Exploring the Relationship Between Linguistics, Paralinguistics, Personality & Depression

Nikita Belliappa

TU Delft

Exploring the Relationship Between Linguistics, Paralinguistics, Personality & Depression

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Nikita Belliappa

Student number: 5027403

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Graduation Committee

Chairperson: Prof. Dr. F.M. Brazier - Systems Engineering

First Supervisor: Dr. L. Rook - Economics, Technology & Innovation

Second Supervisor: Dr. Iulia Lefter - Systems Engineering

Executive Summary

Depression is one of the most common mental health disorders affecting people from different age groups, societies, communities, and countries. Many countries lack awareness about psychological disorders and there is a scarcity of good mental healthcare facilities available globally.

Medical practitioners recognise depression by analysing the patient's behavioural patterns like speech levels, facial expression, body language and language patterns during therapy. Previous research has shown that behavioural studies are effective means for depression recognition. To explore this relationship, the automated depression recognition dataset called Distress Analysis Interview Corpus (DAIC) was evaluated. This dataset was chosen as it consists of paralinguistic (vocal), linguistic (verbal/text) and extralinguistic (visual) features from the dyadic interviews between participants and a virtual human. Prior research has evaluated the relationship between paralinguistics, linguistics and depression but many researchers failed to analyse the relationship between personality and depression for the DAIC database.

The present study explores how different paralinguistic and linguistic features and personality types differentiate between high and low levels of depression. This study was exploratory in nature and used the LIWC software for linguistic and personality analysis, Pandas software for pre-processing the audio and text data files and lastly correlational analysis using JASP software to answer the research questions. The main findings concluded that linguistic features like emotion (sad and negative), feeling and health related words are used most often by depressed people. Additionally, paralinguistic features like high pitch and breathy voice as well as the personality trait neuroticism were characteristic identifiers of depressed people. These results showed that linguistics, paralinguistics, and personality traits help in depression recognition.

These research findings have the scope for broader and cross-disciplinary applications in the future. Further research and development for automated detection technologies is required in the field of behavioural studies, to enable people globally to easily access and use artificial healthcare platforms for mental health diagnosis.

Acknowledgement

In loving memory of Shashank

In the pursuit of gaining an international experience, two years back I moved to the Netherlands. The journey so far has been a rollercoaster ride with happy, sad, stressful and elated moments. But I have learnt a lot during this period and grown to be a much better version of myself. The pandemic is a very a hard period for everyone and has affected the mental wellbeing of many individuals around the world, including me and my friends. This led me to choose the topic of depression for my thesis.

I would like to thank Professor Laurens Rook, who guided me throughout the thesis process and helped me deal with the pressure and stress. My second supervisor, Professor Iulia Lefter who helped steer the thesis research in the right direction. Additionally, Professor Frances Brazier, the Chairperson for this thesis helped me deal with feedback and guided me further with her valuable knowledge and insights.

All of this would not have been possible without the love and support of my parents. Especially, my mother who helped me look at stressful situations with a positive outlook and my dad for having always believed in me. I wholeheartedly thank my parents for having always encouraged and supported me to attain all my aspirations and goals.

I would like to thank my friends Kavya, Florian, Willem, and Roberto for being my family away from home and for being my pillars of strength in this journey. I couldn't have done this without you all. Special thanks to Florian for being a wonderful support and helping me brainstorm through ideas during the thesis. Furthermore, I extend my gratitude to my friends Dhiren, Srisha, Abhikalp, Samit, Mit, Kuko, Jateen and Vaibhav back in India, for having helped and supported me virtually. In the end, I would like to thank my dear friend Shashank, for always motivating me to be better and pushing me to reach for the stars.

For all those reading this paper, I would like to say that -

Give yourself another day, another chance, you will find your courage eventually. Don't give up on yourself just yet!

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1. Introduction

1.1 Background

Mental illness affects almost 10% of the population, and is one of the most common health issues to go undiagnosed (Downey et al., 2012; Ritchie & Roser, 2018). Almost half of the patients suffering from mental illness are not diagnosed in the initial stages by their general physicians (Higgins, 1994). Furthermore, in a lot of countries and communities around the globe the issue of not having easy access to primary healthcare and treatment still persists (Vaidyam et al., 2019).

Depression is one of the most prevalent mental disorders that globally affects over 264 million people from all ages (WHO, 2020). Depression can be defined as a mood disorder that highly affects mental and physical health. The level of depression differs based on age, gender, income and health conditions (Brody, 2018). Generally, depressed individuals have low moods and energy levels, and tend to avoid activities they once found pleasurable (Meng et al., 2013). In extreme cases, depression could lead to suicidal tendencies. Depression has shown high correlations with behavioural factors like reduced social interaction, dampened facial expressiveness, avoidance of eye contact, reduced speech and lower voice levels (Valstar et al., 2014).

Behavioural studies have found a clear link between psychological disorders like depression, and different verbal and non-verbal behaviour patterns (Ellgring, 2007). In many cases an individual may say something verbally, whereas their non-verbal characteristics like body language, facial expressions, pitch, and voice levels contradict their words (Silverman & Kinnersley, 2010). Linguistics is the study of spoken or written language whereas paralinguistics is the study of the vocal features corresponding to speech (Ivic et al., 2020; Schuller et al., 2013). Therefore, identifying and analysing their paralinguistic features along with their linguistic features has the potential to improve the recognition of distress.

Personality can be defined as a distinctive collection of attitudes, cognitions, and emotions affected by genetic and environmental factors (Jaiswal, 2019; Lo et al., 2017). Depression and personality are highly correlated (Canli, 2006). Research states that the people with high trait neuroticism tend to have a higher tendency to be depressed, whereas people with high trait extraversion show a lower tendency towards depression (del Barrio et al., 1997). One such study by Klein et al. (2012) states that personality attributes may contribute to the growth of depression. Additionally, many researchers found a strong relationship between personality, depression and mental health (Hettema et al., 2006; Kreuger et al., 1996; Takahashi et al., 2015).

The following subsections will discuss in detail the research objective, research questions, research strategy for the thesis.

1.2 Research Objective

This thesis explores the relationship between depression, personality, linguistic and paralinguistic features. Many researchers found strong correlations between linguistic and paralinguistics features, and depression (Alghowinem et al., 2018; Mairesse et al., 2007; Schuller et al., 2013). Still, research exploring depression using paralinguistics, linguistics and personality aspects is limited. This led to finding the knowledge gap and goal for this research (see Figure 1).

"To explore the relationship between paralinguistic and linguistic features, and personality for people high or low on depression".

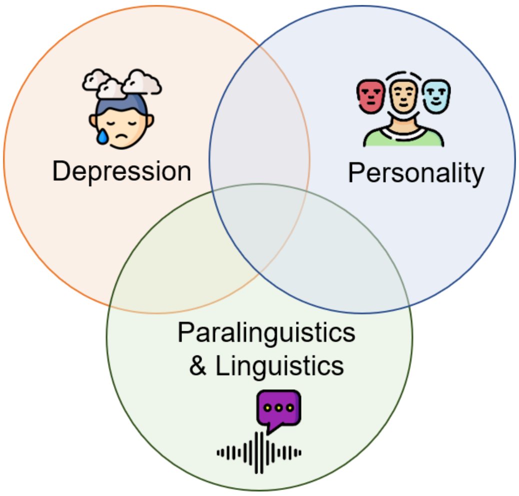

Figure 1: Research Gap

1.3 Research Question

The research question should define the "goal in research" and focus on what is needed to reach the research objective. For this thesis, the main research questions are as follows:

Do people high or low on depression differ in linguistic and paralinguistic characteristics, and how? Does this relate to personality types, and how?

The main research questions encompass all the four aspects that have been discussed in the research objective. The aim is to investigate how certain personality traits are more prone to depression compared to others. This analysis is done using linguistic and paralinguistic analysis (a bimodal method). To examine the main research questions, the following sub-research questions have been formulated.

Sub RQ 1: Which linguistic and paralinguistic characteristics have been found in the literature to be related to depression? And which personality types are connected to depression?

Sub RQ 2: Do linguistic and paralinguistic characteristics depend on a person's personality? If so, how?

Sub RQ 3: Does the level of depression (high or low) relate to linguistic and paralinguistic characteristics and to personality types? If so, how?

These sub-research questions emphasize the need to differentiate between depressed and non-depressed individuals in the exploration of possible correlations between linguistics, paralinguistics, personality and depression.

1.4 Research Strategy

The focus is to answer the research questions that have been mentioned above (subsection 1.3). The research questions require literature research to thoroughly understand the knowledge gap, and research done so far in the field of depression recognition. To answer the sub-research questions, the research needs to be exploratory in nature.

The aim is to identify the relationship between depression, personality, linguistics and paralinguistics correlational studies. To explore this relationship, the Distress Analysis Interview Corpus - Wizard of Oz (DAIC-WOZ) database will be used. This, because it consists of pre-recorded sessions of participants in audio, video and text formats. This database further contains results from depression questionnaire, as well as paralinguistic and linguistic feature information for 189 participants in the form of free text. interviews. This makes it an information-rich database for exploring the relationship between linguistic, paralinguistic features, personality and depression.

1.5 Report Structure

This section presents the structure of the report. **Chapter 1** is an introduction to the thesis consisting of background, and research objective, followed by research questions to be explored, and the research strategy that will be used for analysis. Next, **Chapter 2** is the literature study that reviews existing research related to personality, emotions, paralinguistics, linguistics, different depression datasets and behavioural models discussing depression. **Chapter 3** discusses the Distress Analysis Interview Corpus - Wizard of Oz (DAIC-WOZ) dataset along with an introduction to the DAIC experiment, followed by the experimental setup, the participants involved, the depression scale (PHQ-8), data files available in the corpus and lastly the description of the paralinguistic (audio) and linguistic (text) files and features available. Next, **Chapter 4** describes the methodology used to filter the data files. This includes the methodological steps involved for pre-processing the text and audio files, data reduction methods and data analyses process. **Chapter 5** is the results chapter that presents the correlational analyses between depression, personality, linguistics, and paralinguistics for the DAIC dataset. This is followed by **Chapter 6,** which discusses the scientific relevance, practical relevance, limitations, and possible future research for this topic. Lastly, **Chapter 7** summarises and interprets the results of the findings.

2. Literature Review

This section is focused on reviewing the existing work in the field of depression, personality, behavioural patterns discussing depression, paralinguistic features, linguistics features and depression datasets.

2.1 Depression

Mental health is a condition of psychological maturity that is simply defined as the maximum effectiveness and satisfaction of personal productivity and social interactions that involve the feelings and the positive feedback towards yourself and others (GhorbaniAmir et al., 2011). The latest data indicate that in the long duration of the COVID-19 pandemic, 33 per cent of Americans experienced higher than usual levels of mental health issues like psychological distress (Keeter, 2020). Psychological distress can be defined as "the unique discomforting, emotional state experienced by an individual in response to a specific stressor or demand that results in harm, either temporary or permanent to the person" (Ridner, 2004, p. 539). These mental health disorders can take many forms including depression, anxiety, bipolar disorder, post-traumatic stress disorder (PTSD), eating disorders and schizophrenia (Ritchie & Roser, 2018).

Depression is a chronic disease that can lead to impaired functioning (Pratt, 2014). Depression can be defined as a persistent mood or emotion encountered by a person at different times and is a symptom linked with many psychological conditions, ranging from medical conditions like schizophrenia to milder anxiety disorders (A. LeVine, 2010). Depressed people tend to feel sad, anxious, unworthy, empty, worried, worthless, guilty, or restless. In many cases, they have an aversion to activities, loss of appetite or overeating, engage in overthinking, have trouble concentrating, making decisions or in extreme cases even attempt suicide (Valstar et al., 2014). Generally, depression co-occurs with other forms of mental illness. It is estimated that about 66.7 per cent of patients with depression also have an anxiety disorder (Gorman, 1997).

According to the Anxiety and Depression Association of America, about 6.5 per cent of American adults are affected by depressive disorders, and it is the primary cause of disability for people between the age of 15 to 44 (Dufflin, 2020; Guohou et al., 2020). Especially, in the US during the COVID-19 crisis, depressive symptoms increased by 3 times when compared to the statistics before the pandemic (Ettman et al., 2020).

Depression recognition is a challenge as the symptoms are vague, causes are unknown, and not the result of a single source (Qureshi et al., 2019). In most cases, the severity of depression depends on a variety of factors like genes, psychology, personality, life experiences and social environments of the patients. In severe cases, the patient may develop suicidal tendencies which could be fatal, thus making it necessary to create awareness about mental health and enable quicker diagnosis of depression in patients.

There are different self-reporting diagnostic instruments available for recognising depression. One such instrument is the Patient Health Questionnaire (PHQ) that consists of a two-item scale (PHQ-2), eight-item scale (PHQ-8) and nine-item scale (PHQ-9) commonly used for depression screening (Thombs et al., 2014). Another important (benchmark) scale is the Beck Depression Inventory (BDI), which is a 21 multiple-choice questionnaire that also calculates depression scores (Beck & Steer, 1984). Table 1 mentions other depression measuring instruments like the Geriatric Depression Scale (GDS), Center for Epidemiologic Studies Depression Scale (CES-D), and Hamilton Depression Rating Scale (HAM-D) that are also used in scientific research. Among all these scales, the PHQ-2 and PHQ-8 are briefer scales. They are widely used as they combine individual patient characteristics with screening, thus reducing the bias and increasing the accuracy of results (Thombs et al., 2014).

Table 1: Depression Assessment Scales

Instrument	Number of items	Reference
Patient Health Questionnaire-2 (PHQ-2)	2	(Kroenke et al., 2003)
Patient Health Questionnaire-8 (PHQ-8)	8	(Thombs et al., 2014)
Patient Health Questionnaire-9 (PHQ-9)	9	(Manea et al., 2015)
Beck Depression Inventory (BDI)	21	(Beck & Steer, 1984)
Geriatric Depression Scale (GDS)	30	(Montorio & Izal, 1996)
Center for Epidemiologic Studies Depression Scale (CES-D)	20	(Radloff, 1991)
Hamilton Depression Rating Scale (HAM-D)	17	(Williams, 1988)

The next section discusses the relationship between personality and depression.

