B. J. (2018). Depression and emotion regulation predict objective smartphone use measured over one week. *Personality and Individual Differences*, *133*, 21–28.

Extremera, N., Quintana-Orts, C., Sánchez-Álvarez, N., & Rey, L. (2019). The role of cognitive emotion regulation strategies on problematic smartphone use: Comparison between problematic and non-problematic adolescent users. *International journal of environmental research and public health*, *16*(17), 3142.

Ferdous, R., Osmani, V., & Mayora, O. (2015). Smartphone app usage as a predictor of perceived stress levels at workplace. In *2015 9th international conference on pervasive computing technologies for healthcare (pervasivehealth)* (pp. 225–228).

Fischer-Grote, L., Kothgassner, O. D., & Felnhofer, A. (2019). Risk factors for problematic smartphone use in children and adolescents: A review of existing literature. *neuropsychiatrie*, 1–12.

Frost, J. (2018). *Interpreting correlation coefficients.* Retrieved from `https://statisticsbyjim.com/basics/correlations/`

Fukazawa, Y., Ito, T., Okimura, T., Yamashita, Y., Maeda, T., & Ota, J. (2019). Predicting anxiety state using smartphone-based passive sensing. *Journal of biomedical informatics*, *93*, 103151.

Ge, T., Yeo, B. T., & Winkler, A. (2018). A brief overview of permutation testing with examples. *Organization for Human Brain Mapping*.

Gracová, S., et al. (2019). Report of pew research center about how teens and parents navigate screen time and device distractions. *Media Literacy and Academic Research*, *2*(1), 111–114.

Griffiths, M. (2005). A 'components' model of addiction within a biopsychosocial framework. *Journal of Substance use*, *10*(4), 191–197.

Guggenmos, M., Sterzer, P., & Cichy, R. M. (2018). Multivariate pattern analysis for meg: A comparison of dissimilarity measures. *NeuroImage*, *173*, 434–447.

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., Tatham, R. L., et al. (1998). *Multivariate data analysis* (Vol. 5) (No. 3). Prentice hall Upper Saddle River, NJ.

Haug, S., Castro, R. P., Kwon, M., Filler, A., Kowatsch, T., & Schaub, M. P. (2015). Smartphone use and smartphone addiction among young people in switzerland. *Journal of behavioral addictions*, *4*(4), 299–307.

Hendrickson, D., De Marez, L., Martens, M., Van Meer, M., Muller, G., Paisa, T., ... Vanden Abeele, M. (2019). How do people use their smartphone? a data scientific approach to describe and identify user-related, system-related and context-related patterns in use.

Hoffner, C. A., & Lee, S. (2015). Mobile phone use, emotion regulation, and well-being. *Cyberpsychology, Behavior, and Social Networking*, *18*(7), 411–416.

Holmes, A. P., Blair, R., Watson, J., & Ford, I. (1996). Nonparametric analysis of statistic images from functional mapping experiments. *Journal of Cerebral Blood Flow & Metabolism*, *16*(1), 7–22.

Hunter, J. (2007). Matplotlib: A 2d graphics environment. computing in science engineering 9, 3. 90-95.

Kriegeskorte, N., Mur, M., & Bandettini, P. A. (2008). Representational similarity analysis-connecting the branches of systems neuroscience. *Frontiers in systems neuroscience*, *2*, 4.

Laerd Statistics. (2018). *Spearman's rank-order correlation (cont...)*. Retrieved from https://statistics.laerd.com/statistical-guides/spearmans-rank-order-correlation-statistical-guide-2.php

Lee, H., Ahn, H., Choi, S., & Choi, W. (2014). The sams: Smartphone addiction management system and verification. *Journal of medical systems*, *38*(1), 1.

Leeds, D. D., & Shutov, D. (n.d.). Potential cortical and computational biases in representational similarity analysis. *Neuroscience*, *2*, 4.

Legendre, P., & Legendre, L. F. (2012). *Numerical ecology*. Elsevier.

LiKamWa, R., Liu, Y., Lane, N. D., & Zhong, L. (2013). Moodscope: Building a mood sensor from smartphone usage patterns. In *Proceeding of the 11th annual international conference on mobile systems, applications, and services* (pp. 389–402).

Lin, Y.-H., Lin, Y.-C., Lee, Y.-H., Lin, P.-H., Lin, S.-H., Chang, L.-R., ... Kuo, T. B. (2015). Time distortion associated with smartphone addiction: Identifying smartphone addiction via a mobile application (app). *Journal of psychiatric research*, *65*, 139–145.

McKinney, W., et al. (2010). Data structures for statistical computing in python. In *Proceedings of the 9th python in science conference* (Vol. 445, pp. 51–56).

Nichols, T. E., & Holmes, A. P. (2002). Nonparametric permutation tests for functional neuroimaging: a primer with examples. *Human brain mapping*, *15*(1), 1–25.

Nili, H., Wingfield, C., Walther, A., Su, L., Marslen-Wilson, W., & Kriegeskorte, N. (2014). A toolbox for representational similarity analysis. *PLoS computational biology*, *10*(4).

Our English Class. (2018). *Tone and mood.* Retrieved from http://ourenglishclass.net/class-notes/writing/the-writing-process/craft/tone-and-mood/

Pegors, T. K., Tompson, S., O'Donnell, M. B., & Falk, E. B. (2017). Predicting behavior change from persuasive messages using neural representational similarity and social network analyses. *NeuroImage*, *157*, 118–128.

Popal, H., Wang, Y., & Olson, I. R. (2019). A guide to representational similarity analysis for social neuroscience. *Social Cognitive and Affective Neuroscience*, *14*(11), 1243–1253.

Reber, T. (2017). *Adjectives (positive negative) to describe mood, moment, character, emotions, feelings, behavior.* Retrieved from http://www.tinareber.com/adjectives-positive-negative-to-describe-mood-moment-character-emotions-feelings-behavior/

Ritchie, J. B., Bracci, S., & de Beeck, H. O. (2017). *Avoiding illusory effects in representational similarity analysis: What (not) to do with the diagonal.* Elsevier.

Saenger, V. (2019). *How to assess statistical significance in your data with permutation tests.* Retrieved from https://towardsdatascience.com/how-to-assess-statistical-significance-in-your-data-with-permutation-tests-8bb925b2113d

Seaborn, W. M. (2018). *statistical data visualization. 2016.*

Shapka, J. D. (2019). Adolescent technology engagement: It is more complicated than a lack of self-control. *Human Behavior and Emerging Technologies*, *1*(2), 103–110.

Shulga, D. (2018). *5 reasons why you should use cross-validation in your data science projects.* Retrieved from https://towardsdatascience.com/5-reasons-why-you-should-use-cross-validation-in-your-data-science-project-8163311a1e79

SIDN. (2019). *Smartphone: spin in het nederlandse web. onderzoek trends in internetgebruik 2018.* Retrieved from https://www.sidn.nl/downloads/68qEO2uhSxmnSd9aLQY1uw/68eb230c09be1d364a62b3d16b044165/SIDN_Trends_in_internetgebruik_2018.pdf

Siless, V., Medina, S., Varoquaux, G., & Thirion, B. (2013). A comparison of metrics and algorithms for fiber clustering. In *2013 international workshop on pattern recognition in neuroimaging* (pp. 190–193).

Sim, N., Konovalov, D., & Coomans, D. (2009). High-performance grid computing in chemoinformatics. Elsevier.

Stolier, R. M., Hehman, E., Keller, M. D., Walker, M., & Freeman, J. B. (2018). The conceptual structure of face impressions. *Proceedings of the National Academy of Sciences*, *115*(37), 9210–9215.

Thirion, B., Pedregosa, F., Eickenberg, M., & Varoquaux, G. (2015). Correlations of correlations are not reliable statistics: implications for multivariate pattern analysis..

Tucciarelli, R., Wurm, M., Baccolo, E., & Lingnau, A. (2019). The representational space of observed actions. *eLife*, *8*, e47686.

Van Deursen, A. J., Bolle, C. L., Hegner, S. M., & Kommers, P. A. (2015). Modeling habitual and addictive smartphone behavior: The role of smartphone usage types, emotional intelligence, social stress, self-regulation, age, and gender. *Computers in human behavior*, *45*, 411–420.

Van Rossum, G., & Drake Jr, F. L. (1995). *Python tutorial* (Vol. 620). Centrum voor Wiskunde en Informatica Amsterdam.