2.2 Personality

Personality is an important factor to be considered while analysing depression (Flett et al., 1995). Personality can be conceptualised as a characteristic set of behaviours, cognition, and emotional patterns, influenced by genetic and environmental factors that relate to various mental health conditions such as depression and anxiety (Kreuger et al., 1996; Lo et al., 2017). In many cases, linking an individual's personality type with their diagnostic symptoms has helped correctly identify psychological disorders (Caspi et al., 1997; Kreuger et al., 1996).

Back in 1937, Allport was one of the first psychologists to develop the “Personality Trait Theory”. He believed that personality is biologically determined at birth and further affected by one’s personal experiences (McLeod, 2014). Since then, multiple personality classification models have been proposed like the Five-Factor Model (FFM) or Big-Five model and the Big-Three model. Nowadays, the most widely used model is the Big-Five Model (see section 2.5.2).

The Big-Five Personality model was defined by a group of independent researchers and is widely used to analyse personality types (John & Srivastava, 1999). This model narrowed down the large set of personality traits to five general traits namely neuroticism, agreeableness, extraversion, consciousness and openness (Klein et al., 2012) (this model has been explained in detail further in section 2.5.2). The Big-Three model is a shorter version of the Big-Five model, that includes three main characteristics extraversion, neuroticism and psychoticism (Markon et al., 2005; Zuckerman et al., 1993). Amongst the two models, the FFM is claimed to have a universal and uniform structure that accommodates the cultural, societal, language, social and behavioural differences of humans (Gurven et al., 2013, p. 5).

Many researchers found significant correlations between mental health of an individual and their dominant personality traits (Hettema et al., 2006; Kreuger et al., 1996; Takahashi et al., 2015). Personality traits like neuroticism show a strong relation with depression, whereas traits like extraversion and conscientiousness are more weakly correlated to depression (Boyce et al., 1991; Farmer et al., 2002; Klein et al., 2012; Saklofske et al., 1995). One study used the self-reported personality attributes to show significant improvement in the recognition of depression and anxiety (Jaiswal, 2019). Hirsh & Peterson (2009) took a text-based approach, and, predicted personality based on the types of words that people use in their self-narratives. Another paper examined both the conversation and text of participants to identify the Big-Five traits using text analysis (Mairesse et al., 2007). These research papers showed a clear link between personality and depression detection via natural language processing.

It can be concluded that personality has a strong relationship with depression. To detect these characteristics, an individual’s communication patterns, and behavioural attributes need to be analysed. The next section discusses different behavioural patterns necessary to analyse depression.

2.3 Behavioural Patterns Discussing Depression

Communication is multimodal in nature. In reality, multiple channels like facial and body features, language and vocal aspects are often engaged simultaneously, especially in highly social, group living people (Partan & Marler, 1999). People often communicate using different verbal and non-verbal cues. These behavioural characteristics of humans are important factors for analysing the psychological state of an individual. In the field of psychology, it is known that doctors diagnose the mental health of a patient by observing not just their verbal features but also by studying the patient's changing facial expressions, body language and voice levels to holistically analyse their mental condition (Silverman & Kinnersley, 2010).

Speech, language, and facial expressions are three of the major overt signals widely used for interpreting human psychological states. The multimodal communication system has three main behavioural attributes – extralinguistic features, paralinguistic features, and linguistic features. Extralinguistic (visual or video) features include eye movements, lip movements, facial and postural gestures used by individuals while communicating. Paralinguistic (vocal or audio) features are the gestures accompanying speech like prosody, intonations, and pitch of the voice (see section 2.4). Lastly, linguistic (text or language) features are the verbal/language characteristics of speech like the use negative words, positive words, fillers, pauses (see section 2.5).

Each of the above-mentioned behavioural features when analysed individually are called unimodal. When any of the two modalities like extralinguistic and paralinguistic features are combined, it is called a bimodal model (Partan & Marler, 1999). When more than two modalities are combined, it is called multimodal. In the following sub-sections, I will describe various unimodal, bimodal, multimodal research approaches for depression detection.

Unimodal

Shapiro & Gehricke (2000) and Yulia E. et al. (2010) found that depressive behaviour was generally accompanied by negative facial expressions or reduced facial expressiveness. Another research found that movements in the eyebrows, pupil movement, blink frequency and movement at the corners of the mouth are characteristic predictors of depression (Wang et al., 2018). Patients with severe depression frequently paused before responding and had trouble choosing words (Williamson et al., 2013). Another important voice aspect was pitch variability and duration along with strong but long pause durations which were identified as potential attributes for identifying depression (Parola et al., 2020). All the above-mentioned papers analysed depression using unimodal methods - by analysing either extralinguistic, paralinguistic or linguistic behavioural patterns.

Bimodal

Much research investigates more than one modality to explore the relationships with depression (Al Hanai et al., 2018; Nasir et al., 2016; Williamson et al., 2019, 2014). Pampouchidou et al. (2017) has, for instance incorporated a bimodal framework analysis that extracts extralinguistic and paralinguistic manifestations of depression from facial expressions and speech, with a vision of developing an audio-video based depression diagnostic system. The results showed 94.8% of precision in detecting depression.

Multimodal

Guohou et al. (2020) proposed a multimodal approach that integrates verbal, vocal and visual behaviours to analyse depression in dyadic interviews. A similar approach was adopted by Ghosh et al. (2014) to detect depression. They discovered that multimodal feature analyses significantly improved distress recognition. Similarly, multiple research papers have detected depression levels by analysing audio, video and text features (Nasir et al., 2016; Pampouchidou et al., 2016; Williamson et al., 2016). The multimodal narrative approach makes it easy to integrate learnings from other disciplines, such as conversational analysis and psychology (Kim et al., 2019).

This thesis will be using the bimodal approach by focussing mainly on the linguistic and paralinguistic feature analysis which is explained in detail in the following sections.

2.4 Importance of Paralinguistics for Depression Recognition

For decades, researchers have been investigating the relationship between vocal features and emotions. Paralinguistics is defined by the vocal factors corresponding to verbal messages, in other words also called ‘alongside linguistics’ (Schuller et al., 2013). The acoustic feature analysis along with language processing (linguistics), helps to better identify the psychological state of an individual. It is well-known that coughs, laughter, long pauses, and breathing patterns are important acoustic factors for psychoanalysis. Paralinguistics includes prosodic, spectral and voice quality features:

- **Prosodic features** allow for emotion recognition in human speech utterances. They are perceived by characteristic features like pitch, loudness, duration, silence, and rhythm (Schötz, 2002). These perceived characteristics highly correlate to acoustic features like pitch with fundamental frequency (F0), loudness with short time signal energy and duration with time taken for a spoken utterance (Steidl, 2009)
- **Spectral features** are extracted from the frequency content of the voice signals and are identified by frequency, amplitude and bandwidth (Wu et al., 2011). These features help identify speaker-dependent measures of speech and are mainly used for speech recognition (Přibil & Přibilová, 2011).
- **Voice quality features** identify emotions and attitude like surprise, disgust, anger, dissatisfaction, and admiration, attached to speech based on phonetics (Steidl, 2009). Phonetics is defined as the different speaking styles like breathy, whispery, creaky or harsh voice used by individuals during speech utterances or conversations (Ishi et al., 2006).

Prosodic, spectral and voice-quality features carry emotion rich information of speech utterances. Analysing all the features provides better results for speech-based emotion recognition (Zhou et al., 2009). These acoustic features when measured, act as reliable biomarkers to differentiate between depressed and non-depressed individuals (Mundt et al., 2012).

Prosodic Features

Speech signals carry emotional expression related to the state of the speaker, also called vocal effect. They are easily measured by the prosodic features (Moore et al., 2003). These features help distinguish between different emotional states and emotional disorders. Yang et al. (2013) investigated depression classification based on prosody to achieve an accurate recognition of 69 percent.

Fundamental frequency (F0) is a "vocal expression of emotion and a characteristic function of prosody that highly correlates with pitch" (Gobl & Ní Chasaide, 2003). Furthermore, Cannizzaro et al. (2004) & Nilsonne et al (1988) concluded that low pitch levels are a symptom of increasing depression severity. Depressed individuals tend to speak slowly using lower frequency levels than normal people (Sahu & Espy-Wilson, 2014).

Spectral Features

Spectral features are widely used for speech recognition to understand the "how" behind the speech utterance (Steidl, 2009). Spectral features enhance the speech quality and speaker identification by capturing the vocal tract changes (Nirmal et al., 2014). These features mainly help differentiate between natural and synthetic speech based on frame-level or utterance-level aspects (Bitouk et al., 2010; Chen et al., 2010).

Studies have concluded that spectral features alone do not provide the best discrimination between depressed and non-depressed speech. Combining them with prosodic features provided better results (Alpert et al., 2001; Moore et al., 2008, 2003).

Voice Quality Features

Voice quality characteristics differentiates healthy people from depressed based on breathy to tense speech. This includes jitters[1], shimmers[2], pauses or breathes (S. Scherer et al., 2013). These different voice related speaking styles are often associated with varying attitudes and emotions. Tense voice is associated with anger, creaky voice with boredom, whispery voice with confidentiality, breathy voice with intimacy, harsh voice with high tension and lax-

[1] "The cycle to cycle variability of the duration of the pitch period" (Sahu & Espy-Wilson, 2014)

[2] "The cycle to cycle variability of the duration of the pitch period amplitude" (Sahu & Espy-Wilson, 2014)

creaky voice is a combination of breathy and creaky (Gobl & Ní Chasaide, 2003). A tense voice indicates the arousal of emotions like anger, joy and fear whereas a breathy speech shows sadness (K. R. Scherer, 1986). Researchers like Sahu & Espy-Wilson (2014) and Honig et al. (2014) concluded that the increase in jitters, shimmers and breathiness are significant indicators of depression. Another paper states that the tenseness in the voice relates to higher probability of psychological disorders (Scherer et al., 2013).

Research concluded that prosodic and voice quality features like decreased vocal pitch, increase vocal tenseness and slow rate of speech are crucial characteristics of depressed individuals (Johnstone & Scherer, 1999; S. Scherer et al., 2013; Stasak et al., 2016). Furthermore, studies estimated significant differences in speech characteristics for depressed individuals (Lopez-Otero et al., 2014).

For this thesis, I will be focussing mainly on the prosodic and voice quality features as they help differentiate between healthy and depressed individuals based on emotion recognition. Language processing is an important aspect that follows paralinguistics. The next subchapter thus discusses and explores the relationship between linguistics and depression.

2.5 Importance of Linguistics for Depression Recognition

Humans tend to use language/words/speech to convey their thoughts and feelings to others. This makes language an important social and cultural construct that should be learnt, understood and used for communication (Sapir, 1929). Linguistics is the scientific study of language that tends to analyse spoken language over written texts (Ivic et al., 2020).

One part of linguistics investigates the structure of language like phonetics (speech sounds in physical aspects), phonology (speech sounds in cognitive aspects), morphology (formation of words), syntax (formation of sentences), semantics (study of meaning) and pragmatics (language use). Another part analyses interdisciplinary branches like sociolinguistics (sociology & linguistics), psycholinguistics (psychology & linguistics), neurolinguistics (neurology & linguistics), ethnolinguistics (anthropology & linguistics) (UC Santa Cruz, 2020).

The study of analysing an individual’s linguistic patterns to predict their psychological condition is called Psycholinguistics (Jodai, 2011). The type of words that individuals use, reveals a lot about their social, personal and mental state (J. W. Pennebaker et al., 2003). Both written and spoken language help understand and analyse the behaviour, moods, and state of mind of an individual, as one can differentiate between people based on their linguistic styles (J. W. Pennebaker & King, 1999).

Psycholinguistics emerged in the 19th century when Freud (1901) discovered that misspeaking could reveal an individual's intentions. Since then, several researchers have attempted to build a comprehensive text analysis system that can examine linguistics. In 1992, Pennebaker and Francis (2001) devised a computerised program called the Linguistic Inquiry and Word Count (LIWC) that counted words in each psychological category for multiple text files at the same time (Tausczik & Pennebaker, 2010). This program was revised in 1997, 2007 and 2015. The LIWC 2015 is the most recent version available. The LIWC has over 56 inbuilt dictionaries, along with the option to create your own dictionary. The "Internal Dictionary-2015" is an in-built dictionary that consists of 90 categories that help detect depression, personality, and emotions based on linguistics and word use.

The following sub-sections describes some studies that uses the LIWC software to explore the relationship of linguistics with depression and personality.

2.5.1 LIWC and Depression

Language is a crucial element in examining a patient's mental state of mind. Especially psychologists need to manually understand the underlying meaning behind the patient's language to diagnose their mental illness (Resnik et al., 2013). The key to curing a patient mainly depends on the early and fast diagnosis of their condition. This makes language-based analysis a crucial factor for recognising psychological distress in individuals.

Depressed individuals tend to be more self-focused, use more negative emotion words, use more first-person singular pronouns and in some cases also death-related words (Ramirez-Esparza et al., 2008; Tausczik & Pennebaker, 2010). Another study suggests that absolutist words (certainty index) are a common trait of depression along with the repeated use of negative emotion words and pronouns (Ramirez-Esparza et al., 2008).

Al-Mosaiwi and Johnstone (2018) found the following categories like death, anxiety, negative emotions, sadness, affect, anger, certainty, pronouns and feel to measure depression, anxiety and suicidal ideation to be correlated to depression. Many researchers (Himmelstein et al., 2018; Hussain et al., 2020; Morales & Levitan, 2016; J. W. Pennebaker & King, 1999; Rathner et al., 2018; Tadesse et al., 2019) used similar categories like personal pronouns (like I, we), death, negative emotions, sad, affect, anger, death, positive emotions, past tense, and social for measuring depression. This literature research led to selecting LIWC categories shown in Table 2 for depression recognition, which will be used later for analysis in chapter 5.

Table 2: LIWC Category Selection for Depression

Category	Abbrev	Examples	Words in category
Linguistic Dimensions			
1st pers singular	i	I, me, mine	24
1st pers plural	we	we, us, our	12
Conjunctions	conj	and, but, whereas	43
Negations	negate	no, not, never	62
Psychological Processes			
Affective processes	affect	happy, cried	1393
Positive emotion	posemo	love, nice, sweet	620
Negative emotion	negemo	hurt, ugly, nasty	744
Anxiety	anx	worried, fearful	116
Anger	anger	hate, kill, annoyed	230
Sadness	sad	crying, grief, sad	136
Social processes			
Family	family	daughter, dad, aunt	118
Friends	friend	buddy, neighbor	95
Cognitive processes			
Insight	insight	think, know	259
Causation	cause	because, effect	135
Differentiation	differ	hasn't, but, else	81
Perceptual processes			
Feel	feel	feels, touch	128
Biological processes			
Health	health	clinic, flu, pill	294
Time orientations			
Past focus	focuspast	ago, did, talked	341
Present focus	focuspresent	today, is, now	424
Relativity			
Time	time	end, until, season	310
Personal concerns			
Work	work	job, majors, xerox	444
Home	home	kitchen, landlord	100
Death	death	bury, coffin, kill	74

2.5.2 LIWC and Personality

Conversation is a key factor that identifies different types of personalities. The Big-Five model consist of five factors Openness, Consciousness, Extraversion, Agreeableness, and Neuroticism: Factor I (Openness or Intellect) measures traits like imagination and creativity against traits like shallowness and imperceptiveness; Factor II (Consciousness) contrasts organisation, thoroughness, and reliability with traits like carelessness, negligence and unreliability; Factor III (Extraversion) measures traits related to sociability like talkativeness, assertiveness, and activity level; Factor IV (Agreeableness) maps traits like kindness and trust with selfishness and distrust; and Factor V (Neuroticism) looks into behaviours like nervousness, moodiness and temper against emotional stability (Goldberg, 1993).

In their text-based studies. Hirsh and Peterson (2009) and Mairesse et al. (2007) concluded that extraversion closely relates to sociability aspects, agreeableness to family, feeling and inclusiveness, consciousness correlates with achievement and work-related words, neuroticism with anger, sadness, anxiety and negative emotions and lastly openness with perceptual process words like hearing and seeing. Table 3 shows these LIWC categories mapped against the Big-Five personality traits, as they will be used later for analysis in chapter 5.

Table 3: LIWC Category Selection for Personality

Category	Abbrev	Examples	Words in Category	Big-5 Traits
Linguistic Dimensions				
Conjunctions	conj	and, but, whereas	43	Agreeableness
Psychological Processes				
Negative emotion	negemo	hurt, ugly, nasty	744	Neuroticism
Anxiety	anx	worried, fearful	116	Neuroticism
Anger	anger	hate, kill, annoyed	230	Agreeableness, Consciousness, Neuroticism
Sadness	sad	crying, grief, sad	136	Neuroticism
Social processes	social	mate, talk, they	756	Extraversion
Family	family	daughter, dad, aunt	118	Extraversion, Agreeableness
Friends	friend	buddy, neighbor	95	Extraversion
Female references	female	girl, her, mom	124	Extraversion
Male references	male	boy, his, dad	116	Extraversion
Cognitive processes				
Certainty	certain	always, never	113	Agreeableness
Differentiation	differ	hasn't, but, else	81	Consciousness, Openness
Perceptual processes	percept	look, heard, feeling	436	Openness
Hear	hear	listen, hearing	93	Openness
Biological processes				
Body	body	cheek, hands, spit	215	Agreeableness, Consciousness, Neuroticism
Drives				
Achievement	achieve	win, success, better	213	Consciousness
Personal concerns				
Work	work	job, majors, xerox	444	Consciousness, Neuroticism
Home	home	kitchen, landlord	100	Neuroticism
Death	death	bury, coffin, kill	74	Consciousness

2.6 Depression Datasets

With the aim of finding a corpus that contains linguistic and paralinguistic data for analysis. This section discusses the various datasets that have been used previously in research for detecting depression. Table 4 summarises the corpuses based on modalities (audio, video, and text), scales used for predicting depression, the mental disorder being measured and their references. The evaluation of the datasets mentioned in Table 4, helped narrow down the search to a single dataset that included both linguistic (text) and paralinguistic (audio) features for data analysis. Each of corpuses have been explained further.

Table 4: Depression Detection Datasets

Dataset	Modality	Depression Scale	Focus	References
Distress Analysis Interview Corpus (DAIC) – Human Interviews	Audio, Video	PHQ-9	Depression, PTSD and Distress	(Gratch, Artstein, et al., 2014)
Distress Analysis Interview Corpus– Wizard of Oz (DAIC-WOZ)	Audio, Video, Text	PHQ-8	Depression	(Gratch, Artstein, et al., 2014)
Distress Analysis Interview Corpus- Virtual Human (DAIC-VH)	Audio, Video	PHQ-9	Depression and PTSD	(Gratch, Artstein, et al., 2014)
Audio-Visual Emotion Recognition Challenge (AVEC-2013)	Audio, Video	BDI-II	Depression	(Valstar et al., 2014)
Black Dog Dataset	Audio, Video	HAM-D	Depression	(Alghowinem et al., 2012)
Pitt Depression Dataset	Audio, Video	HAM-D	Depression	(Yang et al., 2013)

Distress Analysis Interview Corpus (DAIC)

Distress Analysis Interview Corpus (DAIC) consists of semi-structured interviews of participants that helps predict psychological distress conditions like anxiety, PTSD and depression (Gratch, Artstein, et al., 2014). The interviews were conducted in three scenarios – by humans, human controlled agents (WOZ) and automated agents (VH).

Distress Analysis Interview Corpus- Human Interviews

This dataset is similar to the DAIC corpus but contains the interview recordings in audio and video formats between the participant and human interviewer. Additionally, it also includes the PHQ-9 scores data for depression measurement of each participant.

Distress Analysis Interview Corpus–Wizard of Oz (DAIC-WOZ)

This dataset is similar to the DAIC corpus, consists of semi-structured interviews between the participants and human-controlled computer (Gratch, Artstein, et al., 2014). The corpus includes the 189 participant's audio, video, and text recordings from the interviews and their PHQ-8 scores.

Distress Analysis Interview Corpus–Virtual human (DAIC-VH)

This corpus is identical to the DAIC dataset, but the interviews are conducted between the participant and a virtual human (Gratch, Artstein, et al., 2014). The data consists of audio and video recordings of interviews along with the responses for the PHQ-9 questionnaire.

Audio-Visual Emotion Recognition Challenge (AVEC-2013)

This dataset comprises of 340 audio-video recordings of participants performing human-computer interaction tasks (Valstar et al., 2014). The depression levels were labelled using the Beck Depression Inventory.

Black Dog Dataset

The interviews for this dataset contain audio and video recordings of participants including speech features, facial expressions, and body gestures (Alghowinem et al., 2018, 2012). This experiment was carried out by the Black Dog Institute Australia and uses the Hamilton Depression Scale (HAM-D) to measure depression.

Pitt Depression Dataset

This depression dataset was collected by the University of Pittsburgh during the treatment of depressed patients (Yang et al., 2013). Both audio and video formats for the interviews were recorded along with depression scores from the Hamilton Depression Scale (HAM-D).

Amongst all the datasets mentioned above, the DAIC-WOZ was the only corpus that recorded the distinctive behavioural characteristics of respondents for depression based on their audio, video and text features. Additionally, it also included the PHQ-8 scale scores for depression per participant. This made this dataset most suitable for the analysis as the aim of this thesis is to analyse the relationship between linguistic (text) and paralinguistic (audio) features with depression.

2.7 Summary Literature Review

This sub-chapter summarises the literature findings. Chapter 2 started by discussing the importance of mental health and awareness about depression, the importance of depression recognition and the different depression scales. Next, the sub-section 2.2 looked into research on personality and their relationship with depression to find strong correlations between them. Sub-section 2.3 investigated the importance of different modalities like extralinguistics, paralinguistics and linguistics for depression recognition. This led to the conclusion to follow a bimodal approach of analysing only paralinguistic and linguistic features in the present study.

The sub-sections 2.4 and 2.5 deep-dives into the different paralinguistic and linguistic features for depression and personality recognition. Lastly, the sub-section 2.6 reviewed different depression datasets for paralinguistic and linguistic interview data to find that the DAIC-WOZ dataset was most suitable for this research.

3. Distress Analysis Interview Corpus – Wizard of Oz (DAIC-WOZ)

The Distress Analysis Interview Corpus (DAIC) is a multimodal collection of semi-structured interviews designed to recognise psychological distress (Gratch, Artstein, et al., 2014). The interviews were part of larger study designed to identify post-traumatic stress disorder (PTSD), major depression and anxiety in participants using interviews (Rana et al., 2019). The experiment was carried out by the researchers at the University of Southern California. They used the SimSensei model (DeVault et al., 2014; Gratch, Artstein, et al., 2014).

The SimSensei system is a fully automated virtual agent (embodied as Ellie) that is capable of engaging in face-to-face interactions with the subject and capturing their behaviours during the process (Stratou et al., 2015). The technology (SimSensei) is designed to create interactive environments favourable for automatically assessing the distress signals related to verbal and nonverbal behaviours of patients (DeVault et al., 2014).

The DAIC database contains three types of interviews namely face-to-face, Wizard-of-Oz (DAIC-WOZ) and automated interviews. In addition to this, the participants also completed a series of questionnaires before and after the interview process (Gratch et al., 2014). For this Master Thesis Project, the DAIC-WOZ study was chosen as it consists of a rich database of recorded responses in audio, video and text formats that can be analysed for recognising depression. Additionally, it consists of interview data for a diverse set of 189 participants, including both men and women. It thus, provides rich linguistic and paralinguistic feature related data along with depression questionnaire results suitable for depression recognition.

To find the knowledge gap for this research, over 160 articles (see Appendix A) that cited the DAIC-WOZ database were read and analysed. The literature study indicated that the relationship between personality and depression using linguistics and paralinguistics was an untouched area. Additionally, not many papers explored the linguistic and personality aspects using the LIWC software. This led to exploring the relationship between depression, personality, linguistics, and paralinguistics.

For the present study, the focus is on Wizard-of-Oz (DAIC-WOZ) depression dataset and the PHQ-8 questionnaire. The experimental setup, participants involved, data files and questionnaire description have been explained in detail in the following subsections.

3.1 Setup

For the DAIC-WOZ, the interviews were conducted by Ellie, while her speech, actions and behaviours were controlled by a human interviewer in another room (Gratch, Artstein, et al., 2014). For the SimSensei system to pick up all the verbal and non-verbal characteristics of the participants: Firstly, a wireless microphone was placed at a 2m distance from the respondent to extract the paralinguistic/verbal features like distress calls, amplitude, tone, pitch (S. Scherer et al., 2014); Next, using a webcam the nonverbal (visual or video) recordings were obtained, and this captured the facial aspects like the head pose, eye gaze, smiling and facial action units (Stepanov et al., 2017). Lastly, the linguistic (language or text) features like word count, sentence, and noun repetitions are derived from the participants' transcripts (Ghosh et al., 2014).

3.2 Participants

All the participants were from the US in the age group of 18 to 65, consisting of veterans of the US Armed Forces and the general public living in the Greater Los Angeles Metropolitan Area (Stratou et al., 2015). There was a total of 189 participants in which 4 participants (342, 394, 398, 460) data files were excluded due to technical reasons.

3.3 PHQ-8 Questionnaire

Before the DAIC interviews, the participants completed a series of questionnaires (Gratch, Artstein, et al., 2014). These questionnaires included the Patient Health Questionnaire (PHQ-8) for depression, PTSD Checklist for PTSD, Positive and Negative Affect (PANAS) to assess mood, and State-Trait Anxiety Inventory to measure anxiety. For this paper, the PHQ-8 scores were used for analysis as it measures the depression levels in patients.

The Patient Health Questionnaire is a scale that can measure depressive disorders and is used in large clinical studies (Kroenke et al., 2009). The PHQ-8 questionnaire measures depression by using questions based on the following 8 criteria's: no interest, depression, sleep, tiredness, appetite, failure, concentration, and fatigue. Depending on the scores from this questionnaire, the participant is declared depressed or not. The PHQ-8 score>10 represented a depressed individual whereas the PHQ-8 score<10 measured a non-depressed individual (Kroenke et al., 2009).

3.4 Data Files

The data collected for the DAIC-WOZ database consisted of audio recordings of the interviews along with data files with the extracted features from the audio and visual sessions for easy analysis. The transcript files included the conversational dialogues between Ellie and the participants but did not include any file with the extracted textual features (Degottex et al., 2014; DeVault et al., 2014; Gratch, Artstein, et al., 2014; Kroenke et al., 2009). The corpus includes 189 folders with sessions named 300-492, although some sessions (342, 394, 398, 460) have been scrubbed due to technical reasons. Each session/folder consisted of 10 files as shown in Table 5 below.

Table 5: Files and their Descriptions

Data File	File Description
XXX_CLNF_features.txt	68 2D points on the face
XXX_CLNF_features3D.txt	69 3D points on the face
XXX_CLNF_gaze.txt	Gaze direction of both eyes
XXX_CLNF_hog.bin	Histogram of Oriented Gradients (HOG) of the face
XXX_CLNF_pose.txt	Head rotation coordinates
XXX_CLNF_AUs.csv	Facial action units
XXX_AUDIO.wav	Audio recording by a microphone
XXX_COVAREP.csv	Audio features sampled at 100Hz
XXX_FORMANT.csv	5 vocal tract resonance frequencies
XXX_TRANSCRIPT.csv	Text conversation with time & speaker value

Note: XXX – Session Number (300-492)

Other than participant sessions, there were data files like "train_split_depression_AVEC2017.csv", "dev_split_depression_AVEC2017.csv", and ""test_split_Depression_AVEC2017.csv" that contained information about participant IDs, PHQ8 scores in binary, PHQ-8 scores for each category separately, and participant gender.

The following sections discuss the features of the COVAREP and TRANSCRIPT files as they carry paralinguistic and linguistic features for analysis.

3.4.1 Audio (COVAREP) File

The audio file or the COVAREP file consists of 74 columns, each of these columns correspond to 74 different acoustic features. These features have been sampled at 100Hz and all the scrubbed (inconsistent, incomplete, wrong) data features have been set to zero (Gratch, DeVault, et al., 2014). Table 6 shows the 74 pre-extracted audio features that have been classified based on binary voicing decision (VUV), prosodic, spectral, and voice-quality categories, along with the description to the abbreviations.