Weiler, N. (2018). Brain signature of depressed mood unveiled in new study. Retrieved from `www.sciencedaily.com/releases/2018/11/181108142410.htm`

Wilcox, R. R., & Keselman, H. (2003). Modern robust data analysis methods: measures of central tendency. *Psychological methods*, *8*(3), 254.

Wolniewicz, C. A., Rozgonjuk, D., & Elhai, J. D. (2020). Boredom proneness and fear of missing out mediate relations between depression and anxiety with problematic smartphone use. *Human Behavior and Emerging Technologies*, *2*(1), 61–70.

Zar, J. H. (1972). Significance testing of the spearman rank correlation coefficient. *Journal of the American Statistical Association*, *67*(339), 578–580.

Zarandona, J., Cariñanos-Ayala, S., Cristóbal-Domínguez, E., Martín-Bezos, J., Yoldi-Mitxelena, A., & Cillero, I. H. (2019). With a smartphone in one's pocket: A descriptive cross-sectional study on smartphone use, distraction and restriction policies in nursing students. *Nurse education today*, *82*, 67–73.

Zenonos, A., Khan, A., Kalogridis, G., Vatsikas, S., Lewis, T., & Sooriyabandara, M. (2016). Healthyoffice: Mood recognition at work using smartphones and wearable sensors. In *2016 ieee international conference on pervasive computing and communication workshops (percom workshops)* (pp. 1–6).

Zopf, R., Schweinberger, S. R., & Rich, A. N. (2019). Limits on visual awareness of object targets in the context of other object category masks: Investigating bottlenecks in the continuous flash suppression paradigm with hand and tool stimuli. *Journal of vision*, *19*(5), 17–17.

Appendices

A Python code

All the code created for this research can be found in the following link:
Github code Thesis M.H.P. Roost

B Smartphone applications without category

Table 4: Categorisation of smartphone applications without category.

Application id	Category
com.huawei.android.internal.app	Phone_Tools
com.example.android.notepad	Document_Editor
com.lenovo.ideafriend	Messaging
com.forgepond.locksmith	Phone_Tools
com.zte.privacyzone	Security
com.oneplus.security	Security
org.wordpress.android	Streaming_Services
com.samsung.android.sm	Phone_Optimization
com.sec.android.preloadinstaller	Phone_Tools
org.codeaurora.gallery	Camera
com.gameloft.android.GloftMBCF	Game_Singleplayer
telecom.IT	Remote_Administration
be.argenta.veiligonderweg	Auto_&_Vehicles
com.oxylane.android.cubeinstore	Online_Shopping

Table 4

C New categories smartphone application

Table 5: Overview new smartphone application categories

	Category	Examples application
1.	Background_Process	Google Play Store, Time and Weather
2.	Communication	OnePlus Community, Android Messages
3.	Entertainment	Apple Music, Adobe Photoshop Express
4.	Facebook	Facebook
5.	Facebook_Messenger	Facebook Messenger
6.	Finance	ING Bankieren, Binance – Cryptocurrency Exchange
7.	Games	Wordfeud, Idle Miner Tycoon
8.	Google_Chrome	Google Chrome
9.	Instagram	Instagram
10.	Lifestyle	Calorie Counter, mobileDNA
11.	Online_Shopping	AliExpress, Bershka
12.	Productivity	Google Calendar, Samsung Cloud
13.	Snapchat	Snapchat
14.	Social	Yubo, Amino: Communities and Chats
15.	Spotify	Spotify
16.	Utility	Google Opinion Rewards, Google Text-to-Speech
17.	Whatsapp_Messenger	Whatsapp Messenger
18.	Youtube	Youtube

Table 5

D Valence of all the moods

Table 6: Categorisation of all the moods

Mood	Category
Anxious	Negative
Bored	Negative
Gloomy	Negative
Stressed	Negative
Tired	Negative
Upset	Negative
Envious	Negative
Calm	Positive
Content	Positive
Cheerful	Positive
Energetic	Positive

Table 6

E Visual overview of all the model comparisons per sub-question

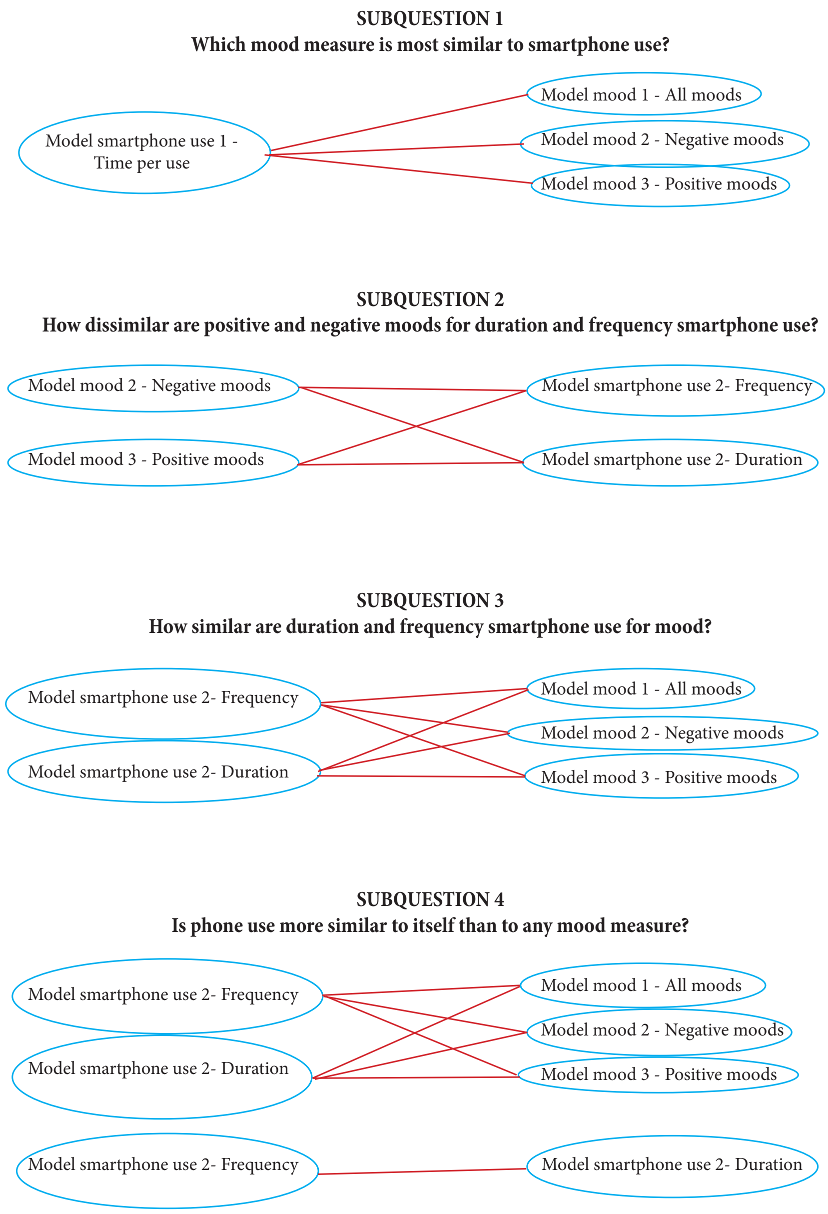

Figure 3: Overview model comparisons

F Heatmaps representational dissimilarity matrices

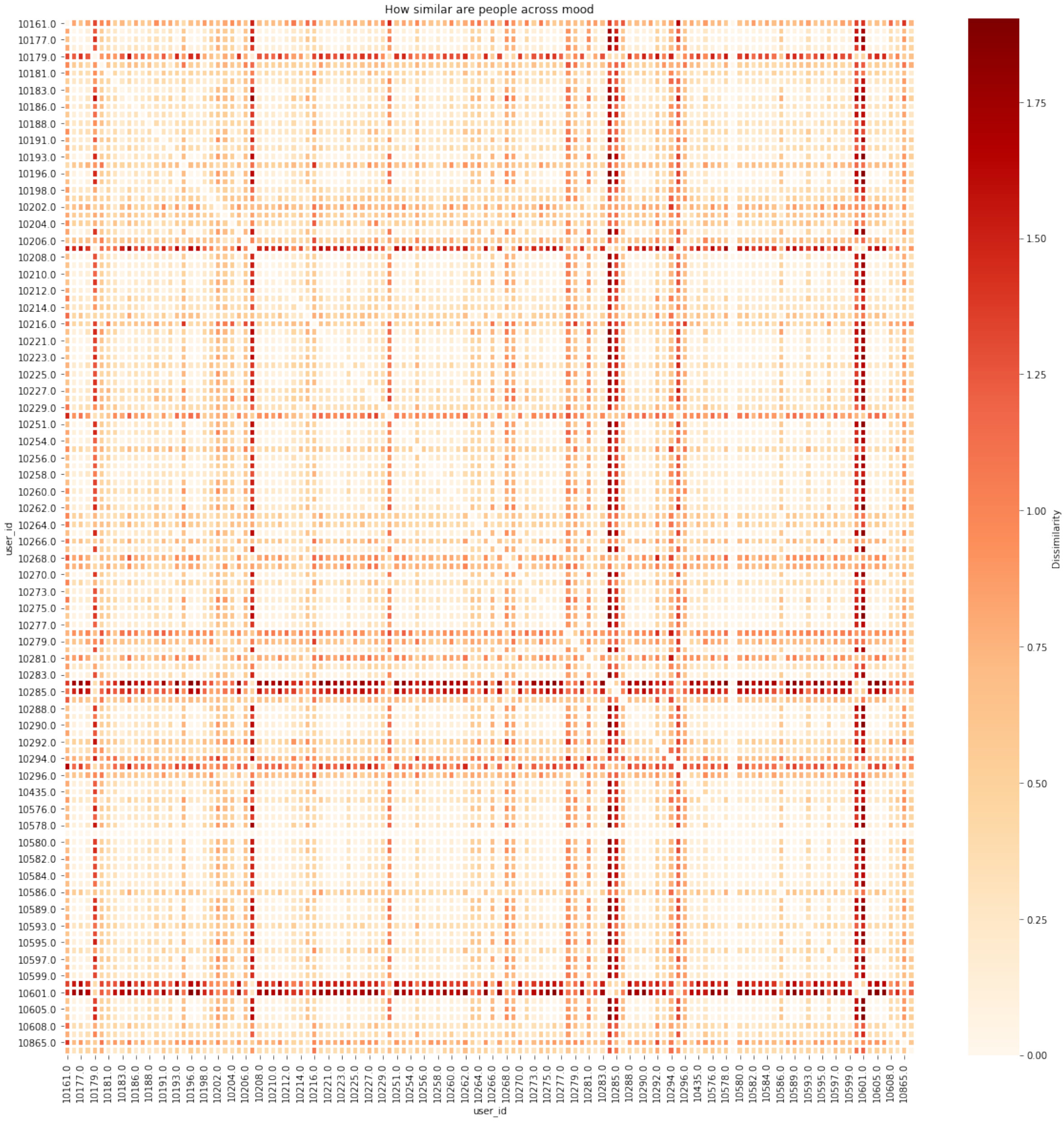

Figure 4: RDM of all moods