Table 6 represents the audio feature with their description. The prosodic feature includes fundamental frequency (F0). Normalised Amplitude Quotient (NAQ), Quasi-Open Quotient (QOQ), glottal harmonics (H1-H2), Parabolic Spectral Parameter (PSP), Maxima Dispersion Quotient (MDQ), Maximum Peaks for the middle part of the utterance (peakSlope), Wavelet based features (Rd) and confidence of Rd (Rd_conf) are all voice quality features. Lastly, the spectral features include Mel Cepstral Coefficient Parameter (MCEP), Harmonic Model and Phase Distortion Mean (HMPDM) and Harmonic Model and Phase Distortion Deviation (HMPDD). These features have been explained in detail in section 4.3.

Table 6: Paralinguistic File Description

Audio Features		Description
Category	Sub-category	
	VUV	Binary voicing decision
Prosodic Features	F0	Fundamental frequency
Voice Quality Features	NAQ	Normalized Amplitude Quotient
	QOQ	Quasi-Open Quotient
	H1-H2	Difference in amplitude of first two glottal harmonics
	PSP	Parabolic Spectral Parameter
	MDQ	Maxima Dispersion Quotient
	peakSlope	Maximum peaks for the middle part of the utterance
	Rd	Wavelet based features
	Rd_conf	The confidence of Rd
Spectral Features	MCEP_0-24	Mel Cepstral Coefficient Parameter
	HMPDM_0-24	Harmonic Model and Phase Distortion Mean
	HMPDD_0-12	Harmonic Model and Phase Distortion Deviation

3.4.2 Text (Transcript) File

The "TRANSCRIPT.csv" files contained the dialogue information between Ellie and the participant in text format. This file mainly included information regarding the start time and stop time of the dialogue along with the corresponding speaker value (Ellie or participant) and the corresponding dialogue statement.

3.5 Summary of DAIC-WOZ

This chapter described the Distress Analysis Interview Corpus-Wizard of Oz (DAIC-WOZ) interview dataset. Sub-sections 3.1, 3.2, 3.3 and 3.4 provide detailed description about the setup of the experiment, participants involved, the depression questionnaire PHQ-8 and the data files along with their descriptions, respectively.

For this thesis, we used only the "COVAREP.csv" and "TRANSCRIPT.csv" files as the scope of this research are to explore the relationship between depression, personality, paralinguistic and linguistic features. The next chapter discusses the methodology involved for the pre-processing the audio (paralinguistic) and text (linguistic) files.

4. Methodology

This chapter describes the procedure used for the pre-processing of the audio and text data files, and the steps involved for data reduction of the files.

4.1 Data Pre-processing of Text Files

The DAIC-WOZ corpus data was used for the analysis of depression and personality in the participants. For text analysis, we used the XXX_TRANSCRIPT.csv files that contained the conversation in words between Ellie and the participant.

The transcript files were in the ".csv" file format that consisted of values like the start time & stop time of the dialogue along with the speaker type and their dialogue in words. The data was populated in one cell and there were no delimiters to separate the data into columns. This resulted in splitting the transcript data into columns (as seen in Table 7) for easy readability and analysis.

Table 7: Transcript File - Format

Column	Description
start-time	Start time of the dialogue
stop_time	Stop time of the dialogue
speaker	Ellie or Participant
value	Dialogue in words

To filter the transcript data into columns for all the 189 participants dynamically, Python code was used in the Pandas software library. Pandas is an open-source Python library consisting of rich data structures and tools for data analysis and statistics (McKinney, 2011). The logic used for creating a single consolidated transcript file with dialogues from all 189 sessions has been explained in detail (see Appendix for detailed explanation).

The steps mentioned in Table 8 resulted in a consolidated transcript file with 189 rows containing dialogues of each session in separate rows. This consolidated file was later used for correlational analysis, which is explained later in Chapter 5. The transcript data needed to be further filtered to improve the quality of data. This is explained in detail in the next session.

Table 8: Text File Pre-Processing Steps

Steps	Pre-Processing
Step 1	Read data from the raw transcript files
Step 2	Split single-cell data into different columns as shown in Table 7
Step 3	Save the column-separated data into new transcript files
Step 4	Select and concatenate dialogues from the "value" column of each session and store dialogues in a single row. Here, each row represents a session and the following cells of that row contain the dialogues.
Step 5	Repeat step 4 to create a file that includes only participant dialogues
Step 6	Repeat step 4 to create a file that includes Ellie & participant dialogues
Step 7	The dialogues present in different cells of each session are concatenated into a single column

4.2 Data Reduction of Text Files

After filtering all the 189 transcript files into a single consolidated file, the final step was to improve the quality of the data. For this, the unscrubbed data was eliminated based on the following conditions and the eliminated words have been mentioned in the Appendix.

- If the speech was cut off, the transcript text contained a complete intended word followed by a comment of the word that was actually pronounced in angle brackets: people <peop>.
- Unrecognized words indicated by 'xxx'.
- Emotions, sounds, and actions were also expressed within angle brackets and square brackets like <laughter>, [exhales], [real], etc.
- Certain sessions had each sentence ending with quotation marks

4.3 Audio (COVAREP) Feature Description

To analyse the participant's paralinguistic features for depression, the XXX_COVAREP.csv files from the DAIC-WOZ database were used. For this, the audio data was extracted using the Cooperative Voice Analysis Repository for Speech Technologies (COVAREP). COVAREP is an open-source repository for speech processing algorithms (Degottex et al., 2014). The audio features of the DAIC-WOZ corpus were extracted using the COVAREP toolbox (v. 1.3.2).

Table 9 is an extended version of Table 6 with additional information about the voicing decisions. The voiced or unvoiced (VUV) decision depends on the pronunciation of the word and the vibrations produced in the vocal cords. According to phonetics, all vowels in English are voiced as they produce vibrations whereas consonants may be voiced (vibrations) or unvoiced (no vibrations) (Britannica, 2017).

According to the DAIC-WOZ parent file, table 9 maps the features F0, NAQ, MDQ, QOQ, H1-H2, PSP, peakSlope, Rd and Rd_conf as voiced (vocal cords vibrate) and MCEP, HMPDM, and HMPDD as unvoiced (no vocal cord vibrations) (Gratch, DeVault, et al., 2014). The different prosodic, voice quality and spectral features are explained in detail ahead.

Table 9: Paralinguistic Feature Description with Voicing Decision

Audio Features		Description	Voicing Decision
Category	Sub-category		
	VUV	Binary voicing decision	Voiced=1 and Unvoiced=0
Prosodic Features	F0	Fundamental frequency	Voiced
Voice Quality Features	NAQ	Normalized Amplitude Quotient	Voiced
	QOQ	Quasi-Open Quotient	Voiced
	H1-H2	Difference in amplitude of first two glottal harmonics	Voiced
	PSP	Parabolic Spectral Parameter	Voiced
	MDQ	Maxima Dispersion Quotient	Voiced
	peakSlope	Maximum peaks for the middle part of the utterance	Voiced
	Rd	Wavelet based features	Voiced
	Rd_conf	The confidence of Rd	Voiced
Spectral Features	MCEP_0-24	Mel Cepstral Coefficient Parameter	Voiced & Unvoiced
	HMPDM_0-24	Harmonic Model and Phase Distortion Mean	Voiced & Unvoiced
	HMPDD_0-12	Harmonic Model and Phase Distortion Deviation	Voiced & Unvoiced

Prosodic Features

Fundamental frequency (F0) highly correlates to pitch and measures the highness or lowness in the voice based on the vibrations in the vocal folds/glottis[3] (Britannica, 1998b). For example, women's glottis vibrate faster than men, thus women tend to have higher values of pitch and fundamental frequency (F0) (Rochman & Amir, 2013).

[3] "The space between the vocal fold and cartilage of the larynx or windpipe" (Britannica, 1998a)

Voice Quality Features

The characteristics of speech vary with changes in phonation[4] and this is the result of changes in the glottis (Degottex et al., 2014). This makes glottal flow parameters like NAQ, QOQ, H1-H2, PSP, MDQ, peakSlope, and Rd important measures to analyse voice quality. These features mainly differentiate between breathy to tense voice qualities based on different measures of the glottis opening and closing periods.

Normalized Amplitude Quotient (NAQ) and Quasi-Open Quotient (QOQ) differentiate between varying singing styles and phonation types by analysing the vocal fold vibrations of the larynx (voice box) (Björkner et al., 2006). In simple words, they distinguish between voice quality from "breathy" to "tense" voiced speech based on vocal fold opening period for QOQ measures and vocal fold closing period for NAQ (Alku et al., 2002; Campbell & Mokhtari, 2003).

Parabolic spectral parameter (PSP) is a frequency parameter that measures the spectral decay waveform of the voice source (Alku et al., 1997). It is based on the speaker's fundamental frequency (Guohou et al., 2020).

Human speech is complex as the fundamental frequencies are accompanied by multiple variations in frequency and pitch. These variations are called overtones or harmonics (Arnold, 2019). H1-H2 is the difference in amplitudes of the first two glottal frequencies that distinguish between different tone qualities. These tones makes the voice sound clearer (Guohou et al., 2020).

The voice quality features like MDQ, peakSlope and Rd are important glottal flow parameters. Maxima dispersion quotient (MDQ) quantifies the extent of maxima dispersion over the glottal period (Kane & Gobl, 2013). PeakSlope measures the maximum peaks in the middle of the utterance (Guohou et al., 2020). MDQ and peakSlope quantifies the dispersion of voice signals for continuous speech to differentiate between breathy to tense voices based on the glottis closing instant (GCI) (Kane & Gobl, 2013). The Wavelet-based feature (Rd) is a shape parameter that measures differences between breathy to tense phonation, whereas Rd_conf is the confidence of Rd which varies from 0 to 1 (Fant, 1995; Guohou et al., 2020).

Spectral Features

Mel Cepstral Coefficient Parameter (MCEP), harmonic model and phase distortion mean (HMPDM), and harmonic model and phase distortion deviations (HMPDD) are reliable and accurate speech recognition factors that detect both voiced/unvoiced signals (On et al., 2006).

[4] "Voice signals controlled by the glottis opening and closing leading breathy, normal or creaky voiced speech" (Gordon & Ladefoged, 2001)

The MCEP provides high resolution for low frequencies and has characteristics similar to the human ear (Fukada et al., 1992). This feature enhances the speech quality and speaker identification by capturing the vocal tract changes (Nirmal et al., 2014). This feature also helps differentiate between natural and synthetic speech (Chen et al., 2010).

Harmonic model and phase distortion mean (HMPDM) is calculated using "harmonic model on voices with phase distortion mean", harmonic model and phase distortion deviations (HMPDD) calculates the "harmonic model on voices with phase distortion deviation" (Guohou et al., 2020). Here, the harmonic model on voices represents the voiced and unvoiced segments uniformly but these characteristics alone are not suitable for statistical modelling and analysis. Thus, we analyse the harmonic measures with instantaneous phase parameters that wrap voices from one instance to the next (Degottex & Erro, 2014).

Table 10 summarises the functions of each of the acoustic features mentioned above. Additionally, to analyse all the acoustic factors, the statistical measures like mean, standard deviation, minimum, maximum and range were calculated based on the voicing decision for each measure. The pre-processing of the audio data and the calculation of the statistics for each of the paralinguistics has been elaborated in section 4.4.

Table 10: Summarized Description of Paralinguistic Features

Audio Features		Physiological Features	Statistical Measures
Category	**Sub-category**		
Prosodic Features	F0	Pitch of the voice based on vocal cords vibration	Mean. Minimum, Maximum, Standard Deviation, Range
	VUV	Vocal cords vibrate/not	
Voice Quality Features	NAQ	Tenseness in the voice based on the vocal fold closing period	
	QOQ	Breathiness in the voice based on the vocal fold opening period	
	H1-H2	Breathiness or tenseness in voice based on difference in amplitudes	
	PSP	Breathiness or tenseness in voice based on glottal source frequency waveform	
	MDQ	Breathiness or tenseness in voice based on GCI	
	peakSlope	Breathiness or tenseness in voice based on GCI	
	Rd	Breathiness or tenseness in voice based on wavelets	
	Rd_conf	The confidence level of Rd	
Spectral Features	MCEP_0-24	Speech recognition based on separation between vocal tract and excitation	
	HMPDM_0-24	Speech recognition based on time varying amplitudes and phase mean	
	HMPDD_0-12	Speech recognition based on time varying amplitudes and phase deviations	

4.4 Data Pre-processing & Reduction of Audio Files

This subsection illustrates the audio file pre-processing methods used to refine the data for correlational analysis. The audio feature names, mentioned in table 6, were not provided in the COVAREP files. These audio feature names were manually entered as headers of columns for the first file and then dynamically read into each file as a header using python code. Another important aspect is the binary voicing decision (VUV), which has been flagged as “1” for the voiced segments and “0” for the unvoiced segments (Gratch, DeVault, et al., 2014).

The cleaning of the audio file data was performed by running a python code in the Pandas software. This was an iterative process, that involved multiple steps to clean the data features and retrieve the necessary statistics for depression analysis. The basic logic behind cleaning the data files was to retrieve only the participant related audio features from the COVAREP file and then perform statistical functions on each of the 74 extracted participant features. The steps involved in creating a consolidated audio feature file has been explained in Table 11 below.

Table 11: Audio File Pre-Processing Steps

Steps	Pre-Processing
Step 1	Read the COVAREP file and read the corresponding transcript file
Step 2	Read start-time and stop_time from the transcript file
Step 3	Check if speaker == “Participant” YES: Then multiply the start_time and stop_time by 100 and save as new variables NO: Then ignore the row
Step 4	Check if COVAREP file index lies within the corrected_start_time & corrected_stop_time YES: Print and append all the rows/indexes that lie in the range into a new dataframe called “df_res” NO: Eliminate the rows/indexes
Step 5	Create 2 new dataframes called “df_new1” and “df_new2”, that have copies of “df_res” data
Step 6	Use “df_new1” for all the voiced feature columns (VUV=1) like F0, NAQ, QOQ, H1, H2, PSP, MDQ, peakSlope and Rd
Step 7	For “df_new1”: Perform the describe() function to get all the statistical measures like mean, count, minimum, 25%, 50%, 75%, maximum and standard deviation

Table 11 (continued)

Step 8	Drop columns count, 25%, 50% and 75%
Step 9	Add a column called “range” that calculates “max-min”
Step 10	Add another column that appends the file number for each file row
Step 11	Use the second dataframe “df_new2” and drop all the voiced columns like (F0, NAQ, QOQ, H1, H2, PSP, MDQ, peakSlope and Rd)
Step 12	Perform describe() function for all the voiced and unvoiced feature columns
Step 13	Repeat Step 8 and Step 9 for “df_new2”
Step 14	Create a new dataframe “df_out” that stores the concatenated data of “df_new1” and “df_new2” in one dataframe
Step 15	Print the file row into a new csv file called “finalop.csv”
Step 16	Step 1-15 is performed for each participant and all the data gets appended into one final csv file called “finalop.csv”

All the above-mentioned steps allowed to create two data frames with calculated statistical measures, one for voiced features and another for both voiced/unvoiced feature columns. The last steps involved combining all the data into a single consolidated file. The steps 1-15 were repeated for each participant session and the data for each session is stored in a single row. This resulted in the “finalop.csv” file having 189 rows of data with each row of data corresponding to a participant.