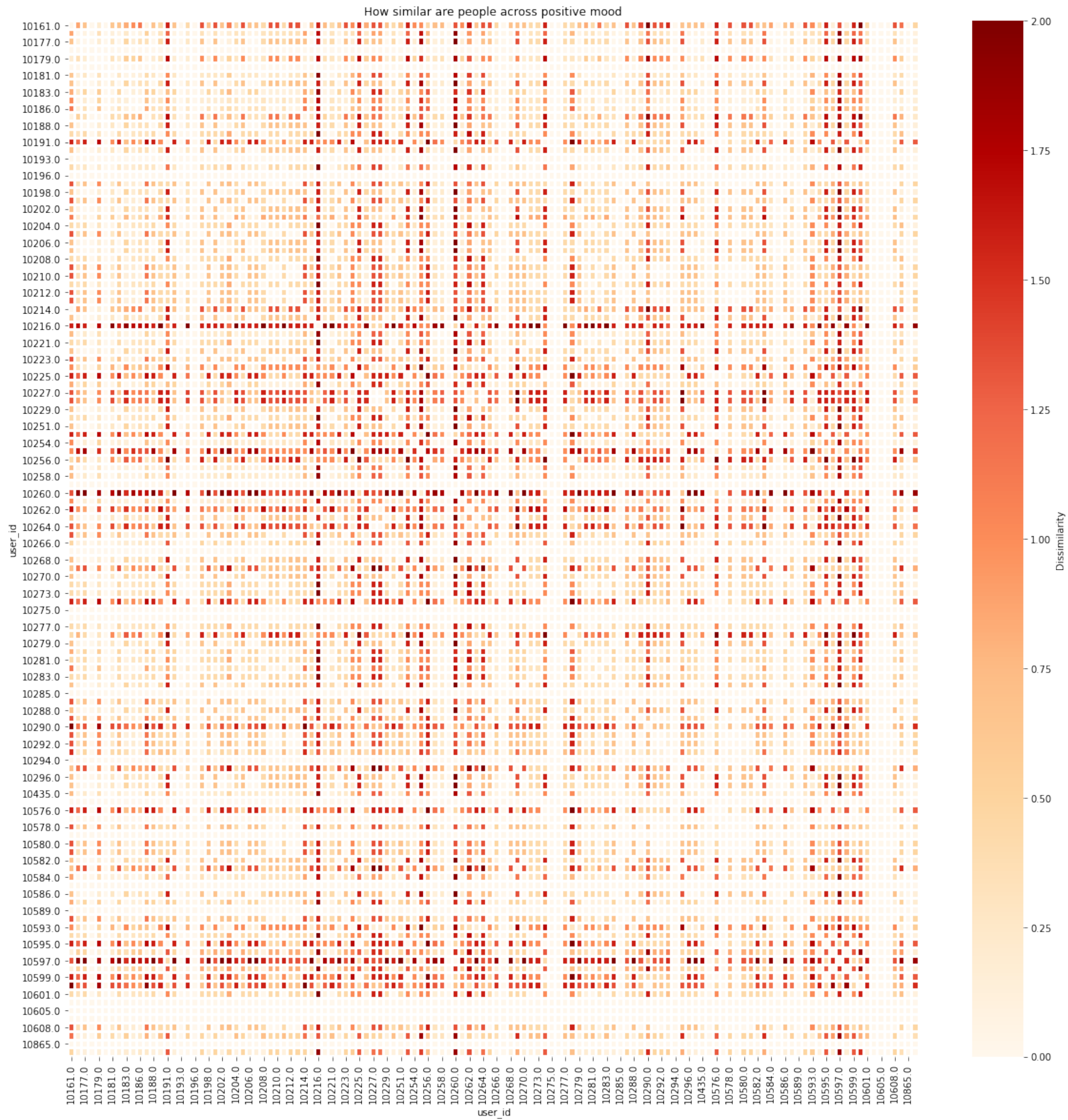

Figure 5: RDM of positive moods

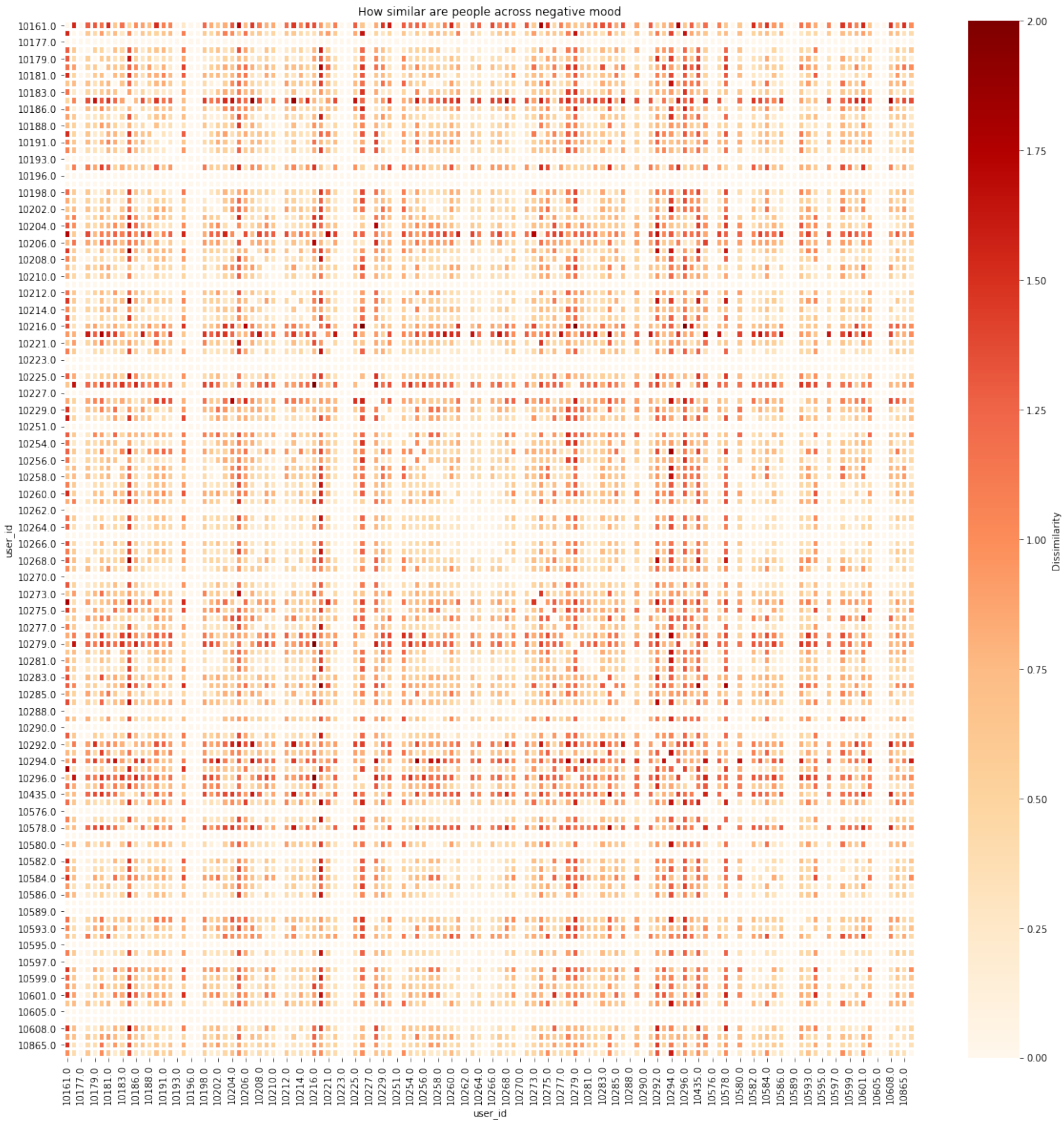

Figure 6: RDM of negative moods

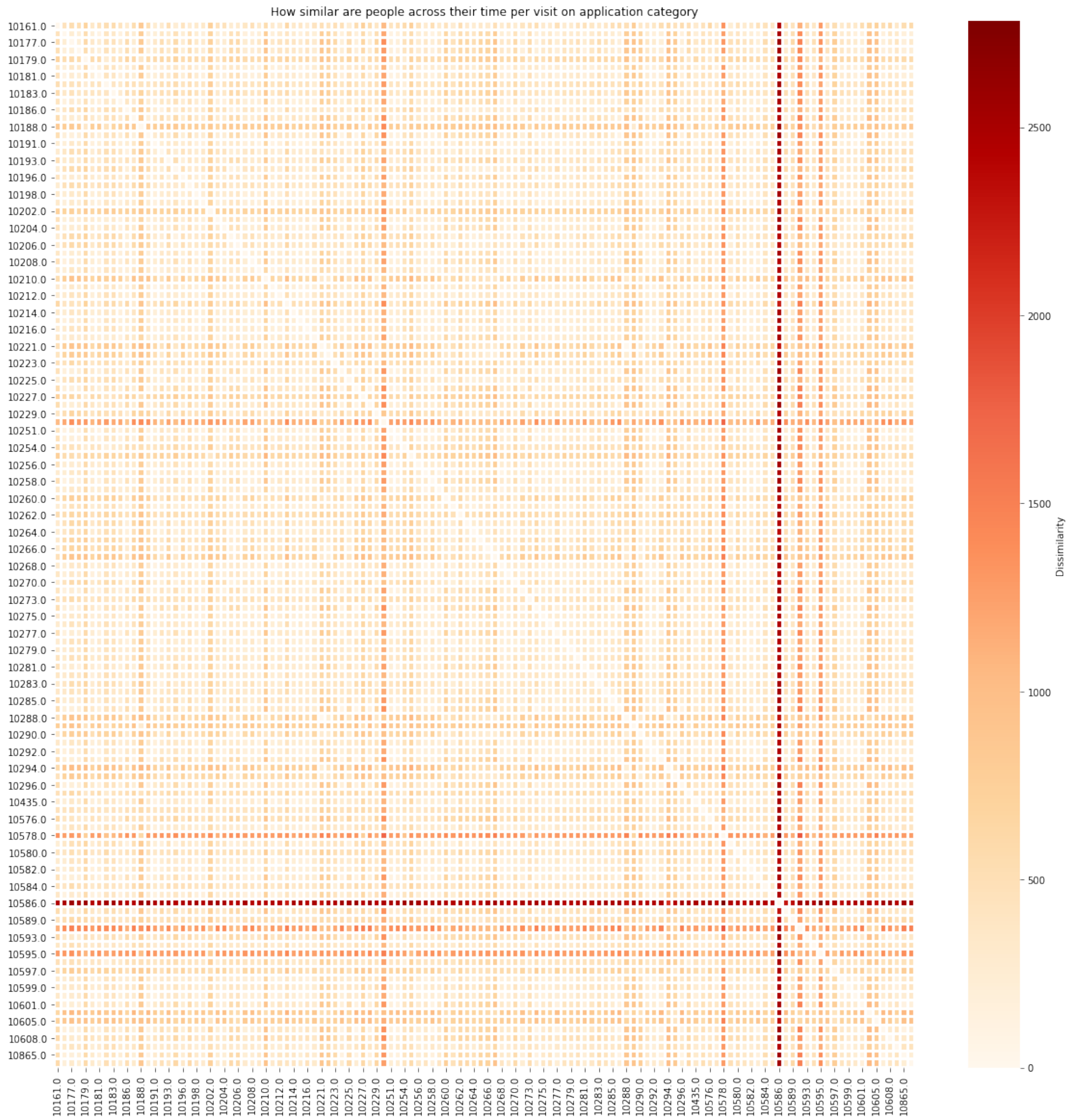

Figure 7: RDM of time per usage

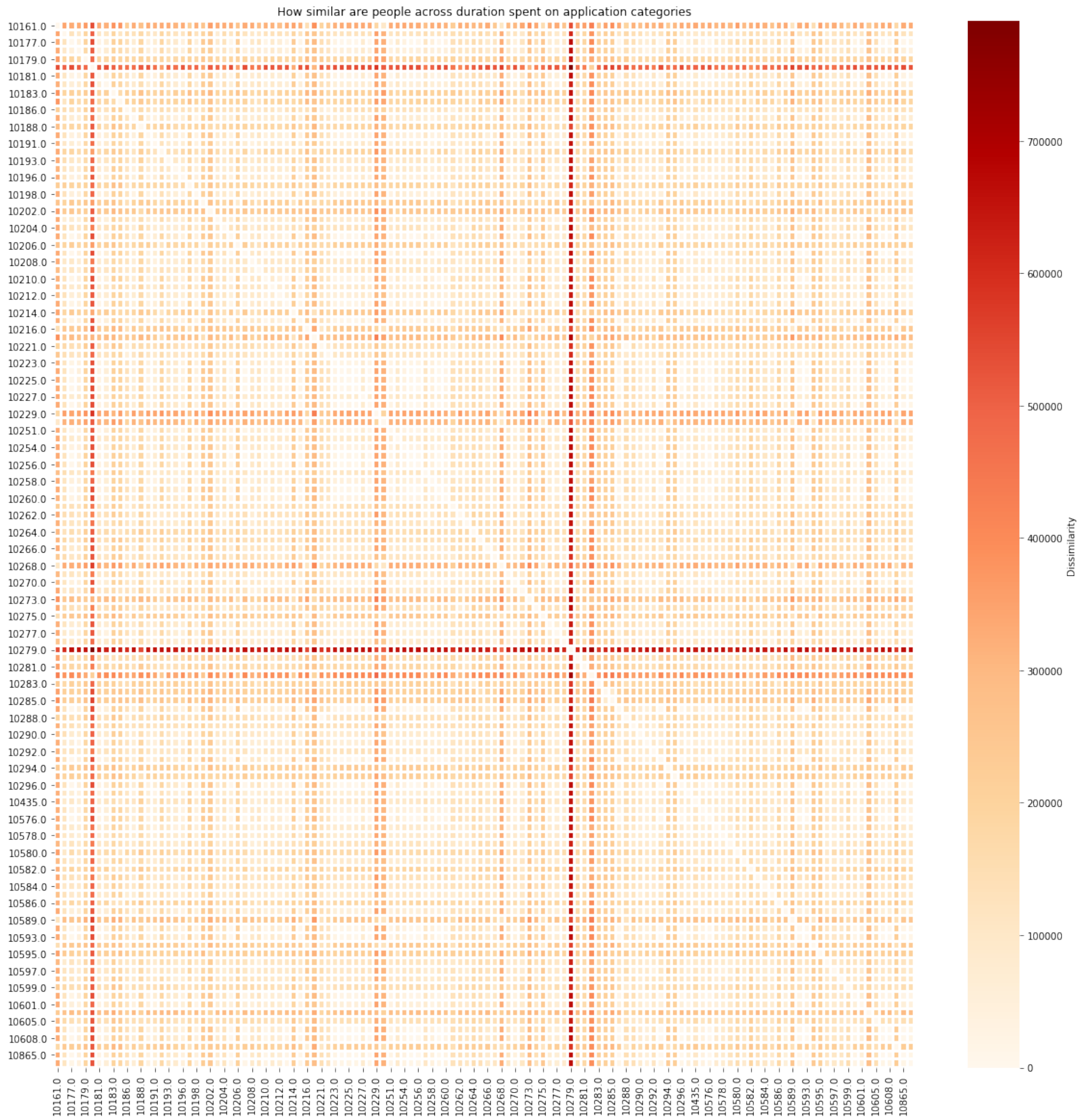

Figure 8: RDM of duration

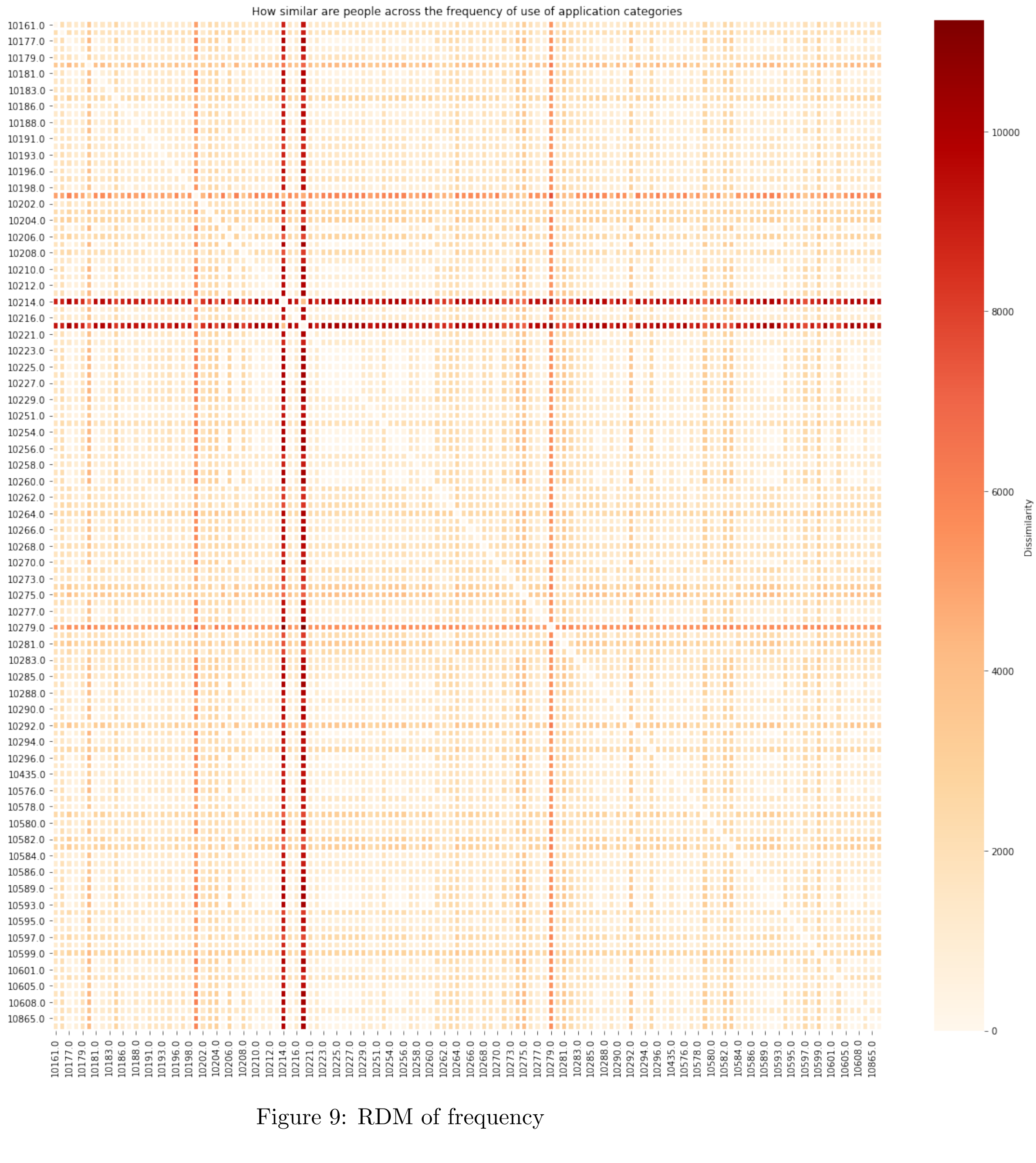

Figure 9: RDM of frequency

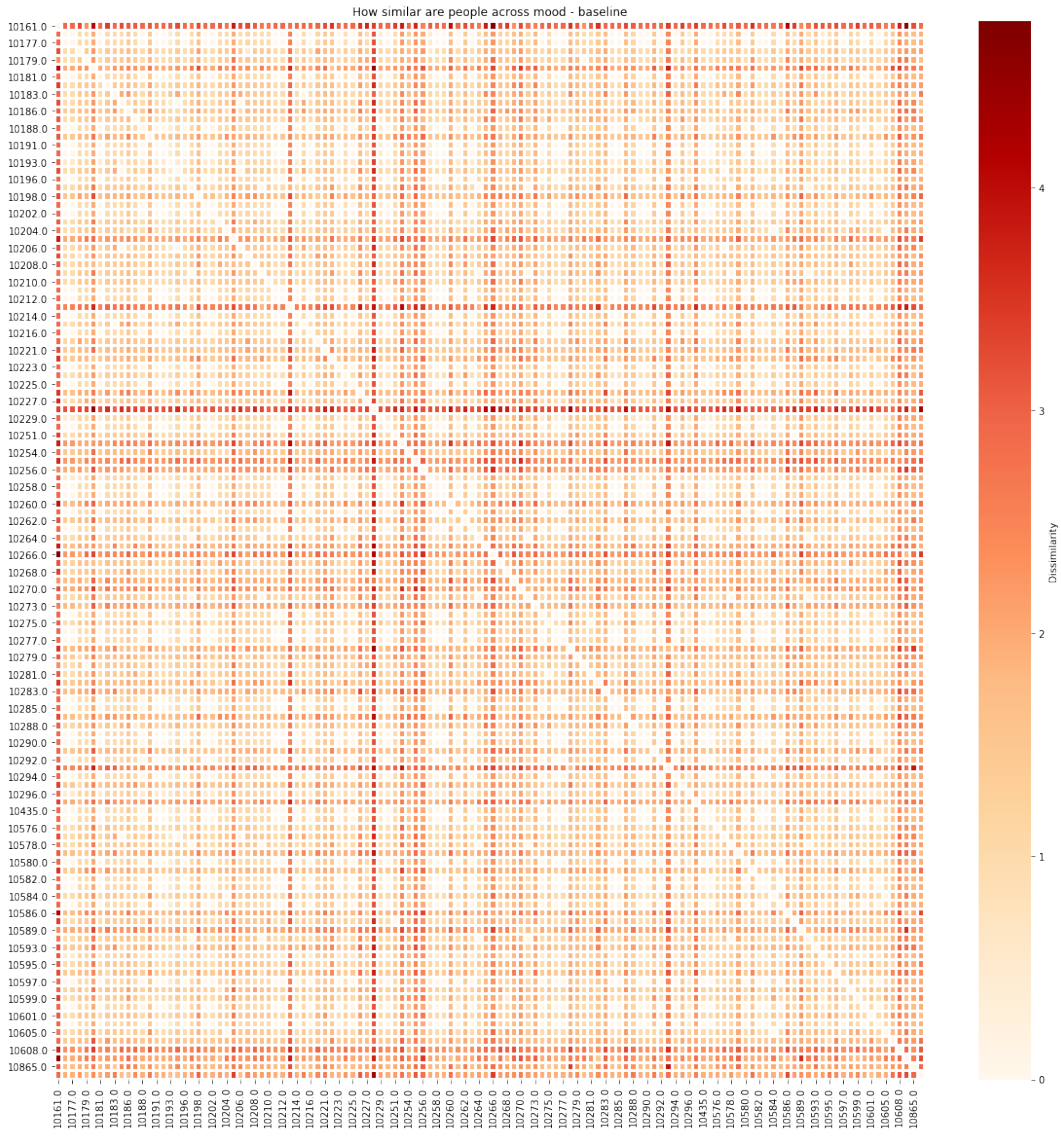

Figure 10: Baseline RDM for mood

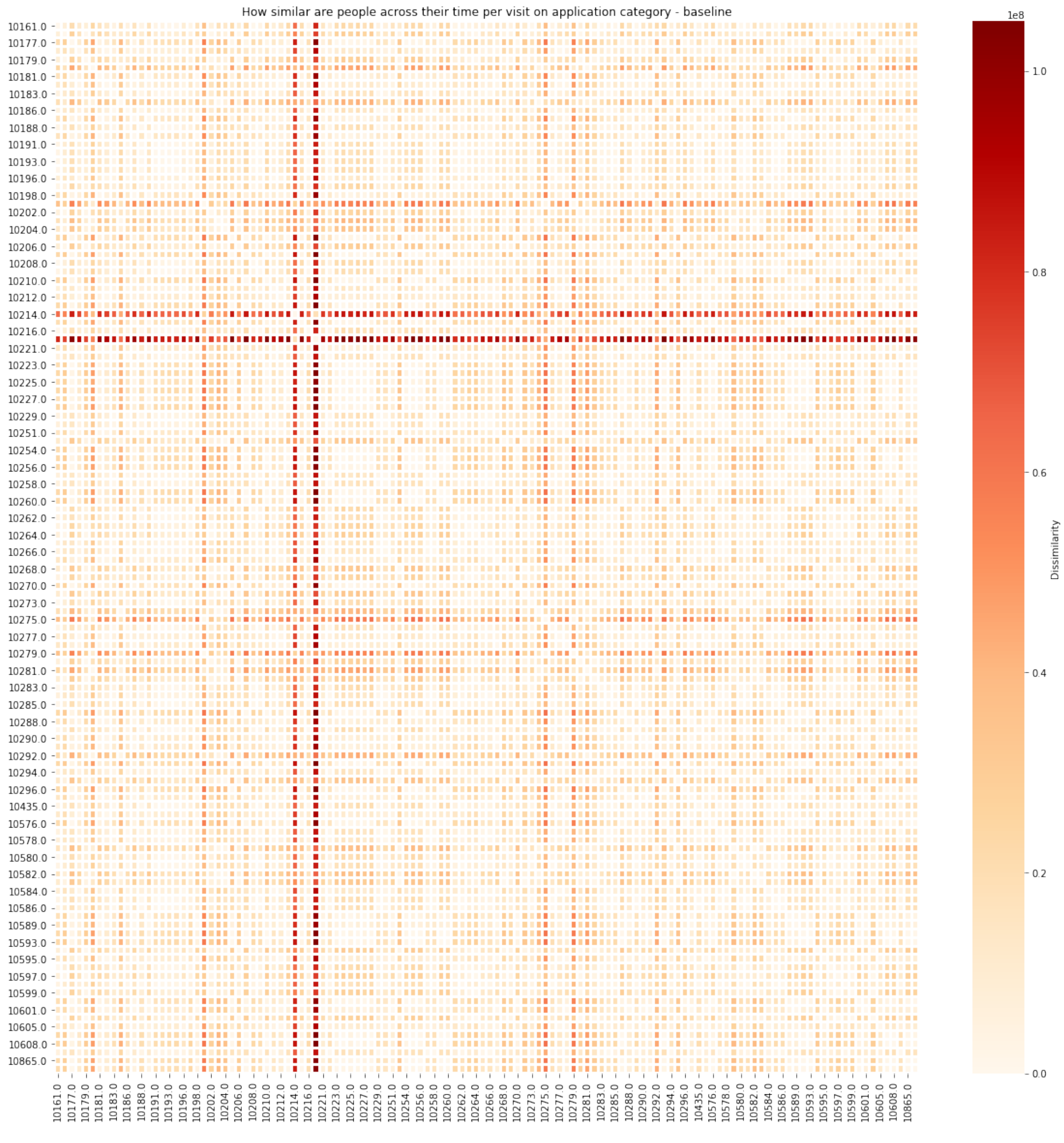

Figure 11: Baseline RDM for smartphone use