4.5 Data Analysis

The DAIC-WOZ dataset was analysed, using only the audio and transcript files. Firstly, the transcript file data was filtered using python code in the Pandas software, to create a single consolidated file with transcript data of all 189 participants. Then, the text features were extracted using the LIWC software. Next, the extracted audio features provided in the

COVAREP files were pre-processed using python code in the Pandas software, to create a single consolidated file with all the participant's audio data. The last step involved statistical method analysis, for which the consolidated text and audio files were analysed using JASP (v0.14.1), an open-source statistics software that helps in making a refined dataset for analysis. The next chapter explains in detail the correlational analysis between paralinguistic (audio) and linguistic (text) features with the depression (PHQ-8) scores using the JASP software.

5. Results

This chapter describes the findings of the analysis. The first part of the chapter summarises the data cleaning process, descriptive statistics and LIWC categories for depression. The second part discusses the correlations of linguistics and paralinguistic features with depression, personality, and emotions.

5.1 Pre- Analysis & Descriptive Statistics

The PHQ-8 questionnaire provides information to distinguish a depressed individual from a non-depressed individual. The PHQ-8 scale has a cut-off of 10, thus marking all scores below 10 as non-depressed and scores above 10 as depressed. From the PHQ-8 scores of the DAIC-WOZ corpus, it was found that out of 189 participants about 30% of the participants were depressed and 70% were not depressed. Figure 2 shows that women had a higher tendency to be depressed than men. The entire dataset without any gender divisions had a PHQ-8 mean score of 6.75 with a standard deviation of 5.92.

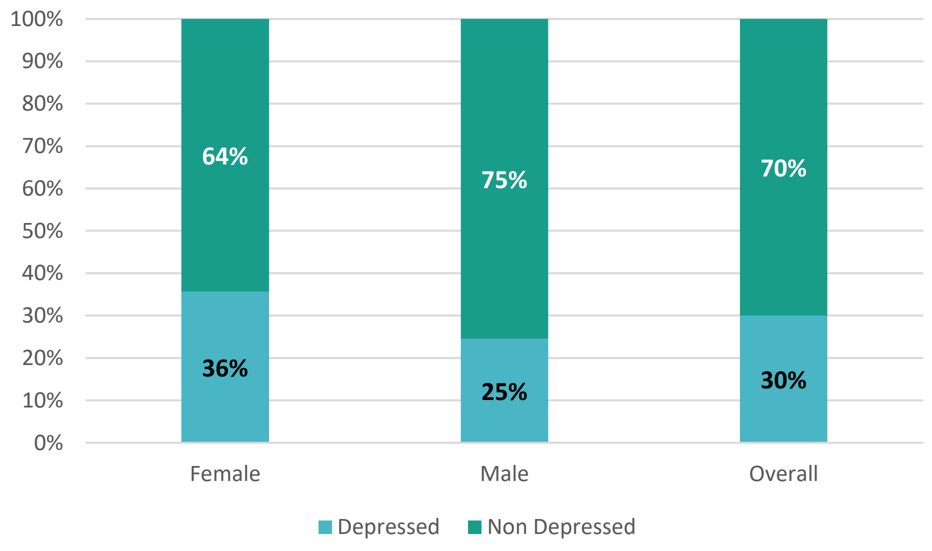

Figure 2: Depressed Vs Non-Depressed Based on Gender

5.2 LIWC Categories

This subsection summarizes the textual patterns that relate to each chosen category of depression and personality. Table 12 shows the word density comparisons for both the DAIC-WOZ participants, LIWC2015 word density norms, and LIWC2015 natural speech word density (J. Pennebaker et al., 2015).

Table 12: LIWC Categories & Word Density Patterns

Category	Word Density for Natural Speech (LIWC2015)	Word density of the sample (Participant)	Word density of LIWC2015 norms
Summary Language Variables			
Words/sentence	-	8.74	**17.40**
Words > 6 letters	10.42	12.07	**15.60**
Linguistic Dimensions			
1st pers singular	7.03	10.41	**4.99**
1st pers plural	0.87	0.47	**0.72**
Conjunctions	6.21	7.20	**5.90**
Negations	2.42	2.91	**1.66**
Psychological Processes			
Affective processes	6.54	6.39	**5.57**
Positive emotion	5.31	4.62	**3.67**
Negative emotion	1.19	1.67	**1.84**
Anxiety	0.14	0.37	**0.31**
Anger	0.36	0.48	**0.54**
Sadness	0.23	0.33	**0.41**
Social processes			
Social	10.42	8.07	**9.74**
Female	0.55	0.72	**0.98**
Male	0.8	0.65	**1.65**
Family	0.31	0.77	**0.44**
Friends	0.37	0.37	**0.36**
Cognitive processes			
Certainty	1.38	1.31	**1.35**
Insight	2.46	3.41	**2.16**
Causation	1.45	1.40	**1.40**
Differentiation	3.73	4.24	**2.99**
Perceptual processes			
Percept	2.11	2.10	**2.70**
hear	0.63	0.61	**0.83**
Feel	1.04	0.78	**0.64**
Biological processes			
Body	0.31	0.38	**0.69**
Health	0.38	0.77	**0.59**
Time orientations			
Past focus	4.92	4.82	**4.64**
Present focus	15.11	13.21	**9.96**
Relativity			
Time	5.00	4.93	**5.46**
Drives			
Achieve	0.99	1.40	**1.30**
Personal concerns			
Work	2.87	1.85	**2.56**
Home	0.29	0.34	**0.55**
Death	0.04	0.06	**0.16**

5.3 Correlation Analysis

This subchapter focuses on answering the research questions mentioned in section 1.3 using the JASP software. The sub-research questions 1, 2 & 3 have been answered in this section.

5.3.1 Linguistic (Text) Features & Depression Correlations

Sub-research question 1 aimed to explore the relationship between linguistic patterns of the participants and depression levels. To analyse this relationship, correlational analysis was carried out between depression and the 25[5] LIWC categories that were chosen in subsection 2.5.1. Using JASP, the correlations between the PHQ-8 and 25 categories were drawn and analysed, to find that 6 variables mentioned in Table 13 showed significant correlations. Note that the remaining results are provided in the Appendix.

Table 13: PHQ-8 Correlations & LIWC Categories

LIWC Categories	Correlations	PHQ8
i	*Pearson's r*	0.228**
	p	0.002
negate	*Pearson's r*	0.161*
	p	0.026
negemo	*Pearson's r*	0.336***
	p	< .001
anx	*Pearson's r*	0.175*
	p	0.016
anger	*Pearson's r*	0.221**
	p	0.002
sad	*Pearson's r*	0.343***
	p	< .001
friend	*Pearson's r*	-0.166*
	p	0.022
health	*Pearson's r*	0.288***
	p	< .001
WPS	*Pearson's r*	-0.169*
	p	0.02

*Note: * p < .05, ** p < .01, *** p < .001; two tailed; r = Pearson's r; p = p*

[5] The 25 selected categories included Words Per Sentence (WPS), words more than six letters (Sixltr), I, we, conjunctions, negations, affect, positive emotions, negative emotions, anxiety, anger, sad, friend, health, death, family, insight, cause, differ, feel, focus past, focus present, time, work, and home.

The variable sadness has the highest significant positive correlation with depression (r = 0.343, $p < 0.001$. This is followed by a strong use of negative emotion words (r = 0.336, $p < 0.001$), and health related words (r = 0.288, $p < 0.001$) respectively.

The words under categories anger (r = 0.221, $p < 0.01$) and I (r = 0.228, $p < 0.01$) have moderate correlations with depression. Negative emotions and personal pronouns showed high positive correlations, a finding similar to prior study (Ramirez-Esparza et al., 2008; Tausczik & Pennebaker, 2010).

The words in categories: negate (r = 0.161, $p < 0.05$), anxiety (r = 0.175, $p < 0.05$), friend (r = -0.166, $p < 0.05$) and WPS (r = -0.169, $p < 0.05$) showed rather weak correlations. The categories friends and words per sentence (WPS) have a negative correlation with depression. This makes these two linguistic categories good indicators for people low on depression, whereas negative emotions which is a good predictor for people high on depression.

Table 14 shows the correlations between depression and LIWC categories based on gender differences. For both men and women, the categories sadness (r = 0.444, $p < 0.001$), negative emotions (r = 0.378, $p < 0.001$), and health (r = 0.355, $p < 0.001$) showed strong correlations with depression. Women showed moderate positive correlations for categories like anger (r = 0.323, $p < 0.01$), feel (r = 0.282, $p < 0.01$), and negative correlations for work (r = -0.28, $p < 0.01$). In comparison, men showed a positive correlation for anxiety related words (r = 0.202, $p < 0.05$) and negative correlations with friends related words (r = -0.197, $p < 0.05$). It can be concluded that depressed women have the tendency to use more negative emotion words. It is a strong variable to recognise depression for both men and women.

Table 14: Depression & Linguistic Feature Correlations Based on Gender

LIWC Categories	**PHQ-8**	
	Female	**Male**
i	0.229*	0.205*
negate	0.257*	0.182
negemo	0.378***	0.26**
anger	0.323**	0.114
sad	0.444***	0.237*
feel	0.282**	-0.033
health	0.355***	0.197*
work	-0.28**	0.03
anx	0.148	0.202*
friend	-0.12	-0.197*

*Note: * p < .05, ** p < .01, *** p < .001; two tailed*

The next section discusses the correlations between personality-based LIWC categories and PHQ-8 scores.

5.3.2 Personality and Depression Correlations Based on Linguistics

Sub-research question 2, aimed to investigate the relationship between depressive disorders and Big-Five personality traits. In this subsection, the Big-Five personality traits were mapped by analysing the text transcripts on certain chosen LIWC categories using LIWC2015 software. Again, JASP was used to analyse the (*Pearson's r*) correlations, as shown below in Table 15.

Table 15: Personality & Depression Correlations (Linguistics)

Big-Five Traits	LIWC Categories	PHQ8
		Pearson's r
Openness	differ	-0.029
	percept	-0.028
	hear	-0.106
Neuroticism	negemo	0.336***
	anx	0.175*
	anger	0.221**
	sad	0.343***
	body	0.197**
	work	-0.093
Extraversion	social	-0.12
	family	0.005
	friend	-0.166*
	female	0.101
	male	-0.079
Consciousness	anger	0.221**
	differ	-0.029
	body	0.197**
	achieve	-0.046
	work	-0.093
	death	0.079
Agreeableness	conj	-0.065
	anger	0.221**
	family	0.005
	certain	0.005
	body	0.197**

*Note: * p < .05, ** p < .01, *** p < .001; two tailed*

Table 15 shows the correlational values for all the participants. The linguistic categories negative emotions (r = 0.336, p < 0.001), sad (r = 0.343, p < 0.001), anger (r = 0.221, p < 0.01), anxiety (r = 0.175, p < 0.05) and body (r = 0.197, p < 0.01) showed the most significant positive correlations with depression. All these categories were a characteristic feature of the "neuroticism" personality trait. The Big-Five dimensions extraversion, consciousness and agreeableness showed weak correlations, whereas openness did not correlate with depression.

This implies that the neuroticism trait is highly related to depression in comparison to for instance trait extraversion. These correlational results were similar to prior findings (Boyce et al., 1991; Farmer et al., 2002; Klein et al., 2012).

The correlations between personality and depression based on gender were also analysed as shown in Table 16. It was found that the neuroticism trait had a stronger correlation with depression for women than men.

Table 16: Personality & Depression Correlations Based on Gender (Linguistics)

Big-5 Traits	LIWC Categories	PHQ8	
		Female (r)	Male (r)
Openness	differ	-0.149	0.082
	percept	0.106	-0.144
	hear	-0.11	-0.088
Neuroticism	negemo	0.378***	0.26**
	anx	0.148	0.202*
	anger	0.323**	0.114
	sad	0.444***	0.237*
	body	0.191	0.222*
	work	-0.28**	0.03
Extraversion	social	-0.13	-0.147
	family	-0.002	-0.02
	friend	-0.12	-0.197*
	female	0.126	0.068
	male	-0.063	-0.135
Consciousness	anger	0.323**	0.114
	differ	-0.149	0.082
	body	0.191	0.222*
	achieve	-0.138	0.043
	work	-0.28**	0.03
	death	0.139	0.012
Agreeableness	conj	-0.069	-0.107
	anger	0.323**	0.114
	family	-0.002	-0.02
	certain	0.026	-0.014
	body	0.191	0.222*

*Note: * $p < .05$, ** $p < .01$, *** $p < .001$; two tailed; r=Pearson's r*

Both men and women with neuroticism had a higher tendency to suffer from depression when compared to other traits. For women, the work category showed a strong negative correlation (r = -0.28, p < 0.01) with depression in comparison to men (r = 0.03). The use of negative emotion words showed a significantly strong positive relationship with depression for both men (r = 0.26, p < 0.01) and women (r = 0.378, p < 0.001).

The next section discusses the correlations between audio features and depression for the overall participant group and the participants split based on gender.

5.3.3 Paralinguistic (Audio) Features & Depression Correlations

This sub-chapter illustrates the relationship between different paralinguistic features and depression. To answer sub-research question 1, a correlational analysis between all the prosodic, spectral and voice quality features and depression was conducted (see Appendix K). For this thesis, especially the prosodic and voice quality features were closely analysed as they allow emotion recognition of speech. The spectral[6] features were also analysed, but not described as these features help differentiate between natural and synthetic speech. This distinction is not very helpful for depression and personality (see section 2.4).