G Histograms distribution of sample correlations for permutation test

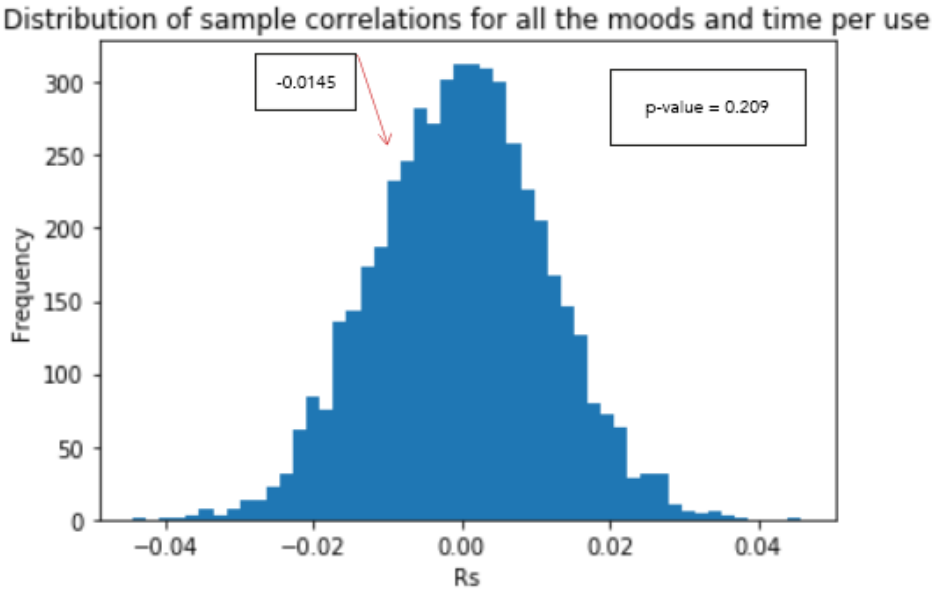

Figure 12

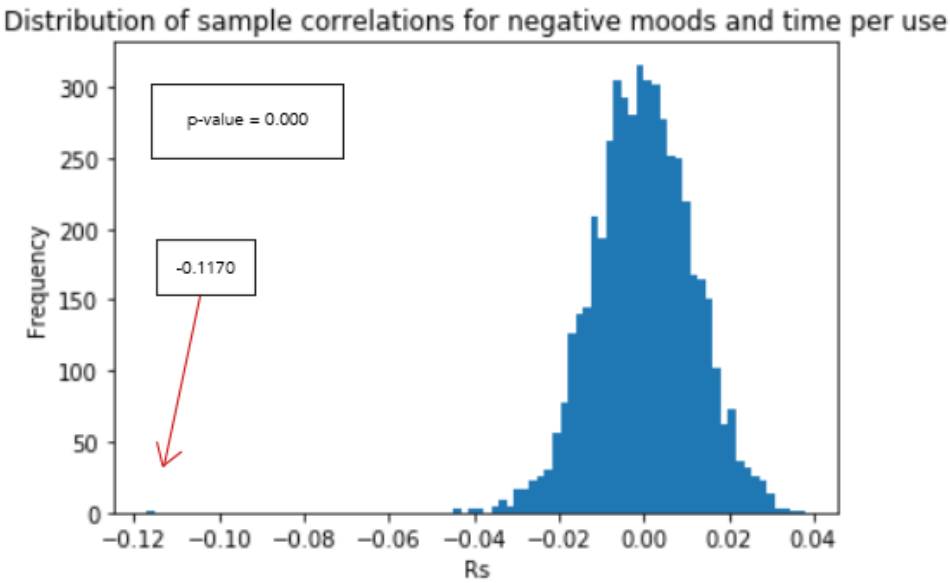

Figure 13

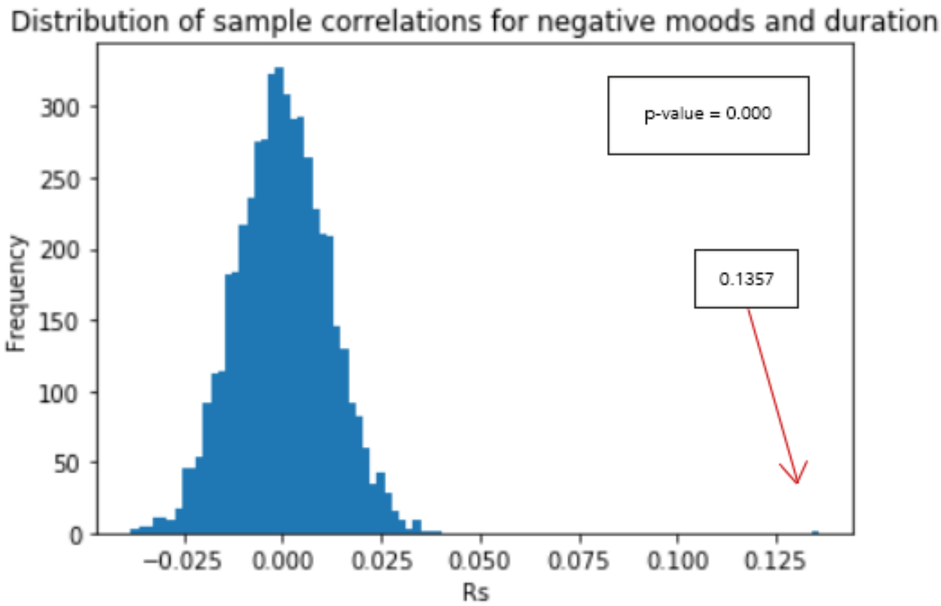

Figure 14

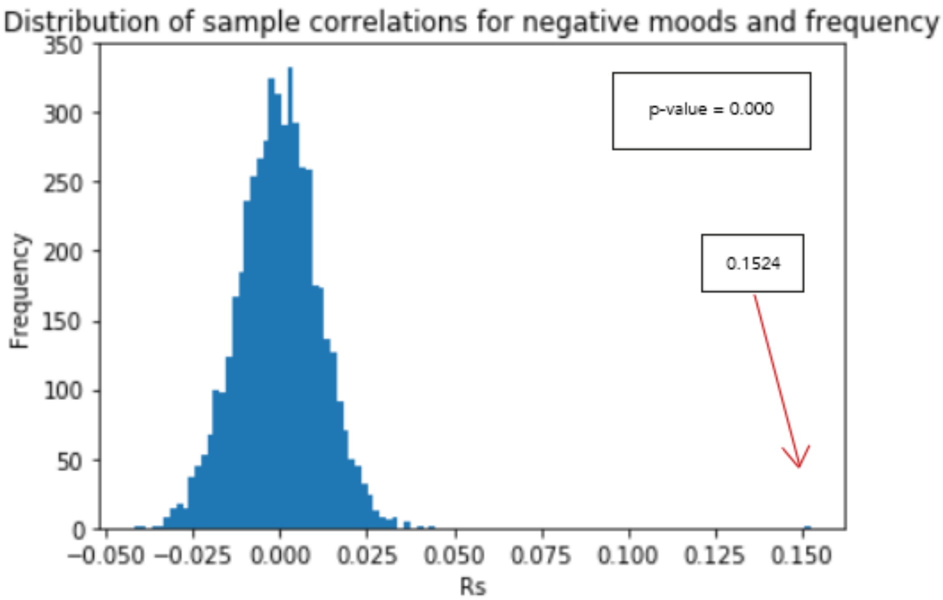

Figure 15

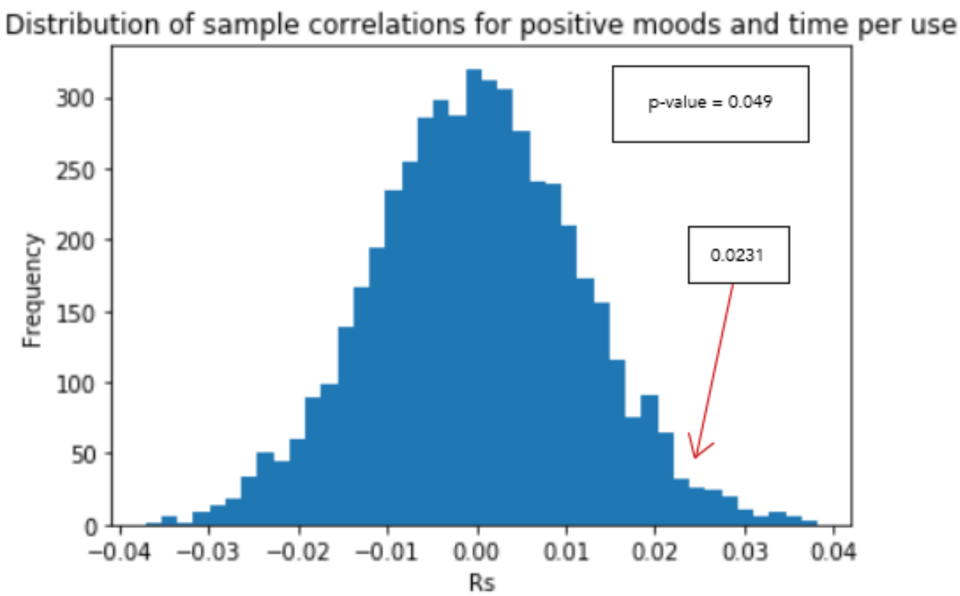

Figure 16

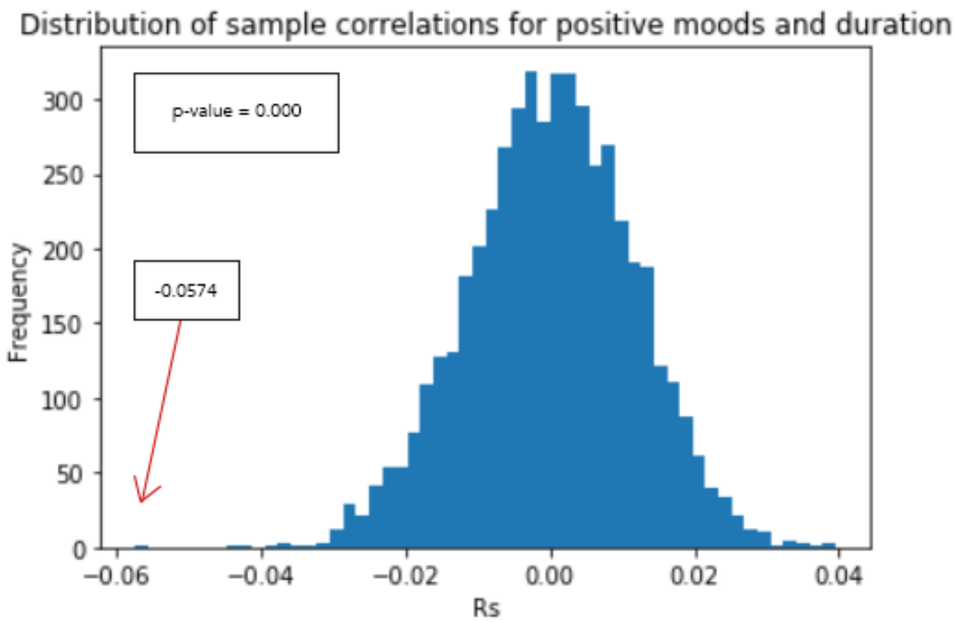

Figure 17

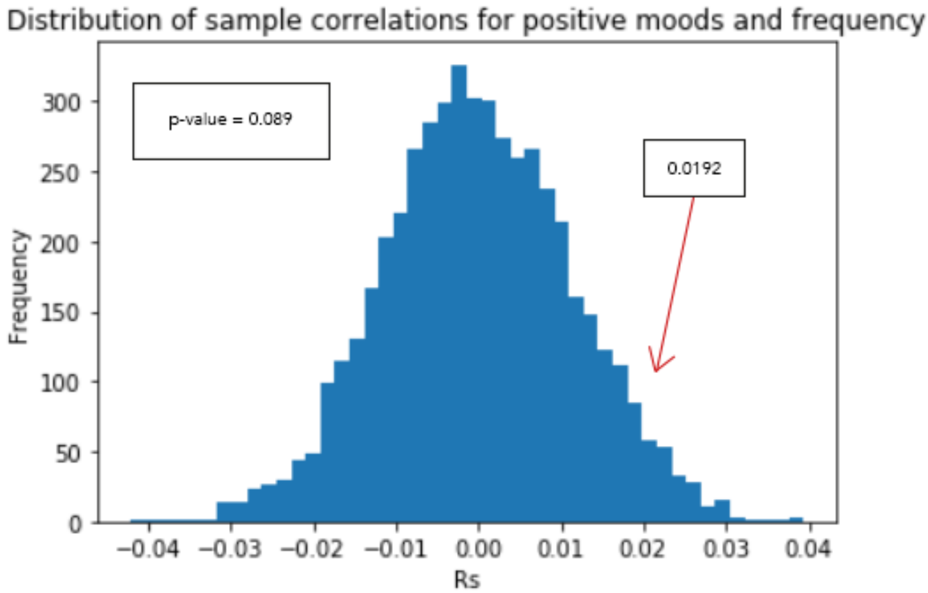

Figure 18

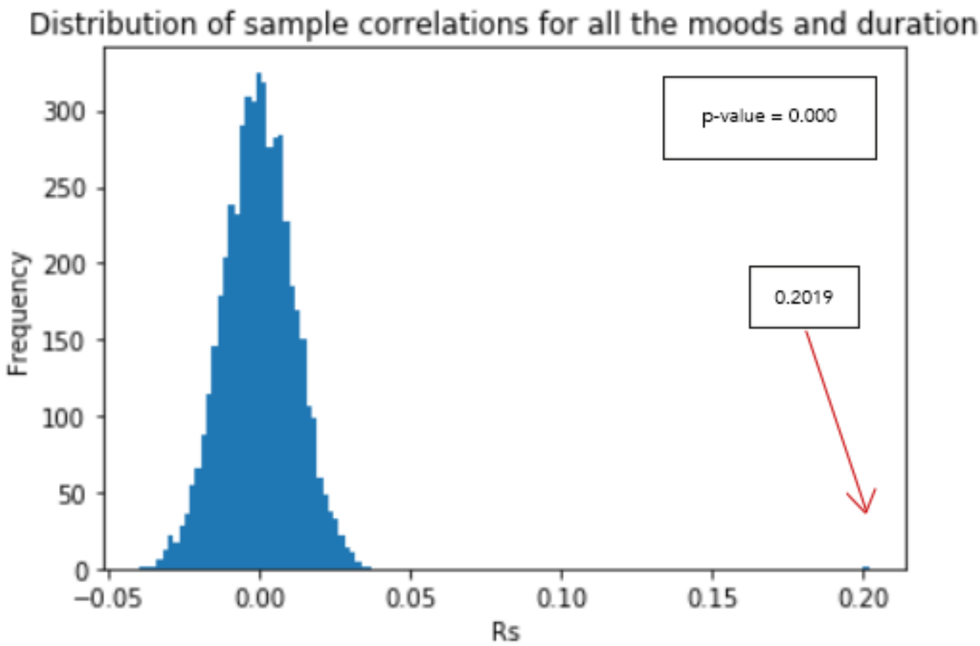

Figure 19

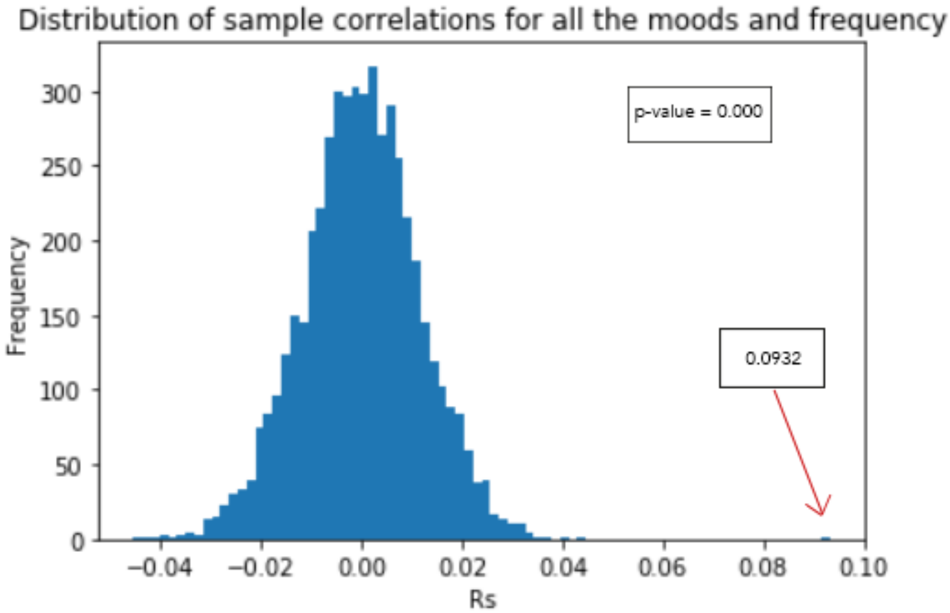