The prosodic and voice quality features investigated are fundamental frequency of pitch (F0), binary voicing decision (VUV), normalized amplitude quotient (NAQ), quasi-open quotient (QOQ), amplitude of first two glottal harmonics (H1-H2), parabolic spectral parameter (PSP), maxima dispersion quotient (MDQ), maximum peaks at each scale for the middle part of the utterance (peakSlope), and wavelet-based features (Rd). Table 17 shows the most significant prosodic and voice quality feature correlations with depression.

Table 17: Correlations Between Paralinguistic Features & Depression

Speech Category	**Audio Features**	**PHQ8**
		Pearson's r
Prosodic Features	F0_min	0.157*
	F0_max	0.169*
	F0_range	0.169*
Voice Quality Features	NAQ_std	0.165*
	QOQ_std	0.214**

*Note: * p < .05, ** p < .01, *** p < .001; two tailed*

[6] The spectral features like mel ceptral coefficient parameter (MCEP_0-24), harmonic model and phase distortion mean (HMPDM_0-24) and harmonic model and phase distortion deviations (HMPDD_0-12) were also analysed but will not be described here (see Appendix).

The vocal feature QOQ_std showed the most significant correlation with depression (r = 0.214, p < 0.01). QOQ is a glottal flow feature, described as the open time between the vocal folds of the larynx (Guohou et al., 2020). This allows to measure the changes in voice quality based on the breathiness in the voice (Kane et al., 2013). The QOQ_std showed a positive correlation, this means that depressed individuals show more variations in the breathiness of the voice.

NAQ is another important glottal feature that allows to separate different phonation types and NAQ_std had a significant correlation with depression (r = 0.165, p < 0.05). This feature measures differences between normal, breathy and pressed sounds or utterances (Alku et al., 2002). Like QOQ_std, the NAQ_std has a positive correlation with PHQ-8, thus implying larger variations in the tenseness of voice for depressed individuals.

The fundamental frequency (F0_min, F0_max and F0_range) is a primary acoustic feature of pitch and displayed strong correlations with PHQ-8 (r = 0.157, p < 0.05; r = 0.169, p < 0.05; r = 0.169, p < 0.05). F0 helps differentiate between talkers by identifying differences in voice pitch (Carroll et al., 2011). The frequency values (F0_min, F0_max, F0_range) correlate positively with depression. This implies that higher frequency variations are more likely to relate to depression.

Table 18 shows the significant correlations with depression based on gender. For women, the variations in QOQ_std (r = 0.241, p < 0.05) and NAQ_std (r = 0.240, p < 0.05) of voice quality display a significant correlation with PHQ-8 in comparison to men.

Table 18: Paralinguistic Features & Depression Correlation Based on Gender

Speech Category	Audio Features	PHQ8	
		Female (r)	Male (r)
Voice Quality Features	NAQ_std	.240*	0.063
	QOQ_std	.241*	0.146

*Note: * p < .05, ** p < .01, *** p < .001; two tailed*

The next section shows the mapping of the personality traits with their corresponding audio features.

5.3.4 Personality Trait Mapping for Audio Features

This section aimed to map audio features to their corresponding personality traits. To map the personality traits with the audio features, an individual's personality-based linguistic feature average scores were compared to the LIWC2015 natural speech linguistic feature average scores (see Table 12). If the combination of linguistic features for a personality trait (see Table

M in Appendix) was higher than the average natural speech values, the individual was classified with that respective personality trait. This novel approach was developed for the present thesis.

For example, participant 359 showed openness as their LIWC category values for differ (6.27), percept (4.79) and hear (1.28) were clearly above the average threshold values of LIWC2015 natural speech linguistic features of differ (3.73), percept (2.11) and hear (0.63). For participant 359 the other personality traits were less distinctive. This approach was carried out to map the personality traits for each of the participants.

Table 19 below helps answer sub-research question 2, as it shows the mapping of the significant correlations between the audio features with each of the personality traits separately. Voice quality features showed stronger correlations with the personality traits than prosodic features.

Table 19: Big-Five Personality Trait Mapping for Paralinguistic Features

Big-Five Traits	Audio Features	Pearson's r
Openness	H2_mean	-0.181*
	H2_std	-0.145*
	H1_min	0.2**
	QOQ_max	0.152*
	QOQ_range	0.152*
	H1_range	-0.195**
Consciousness	NAQ_mean	0.148*
	peakSlope_mean	0.171*
Extraversion	H2_mean	0.162*
Agreeableness	H1_min	-0.205**
	PSP_max	0.162*
	PSP_range	0.162*

*Note: * p < .05, ** p < .01, *** p < .001; two tailed*

Openness showed significant positive correlations with voice quality features like H1_min (r = 0.2, p < 0.01), QOQ_max and QOQ_range (r = 0.152, p < 0.05). Individuals with openness trait tended to have a breathier voice. Other glottal harmonics like H2_mean (r = -0.181, p < 0.05), H2_std (r = -0.145, p < 0.05), and H1_range (r = -0.195, p < 0.01) showed a negative correlation with openness.

Consciousness was positively correlated with peakSlope_mean (r = 0.171, p < 0.05), and NAQ-mean (r = 0.148, p < 0.05). This implied a slight tenseness in voice for conscious people.

The extraversion trait showed moderate variations in voice amplitudes with significant correlation with the glottal harmonics H2_mean (r = 0.162, p < 0.05).

Trait agreeableness showed correlations with the voiced parabolic spectral parameters, PSP_max (r = 0.162, p < 0.05) and PSP_range (r = 0.162, p < 0.05).

Neuroticism showed no significant correlations with any of the prosodic and voice quality features but with the spectral features (see Appendix N).

Table 20 shows the mapping of personality traits with the audio features based on gender. When the participants were split based on gender the prosodic and voice quality features did not show any significant correlations with neuroticism, as observed in the previous analysis of all the participants.

Table 20: Big-Five Personality Trait Mapping Based on Gender (Paralinguistics)

Big-Five	Audio Features	Female (r)	Male (r)
Openness	H1_min	0.319**	0.17
	QOQ_max	0.259*	0.014
	PSP_max	-0.221*	0
	QOQ_range	0.259*	0.014
	H1_range	-0.236*	-0.151
	PSP_range	-0.222*	0.001
	F0_min	0.112	-0.208*
	F0_max	0.065	-0.212*
	F0_range	0.048	-0.197*
Consciousness	NAQ_mean	0.002	0.238*
	QOQ_mean	-0.094	0.237*
	H1_mean	-0.045	0.252*
	peakSlope_mean	0.006	0.261**
Extraversion	QOQ_mean	0.259*	-0.257**
	H2_mean	-0.001	0.311**
	Rd_mean	0.105	-0.288**
	H2_std	-0.075	0.378**
	MDQ_std	-0.052	-0.201*
	peakSlope_std	-0.121	0.281**
	PSP_min	-0.006	0.195*
	Rd_min	0.02	-0.202*
Agreeableness	H2_mean	0.275**	-0.119
	H2_std	0.234*	-0.019
	H1_min	-0.240*	-0.206*
	MDQ_mean	-0.065	0.215*

*Note: * p < .05, ** p < .01, *** p < .001; two tailed*

Women with openness tended to have more glottal harmonics like H1_min (r = 0.319, p < 0.01), QOQ-max (r = 0.259, p < 0.05) and QOQ_min (r = 0.259, p < 0.05). Men showed no significant correlations with the trait openness (see table 21). But men showed significant negative correlations with voice quality features like QOQ_mean (r = -0.257, p < 0.01) and Rd_mean (r = -0.288, p < 0.01) for the trait extraversion.

The next section compares depressed versus non-depressed individuals based on their linguistics, paralinguistics, and personality features.

5.3.5 Comparison between Depressed and Non-depressed Features

This section investigates sub-research question 3 to provide significant correlations to differentiate between people high on PHQ-8 scores (depressed) and people low on PHQ-8 scores (non-depressed) based on linguistics, paralinguistics, and personality.

The correlations mentioned in Table 21 showed that non-depressed individuals tend to use sad words (r = 0.344, p < 0.001), health words (r = 0.272, p < 0.01) and negative emotions words (r = 0.245, p < 0.01). In comparison, depressed individuals tend to talk more about their feelings (r = 0.43, p < 0.001), use more sad words (r = 0.267, p < 0.05) and use lesser words per sentence sadness (r = -0.354, p < 0.01).

Furthermore, women who scored low on depression tend to use more negative emotion (r = 0.456, p < 0.001), sad (r = 0.559, p < 0.001) and health (r = 0.349, p < 0.01) related words in comparison to women who scored high on depression. Depressed men tend to use feeling words (r = 0.72, p < 0.001), singular pronouns like "I" (r = 0.52, p < 0.01) and negations (r = 0.401, p < 0.05) more often than non-depressed men. It can be concluded that individuals who scored high on depression (PHQ-8) have a higher tendency to talk about their feelings and use less words per sentence while conversing.

Table 21: Depressed Vs Non-Depressed Based on Linguistics

LIWC Categories	Non-Depressed			Depressed		
	Female	Male	Overall	Female	Male	Overall
negemo	0.456***	0.085	0.245**	0.233	0.079	0.196
sad	0.559***	0.19	0.344***	0.446*	-0.006	0.267*
cause	-0.273*	-0.032	-0.13	-0.274	-0.022	-0.185
health	0.349**	0.209	0.272**	-0.187	0.369	0.024
WPS	-0.227	-0.142	-0.179*	-0.425*	-0.237	-0.354**
negate	0.061	0.171	0.136	0.364*	0.401*	0.309*
insight	-0.226	0.127	-0.002	-0.358*	0.098	-0.11
feel	0.209	-0.047	0.052	0.354	0.72***	0.43***
i	0.196	0.012	0.092	0.135	0.524**	-0.297*

*Note: * p < .05, ** p < .01, *** p < .001; two tailed*

Table 22 below shows the differences between depressed and non-depressed individuals based on their significant correlations with paralinguistic features. Depressed individuals showed more glottal harmonics H1_min (r = 0.428, p < 0.001) and PSP_min (r = 0.281, p < 0.05) than non-depressed individuals. The voice quality features H1_min (r = 0.532, p < 0.001) and NAQ_std (r = 0.356, p < 0.05) are good indicators for identifying depressed women. It can be concluded that voice quality features are good predictors of depression.

Table 22: Depressed Vs Non-Depressed Based on Paralinguistics

Audio Features	Non-Depressed			Depressed		
	Female	Male	Overall	Female	Male	Overall
H2_std	-.298*	0.131	-0.077	0.087	-0.04	0.063
PSP_std	-0.24	0.256*	0.042	-0.166	-0.09	-0.1
Rd_mean	0.02	-0.068	-0.03	-0.425*	-0.27	-0.332*
NAQ_std	-0.116	0.009	-0.043	0.356*	0.058	0.211
MDQ_std	-0.068	-0.165	-0.106	-0.404*	0.046	-0.16
H1_min	0.029	-0.057	-0.026	0.532**	0.271	0.428**
Rd_max	0.096	-0.149	-0.034	-0.376*	-0.267	-0.330*
H1_range	0.112	-0.014	0.035	-0.477**	-0.124	-0.355**
PSP_min	-0.158	0.061	-0.04	0.338	0.05	0.281*

*Note: * p < .05, ** p < .01, *** p < .001; two tailed*

Table 23 on the next page shows the Big-Five personality mapping for depressed versus non-depressed individuals. The results illustrated that people with high depression scores showed positive correlations with the neuroticism trait and negative correlations with the openness trait. Furthermore, non-depressed individuals tend to display traits like openness, extraversion and agreeableness.

Table 23: Depressed vs Non-Depressed Based on Big-Five Personality Traits

Big-Five	Correlations	Non-depressed			Depressed		
		Female	Male	Overall	Female	Male	Overall
Openness	Pearson Correlation	-0.237	-0.145	-.173*	-0.097	-0.075	-0.087
	Sig. (2-tailed)	0.079	0.207	0.046	0.602	0.722	0.523
	N	56	77	133	31	25	56
Consciousness	Pearson Correlation	-0.007	-0.19	-0.117	0.094	-0.034	0.033
	Sig. (2-tailed)	0.957	0.099	0.178	0.613	0.871	0.808
	N	56	77	133	31	25	56
Extraversion	Pearson Correlation	-0.04	0.029	-0.006	0.144	0.07	0.118
	Sig. (2-tailed)	0.768	0.803	0.942	0.439	0.739	0.385
	N	56	77	133	31	25	56
Agreeableness	Pearson Correlation	-.286*	0.022	-0.111	-0.149	0.01	-0.089
	Sig. (2-tailed)	0.033	0.846	0.203	0.424	0.963	0.512
	N	56	77	133	31	25	56
Neuroticism	Pearson Correlation	0.370**	0.19	0.268**	0.077	0.024	0.055
	Sig. (2-tailed)	0.005	0.099	0.002	0.68	0.907	0.688
	N	56	77	133	31	25	56

*Note: * p < .05, ** p < .01, *** p < .001; two tailed*

6. Discussion

This chapter discusses the relevance of the empirical findings based on scientific and practical aspects. Then chapter also elaborates on the limitations of the research and the future applications of this study.

6.1 Scientific Relevance

This section discusses the empirical findings of this research against the literature study.

Linguistics & Depression

Firstly, the study showed that individuals suffering from depression have a higher inclination to use language with negative emotion and singular pronoun words in comparison to non-depressed individuals. Additionally, it was also found that depressed individuals were less likely to use social (friends and family) words. The above-mentioned results confirm the findings of previous research for depressed individuals (Al-Mosaiwi & Johnstone, 2018; Ramirez-Esparza et al., 2008; Tausczik & Pennebaker, 2010).

Furthermore, this study found significantly stronger correlations for highly depressed people in terms of emotion (sad and anger) and health related words than for non-depressed people. Additionally, depressed people used fewer words per sentence than non-depressed people. These results contradicted the previous research that claimed depressed people use more negative emotion words, singular pronouns and lesser social words (Ramirez-Esparza et al., 2008; Tausczik & Pennebaker, 2010). But some prior research found that emotion words like sad and anger related words were linked to major depressive disorder (Bodner et al., 2007; Demiralp et al., 2012). This study's results concluded that sad and health related words are equally important linguistic features for depression recognition.

Paralinguistics & Depression

Secondly, the present study analysed the prosodic and voice quality features to find significant correlations between the breathiness (QOQ) (r = 0.214, p < 0.01) in voice and depression. This finding was similar to previous research that investigated the effects of depression on speech and concluded that increased jitters, shimmers and breathiness are good indicators of depression (Honig et al., 2014; Sahu & Espy-Wilson, 2014).

Importantly, this study showed high correlations for pitch and NAQ with depression. The high NAQ value showed that increased tenseness in voice was an important characteristic of depression. Also, this finding confirms previous research, where many researchers argued that the increase in tenseness of voice and lower pitch are significant indicators of depression

(Johnstone & Scherer, 1999; K. R. Scherer, 1986; S. Scherer et al., 2013; Stasak et al., 2016). In contrast to prior work, this study found that high depression levels were related to high frequency/pitch levels. This contradicted the results of previous research, that claimed that low pitch levels are a characteristic identifier for depression severity (McGinnis et al., 2019).

Personality & Depression (Linguistics & Paralinguistics)

The third correlational analysis showed that depressed people possessed strong neuroticism traits. Depressed people had the tendency to use more negative emotions, anxiety, anger, sadness and body related words while conversing. Non-depressed people, in contrast displayed characteristics of extraversion. These findings confirmed previous research, in which high correlations were found between depressed people and neuroticism and low correlations between depression and extraversion (Boyce et al., 1991; Farmer et al., 2002; Klein et al., 2012; Saklofske et al., 1995). Additionally, this experiment found that depressed people lacked openness in terms of perceptual processes like listening, hearing, feeling, expressing, talking, etc. This results was in line with the prior research that found openness to have low correlations with depression (Carrillo et al., 2001; Khoo & Simms, 2018; Takahashi et al., 2013).

The next correlational analysis involved mapping the relationship between Big-Five personality traits and depression based on paralinguistic features. None of the previous studies mapped the personality traits based on the paralinguistic features.

Especially, the difference between high and low depression levels based on linguistics, personality and paralinguistics for female, male, and overall participants was explored. This study confirmed that women showed a higher tendency towards depression in comparison to men. These results aligned with previous studies that confirm that depression is more prevalent in women (Albert, 2015; Noble, 2005).

6.2 Practical Relevance

As previously observed, an individual’s personality plays an important role in depression recognition (Boyce et al., 1991; Flett et al., 1995; Klein et al., 2012). The present research concluded that individuals suffering from depression use different linguistic patterns and speech variations depending on their personality.

The suggestion of this research has notable practical advantages. Firstly, in this digital era, as the influence of the phones, technology, virtual reality is increasing globally, the introduction of AI (virtual human) based mental health diagnosis platforms/applications will allow people from any corner of the world to get fast, easy, and cheap treatment for their condition. For example, the existing virtual therapy platforms like SpeakOut and Tess has helped connect the patients with therapists for online therapy sessions (Fulmer et al., 2018; Wiederhold, 2018). These platforms have the potential to help people while addressing the stigma connected to mental health.

Secondly, this research has the potential to provide valuable knowledge for the healthcare sector and proliferate the growth of virtual mental healthcare platforms. Especially, since the COVID-19 pandemic, the number of cases with psychological disorders has increased by more than 3 times (Ettman et al., 2020). The pandemic crisis enforced restrictions on social interactions, lockdowns, curfews, and other limitations worldwide which led to a spike in the mental distress cases all over the world (Sharma et al., 2020; Ustun, 2021). This emphasizes the need to further develop the virtual reality technology for the medical field to provide easily accessible and economical means for automatic detection of mental disorders like depression.

Lastly, this research study was exploratory in nature and only focussed on personality, linguistics and paralinguistics aspects for depression recognition. There are other possible factors that could be explored to further strengthen the results. Therefore, this study aims to promote further discussion on the possibilities of automated depression recognition and its relationship with different behavioural features.

6.3 Limitations

There are some limitations to this study considering the methodology of the experiment. Firstly, the experiment analysed the emotion recognition (prosodic and voice quality) features of speech while speech recognition (spectral) features were not considered. Previous studies claimed that spectral features along with prosodic features provide better results for depression recognition (Alpert et al., 2001; Moore et al., 2008, 2003). This is an area that could be further explored.

The second limitation was regarding the dataset itself. The DAIC-WOZ database is a collection of semi-structured interviews to support the diagnosis of psychological distress conditions. The database has limited variability as all the participants are English speaking Americans and US army veterans (Gratch, DeVault, et al., 2014). Especially in this case, the dataset consisted of a large army veteran population making the analysis results inclined towards a particular occupational disorder, like in this case PTSD (Boscarino, 2006; Ismail et al., 2000; Schnurr et al., 2009). Therefore, having a diverse sample makes the results applicable to a larger population and helps reduce biases towards a particular group of people.

The next limitation was the number of words available in the transcript files for linguistic analysis. Previous research states that larger texts have the ability to increase the accuracy and quality of results from the LIWC analysis (Al-Mosaiwi & Johnstone, 2018; J. Pennebaker et al., 2001). As this dataset had a few transcript files that consisted of less than 200 words, making it difficult to provide accurate results. Therefore, collecting a better text sample with larger number of words could help increase accuracy of the results.

Lastly, the present study used a bimodal analysis approach to explore the relationship between linguistics and paralinguistics individually with depression. Recent research has analysed depression using extralinguistics, multimodality and fusion models to confirm better results when compared to unimodal and bimodal approaches (Alghowinem et al., 2018; Guohou et al., 2020; Kim et al., 2019; Nasir et al., 2016; Wang et al., 2018). This implies that richer analyses have the scope to led to richer insights.

6.4 Future Work

The research on virtual human based mental health diagnosis models is only at the starting phase and this field needs much more research and development. Firstly, future researchers should use a database that includes individuals from different nationalities, backgrounds (social, cultural, and ethnic), and age groups. In the DAIC database, the participants were all English-speaking US army veterans and American citizens. Therefore, making it necessary in the future to involve more people from different occupations, geographical locations, culturally and socially diverse backgrounds as well as different age groups. Thus, allowing the research findings to be applicable to not only English-speaking Americans but also to a vast and diverse population.

Secondly, this study evaluated depression recognition using only the paralinguistic (speech) and linguistic (text) features from the DAIC database and left out the extralinguistic (visual) features. Future researchers could explore the relationship between extralinguistic features and depression. Previous research stated that facial expressions have significant relationship with depression recognition (Pampouchidou et al., 2017; Shapiro & Gehricke, 2000; Wang et al., 2018). Depressed people were found to have facial expressions like controlled smiling, gaze down, frowns, and lesser emotional expressivity when compared to non-depressed people (Alghowinem et al., 2018; S. Scherer et al., 2014).

The last suggestion would be to explore multimodal/fusion behavioural feature analysis for depression. This would involve the evaluation of linguistic, paralinguistic, and extralinguistic features together. Prior research has proven that fusion/multimodal approaches provided for better and more accurate depression recognition results (Alghowinem et al., 2018; Guohou et al., 2020; Kim et al., 2019; Nasir et al., 2016). For instance, some researchers reached over 88 percent accuracy in results when more than one modality was analysed (Alghowinem et al., 2018; Dibeklioğlu et al., 2015).

7. Conclusion

Psychological distress, especially depression is prevalent health condition that has globally affected over 264 million people (WHO, 2020). The present study explored the relationship between depression, personality, linguistics, and paralinguistics. This section discusses the answers to the research questions mentioned in Table 24.

Table 24: Research Questions Results

#	Research Questions (RQ)	Results
Main RQ	Do people high or low on depression differ in linguistic and paralinguistic characteristics, and how? Does this relate to personality types, and how?	Answered in section 5.3
Sub RQ 1	Which linguistic and paralinguistic characteristics have been found in the literature to be related to depression? And which personality types are connected to depression?	Answered in sections 2.2, 2.4, 2.5, 5.3.1 & 5.3.3
Sub RQ 2	Do linguistic and paralinguistic characteristics depend on a person's personality? If so, how?	Answered in sections 5.3.2 & 5.3.4
Sub RQ 3	Does the level of depression (high or low) relate to linguistic and paralinguistic characteristics and to personality types? If so, how?	Answered in section 5.3.5

The main research question of this study was "*Do people high or low on depression differ in linguistic and paralinguistic characteristics, and how? Does this relate to personality types, and how?".* To answer the main research question, three main correlational analysis were carried out (see section 5.3).

The first study involved correlational analysis between linguistic features and depression (see section 5.3.1). The results showed that depressed individuals used sad, negative emotion and health related words while non-depressed people used more words per sentence and social words. The second analysis involved correlational analysis between paralinguistic features and depression (see section 5.3.3). The results concluded that significant variations in the breathiness and tenseness of voice as well as increased frequency levels are a characteristic of depressed individuals. The last analysis involved correlational analysis between Big-Five personality traits and depression based on linguistic and paralinguistic features (see section 5.3.2 & 5.3.4). It was found that the neuroticism trait was highly related to depressed individuals whereas the openness and extraversion trait were related to non-depressed individuals.

The sub-research question 1 was answered in detail in sections 2.2, 2.4, and 2.5. According to literature, linguistic characteristics like the use of negative emotion and singular pronouns and paralinguistic features like low pitch and breathy voice were important characteristics of depression. Further, prior research about personality and depression found that neuroticism trait was a predictor of depression when compared to extraversion. This study's results found that linguistic features such as sad, negative emotion and health related words were highly correlated to depression whereas high pitched voice and variations in breathy voice were characteristic identifiers for depression (see section 5.3.1 and 5.3.3)

The sub-research question 2 was answered in section 5.3.2 and 5.3.4 of Chapter 5. According to the results, linguistic and paralinguistic features depend on personality. Previous text analysis research helped map the linguistic features with each of the Big-Five personality traits (see table 15). The neuroticism trait was a good identifier for high depression whereas openness was for low depression. The results from the linguistic correlations were used to map paralinguistic features against the personality types (neuroticism, extraversion, openness, consciousness, and agreeableness).

The sub-research question 3 was answered in section 5.3.5 of Chapter 5. This section investigated the differences in paralinguistic, linguistic and personality features between high and low levels of depression. Depressed individuals used more feelings related words whereas non-depressed individuals use more words per sentence (Table 21). Variations in voice quality features helped distinguish between depressed and non-depressed individuals based on variations in voice (Table 22). Lastly, neuroticism was strongly related to high levels of depression whereas openness was related to low levels of depression (Table 23).

The findings of this research have multiple applications for the future. This study was limited to analysing English speaking American natives, but future research can be carried out to explore the relationship for a culturally diverse sample. This study showed that an individual's personality type, linguistic and paralinguistic features are important characteristics for differentiating between depressed and non-depressed people.

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9. Appendix

A. Literature Research – Article summary table

ARTICLE	DAIC-WOZ	Other Dataset	Depression	Visual	Audio	Text	Personality	Emotion
AVEC 2016: Depression, Mood, and Emotion Recognition Workshop and Challenge	✓	✓	✓	✓	✓			✓
SimSensei Kiosk: A Virtual Human Interviewer for Healthcare Decision Support	✓		✓	✓	✓	✓		
AVEC 2017: Real-life Depression, and Affect Recognition Workshop and Challenge	✓	✓	✓	✓	✓			✓
Automatic audiovisual behavior descriptors for psychological disorder analysis	✓		✓	✓	✓			
Self-Reported Symptoms of Depression and PTSD Are Associated with Reduced Vowel Space in Screening Interviews	✓		✓		✓	✓		
DepAudioNet: An Efficient Deep Model for Audio based Depression Classification	✓		✓		✓			
Reporting Mental Health Symptoms: Breaking Down Barriers to Care with Virtual Human Interviewers		✓		✓				
Detecting Depression with Audio/Text Sequence	✓		✓		✓	✓		

Modeling of Interviews								
Multimodal Measurement of Depression Using Deep Learning Models	✓		✓	✓	✓	✓		
Decision Tree Based Depression Classification from Audio Video and Language Information	✓		✓	✓	✓	✓		
Multimodal and Multiresolution Depression Detection from Speech and Facial Landmark Features	✓		✓	✓	✓			
Automatic Assessment of Depression Based on Visual Cues: A Systematic Review	✓		✓	✓				
Depression Assessment by Fusing High and Low Level Features from Audio, Video, and Text	✓		✓	✓	✓	✓		
AVEC 2019 Workshop and Challenge: State-of-Mind, Detecting Depression with AI, and Cross-Cultural Affect Recognition	✓		✓	✓	✓			
Depression Assessment by Fusing High and Low LevelFeatures from Audio, Video, and Text	✓		✓	✓	✓	✓		
Topic Modeling Based Multi-modal Depression Detection	✓		✓	✓	✓	✓		
Predicting Co-verbal Gestures: A Deep and Temporal Modeling Approach	✓		✓	✓	✓	✓		

Reduced vowel space is a robust indicator of psychological distress: A cross-corpus analysis	✓		✓		✓			
MultiSense—Context-Aware Nonverbal Behavior Analysis Framework: A Psychological Distress Use Case		✓	✓	✓	✓			
Human Behaviour-Based Automatic Depression Analysis Using Hand-Crafted Statistics and Deep Learned Spectral Features	✓		✓	✓				
Speech analysis for health: Current state-of-the-art and the increasing impact of deep learning	✓		✓		✓			
Measuring Depression Symptom Severity from Spoken Language and 3D Facial Expressions	✓		✓	✓	✓	✓		
Investigating Word Affect Features and Fusion of Probabilistic Predictions Incorporating Uncertainty in AVEC 2017	✓		✓			✓		
Dyadic Behavior Analysis in Depression Severity Assessment Interviews		✓	✓		✓			
Staircase Regression in OA RVM, Data Selection and Gender Dependency in AVEC 2016	✓	✓	✓		✓			✓
Hybrid Depression Classification and Estimation from	✓		✓	✓	✓	✓		