Figure 20

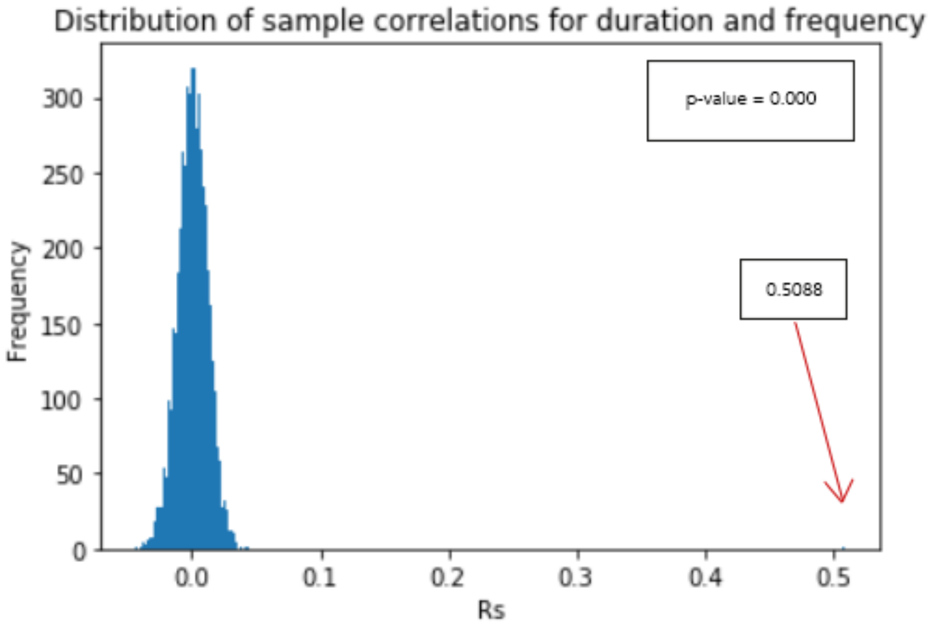

Figure 21

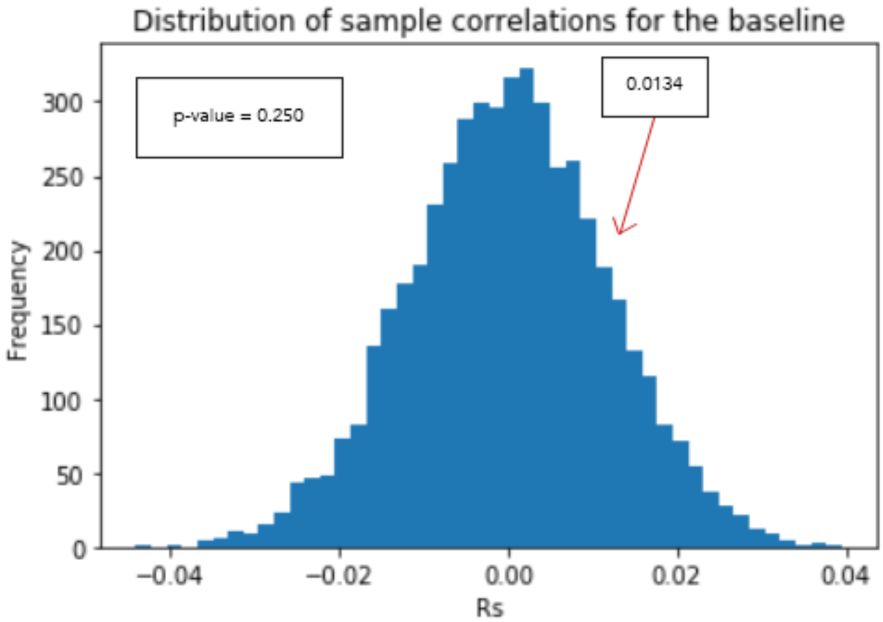
Distribution of sample correlations for the baseline
p-value = 0.250
0.0134
300
250
200
150
100
50
0
Frequency
−0.04
−0.02
0.00
0.02
0.04
Rs

Figure 22