Audio Video and Text Information								
A Random Forest Regression Method With Selected-Text Feature For Depression Assessment	✓		✓	✓	✓	✓		
Automatic for the people: the automation of communicative labor		✓	✓					
A Multimodal Context-based Approach for Distress Assessment		✓	✓	✓	✓	✓		
Summary for AVEC 2016: Depression, Mood, and Emotion Recognition Workshop and Challenge	✓	✓	✓	✓	✓			✓
Towards an affective interface for assessment of psychological distress	✓		✓	✓	✓			
Automated screening for distress: A perspective for the future	✓		✓	✓	✓			
Facial geometry and speech analysis for depression detection		✓	✓	✓	✓			
Elicitation Design for Acoustic Depression Classification: An Investigation of Articulation Effort, Linguistic Complexity, and Word Affect	✓		✓		✓	✓		
Depression Severity Estimation from Multiple Modalities		✓	✓	✓	✓	✓		

DCNN and DNN based multi-modal depression recognition	✓		✓	✓	✓			
Summary for AVEC 2017: Real-life Depression and Affect Challenge and Workshop		✓	✓	✓	✓			✓
Refactoring facial expressions: An automatic analysis of natural occurring facial expressions in iterative social dilemma	✓			✓				
MFCC-based Recurrent Neural Network for Automatic Clinical Depression Recognition and Assessment from Speech	✓		✓		✓			
What really matters — An information gain analysis of questions and reactions in automated PTSD screenings	✓			✓	✓	✓		
Voice patterns in schizophrenia: A systematic review and Bayesian meta-analysis		✓						
Depression Detection Using Automatic Transcriptions of De-Identified Speech	✓		✓		✓			
Multitask Representation Learning for Multimodal Estimation of Depression Level	✓		✓	✓	✓	✓		
A demonstration of the perception system in SimSensei, a virtual human application for healthcare interviews		✓						

Facial expression video analysis for depression detection in Chinese patients		✓	✓	✓				
Multimodal Fusion of BERT-CNN and Gated CNN Representations for Depression Detection	✓		✓	✓	✓	✓		
Learning Voice Source Related Information for Depression Detection	✓		✓		✓			
Mining multimodal repositories for speech affecting diseases	✓		✓	✓	✓	✓		
Aggression recognition using overlapping speech		✓			✓			
Do Variations in Agency Indirectly Affect Behavior with Others? An Analysis of Gaze Behavior		✓	✓	✓				
Multi-level Attention Network using Text, Audio and Video forDepression Prediction	✓		✓	✓	✓	✓		
Multimodal Depression Detection: An Investigation of Features and Fusion Techniques for Automated Systems	✓		✓	✓	✓	✓		
Psychomotor cues for depression screening	✓		✓	✓				
Depression Prediction Via Acoustic Analysis of Formulaic Word Fillers	✓		✓		✓	✓		
Patient Privacy in Paralinguistic Tasks	✓		✓		✓			

Automated speech-based screening of depression using deep convolutional neural networks		✓						
A Hierarchical Attention Network-Based Approach for Depression Detection from Transcribed Clinical Interviews	✓		✓			✓		
Predicting Depression and Emotions in the Cross-roads of Cultures, Para-linguistics, and Non-linguistics	✓		✓		✓			
Multimodal Machine Learning for Interactive Mental Health Therapy	✓		✓	✓	✓	✓		
An investigation of linguistic stress and articulatory vowel characteristics for automatic depression classification	✓		✓		✓			
Automatic prediction of Depression and Anxiety from behaviour and personality attributes		✓	✓	✓			✓	
Pathological speech detection using x-vector embeddings		✓						
Querying Depression Vlogs	✓	✓	✓		✓	✓		
Towards A Multi-Dimensional Taxonomy Of Stories In Dialogue		✓						
Privacy-preserving Paralinguistic Tasks	✓	✓	✓		✓			

Automatic Assessment of Depression From Speech via a Hierarchical Attention Transfer Network and Attention Autoencoders	✓		✓		✓			
Feature Augmenting Networks for Improving Depression Severity Estimation From Speech Signals		✓	✓		✓			
The Verbal and Non Verbal Signals of Depression -- Combining Acoustics, Text and Visuals for Estimating Depression Level	✓		✓	✓	✓	✓		
Voice patterns in schizophrenia: A systematic review and Bayesian meta-analysis		✓			✓			
Improving Depression Level Estimation by Concurrently Learning Emotion Intensity	✓	✓	✓			✓		✓
The Multimodal Dataset of Negative Affect and Aggression: A Validation Study		✓		✓	✓	✓		✓
DEPA: SELF-SUPERVISED AUDIO EMBEDDING FOR DEPRESSION DETECTION	✓	✓	✓		✓			
A multi-modal human robot interaction framework based on cognitive behavioral therapy model	✓		✓	✓	✓	✓		
Graph Attention Model Embedded With Multi-Modal Knowledge For	✓		✓	✓	✓	✓		

Depression Detection								
Hierarchical Attention Transfer Networks for Depression Assessment from Speech	✓		✓		✓			
Automatic Detection of Self-Adaptors for Psychological Distress		✓	✓	✓			✓	
Clinical depression detection for adolescent by speech features	✓		✓		✓			
Unsupervised Counselor Dialogue Clustering for Positive Emotion Elicitation in Neural Dialogue System		✓			✓			✓
Analysis of phonetic markedness and gestural effort measures for acoustic speech-based depression classification	✓		✓		✓			
Detecting the magnitude of depression in Twitter users using sentiment analysis		✓	✓			✓		
Improving LIWC Using Soft Word Matchin								
An End-to-End Model for Detection and Assessment of Depression Levels using Speech	✓		✓		✓			
Affective Conditioning on Hierarchical Attention Networks applied to Depression Detection from	✓		✓			✓		✓

Transcribed Clinical Interviews								
Vision based body gesture meta features for Affective Computing	✓	✓	✓	✓				
Detecting Levels of Depression in Text Based on Metrics	✓		✓			✓		✓
An automatic diagnostic network using skew-robust adversarial discriminative domain adaptation to evaluate the severity of depression	✓	✓	✓	✓	✓			
Tension Analysis in Survivor Interviews: A Computational Approach		✓						
Attachment Theory in Long-Term Human-Robot Interaction		✓						
Domain Adaptation for Enhancing Speech-based Depression Detection in Natural Environmental Conditions Using Dilated CNNs		✓	✓		✓			
The sound of silence: Breathing analysis for finding traces of trauma and depression in oral history archives	✓		✓		✓			
A Deep Learning Approach for Work Related Stress Detection from Audio Streams in Cyber Physical Environments	✓				✓			

Bag-of-Acoustic-Words for Mental Health Assessment: A Deep Autoencoding Approach		✓	✓		✓			
Audio/Visual Emotion Challenge 2019: State-of-Mind, Detecting Depression with AI, and Cross-Cultural Affect Recognition	✓	✓	✓	✓	✓			
Identifying Depressive Symptoms from Tweets: Figurative Language Enabled Multitask Learning Framework		✓	✓			✓		
AudVowelConsNet: A phoneme-level based deep CNN architecture for clinical depression diagnosis	✓		✓		✓			
Audio-based Depression Screening using Sliding Window Sub-clip Pooling	✓	✓	✓		✓			
Automated voice biomarkers for depression symptoms using an online cross-sectional data collection initiative	✓		✓		✓			
AudVowelConsNet: A phoneme-level based deep CNN architecture for clinical depression diagnosis	✓		✓		✓			
Depression Detection from Speech	✓		✓		✓			
On the State of Social Media Data for Mental Health Research		✓						
Automatic Detection of Depression in Speech Using Ensemble		✓						

Convolutional Neural Networks								
Conversational agents for mental health and wellbeing		✓						
Multimodal Representation Learning of Affective Behavior	✓	✓	✓	✓	✓			
A review on depression detection and diagnoses based on visual facial cues		✓	✓	✓				
Chatbot for Configuration		✓	✓			✓		
Behavioral Sentiment Analysis of Depressive States	✓		✓	✓	✓	✓		
Towards Automatic Depression Detection: A BiLSTM/1D CNN-Based Model		✓						
Looking At The Body: Automatic Analysis of Body Gestures and Self-Adaptors in Psychological Distress		✓						
Automatic Audiovisual Behavior Descriptors for Psychological Disorder Analysis	✓		✓	✓	✓			
In-the-Wild End-to-End Detection of Speech Affecting Diseases	✓	✓	✓		✓			
Audio, Speech, Language, & Signal Processing for COVID-19: A Comprehensive Overview		✓	✓		✓			
Decoding depressive		✓	✓					

disorder using computer vision								
Computer-Based PTSD Assessment in VR Exposure Therapy	✓			✓	✓	✓		
Categorical assessment of depression based on high level features		✓	✓					
On the Optimum Speech Segment Length for Depression Detection	✓		✓		✓			
Automatic detection of visual cues associated to depression	✓	✓	✓	✓				
Detecting Depression in Dyadic Conversations with Multimodal Narratives and Visualizations	✓		✓			✓	✓	
Automatic Depression Detection via Facial Expressions Using Multiple Instance Learning	✓		✓	✓				
Raw Audio for Depression Detection Can Be More Robust Against Gender Imbalance than Mel-Spectrogram Features	✓		✓		✓			
Crosslinguistic Multimodal Feature and Fusion Analysis for Automatic Detection of Depression		✓						
What reveals about depression level? The role of multimodal features at the level of interview questions	✓		✓	✓	✓	✓		

Speech databases for mental disorders: A systematic review	✓	✓	✓		✓			
Topological Data Analysis to Engineer Features from Audio Signals for Depression Detection	✓		✓		✓			
Linguistic Feature Extraction for Clinical Analysis in Multiple Languages		✓	✓			✓		
Diagnosing clinical depression from voice: Using Signal Processing and Neural Network Algorithms to build a Mental Wellness Monitor	✓		✓		✓			
Emotion and Depression Detection from Speech	✓		✓		✓			✓
Object-based Image Discrimination Relationship Recognition		✓						
Dialogue Model and Response Generation for Emotion Improvement Elicitation		✓						✓
Generating Gestures from Speech for Virtual Humans Using Machine Learning Approaches		✓			✓			
Analyzing acoustic and prosodic fluctuations in free speech to predict psychosis onset in high-risk youths		✓			✓			
Transferring a facial depression model to estimate mood in a natural web browsing task	✓	✓	✓	✓				✓

Depression Severity Assessment for Adolescents at High Risk of Mental Disorders		✓	✓					
Hybrid CNN-SVM classifier for efficient depression detection system	✓		✓		✓			

B. Top 25 - Depressed words

Words	Count	LIWC Categories				
		i	negemo	anx	anger	sad	health
i, my, i'm, me, i've, myself, i'd, i'll	27671	X					
bad, badly, worse, worst, worsened	232		X				
argue,argued, argument, arguments	218		X		X		
regret, regrets, regretted, regretting, regretful, regrets like	149		X			X	
problem	131		X				
depress, depressed, depression, depressive, depressant	131		X			X	
difficult, difficulties, difficulty	125		X				
anger,angry, angered	125		X		X		
stress, stressed, stressul, stresses, stressing	113		X	X			
lose, lost, loss, loser, losers	109		X			X	
temper	81		X		X		
shy, shyness,shyer	78		X	X			
guilty, guilt	69		X	X			
upset, upsetting, upsetting	66		X	X			
anxious, anxiety, anxiousness	64		X	X			
mad	64		X		X		
worries, worrying, worries, worry	63		X	X			
trouble, troubling, troubles	62		X				
wrong, wrongdoing	52		X				
wrong	50		X				
hurt, hurting, hurts, hurtful	47		X			X	
fight, fighting, fights, fighter,	44		X		X		
annoyed, annoy, annoys, annoying	42		X		X		
irritable, irritated, irritating, irritate, irritates	38		X	X			
alone, loneliness, loner, lonely	33		X			X	

C. Top 25 – Non depressed words

Words	Word Count	Category	
		Posemo	Friend
well, okay, fine	1276	X	
good, goodness	959	X	
pretty	706	X	
friend, friends, friendlier, frien	469		X
love, loved, loving, loves, lover, lovely	407	X	
kind, kindness	395	X	
happy, happiness, happier, happiest, happily	286	X	
best, bestest	247	X	
easy, easier, easily, easygoing, ease, easiest,easygoingness	242	X	
better	235	X	
fun, funny	198	X	
enjoy, enjoyment, enjoyable, enjoyed, enjoying, enjoys	190	X	
care, caring, carefree, cared, cares	179	X	
sure, surely, assured	165	X	
proud, proudes, prouder	164	X	
nice, nicer, nicely	164	X	
positive, positives, positively, positivity	146	X	
play, playing, played, playful, plays	125	X	
girlfriend, girlfriends, ex-girlfriends, boyfriends, ex-boyfriend, boyfriend	112		X
helps, helping, helpful	106	X	
relax, relaxed, relaxing, relaxes, relaxation	99	X	
certain, certainly, certainty	98	X	
interest, interesting, interested, interests	91		
outgoing	89	X	
definitely	86	X	

D. Top 25 - Frequently used words

No.	All Participants	Depressed Participants	Non-Depressed Participants
1	**i**	**i**	**good**
2	and	and	i
3	**to**	**to**	**and**
4	a	a	to
5	**the**	**the**	**a**
6	that	that	the
7	**uh**	**my**	**uh**
8	you	um	you
9	**my**	**was**	**that**
10	um	of	my
11	**of**	**it**	**um**
12	it	you	of
13	**was**	**like**	**it**
14	like	uh	know
15	**know**	**just**	**was**
16	i'm	i'm	like
17	**just**	**in**	**i'm**
18	in	know	in
19	**so**	**it's**	**just**
20	it's	so	so
21	**but**	**don't**	**but**
22	don't	but	it's
23	**have**	**not**	**with**
24	with	really	have
25	**not**	**have**	**don't**

E. LIWC & depression correlations (Text)

Variable		PHQ-Score	WPS	Sixltr	i	we	conj	negate	affect	posemo	negemo	anx	anger	sad	family	friend	insight	cause	differ	feel	health	focuspast	focuspres	time	work	home	death
1. PHQ-Sc	Pearson's	—																									
	p-value	—																									
2. WPS	Pearson's	-0.169	—																								
	p-value	0.02	—																								
3. Sixltr	Pearson's	-0.055	-0.169	—																							
	p-value	0.453	0.02	—																							
4. i	Pearson's	0.228	0.024	-0.34	—																						
	p-value	0.002	0.748	< .001	—																						
5. we	Pearson's	-0.084	0.147	-0.133	-0.079	—																					
	p-value	0.25	0.044	0.068	0.283	—																					
6. conj	Pearson's	-0.065	0.452	-0.061	0.042	0.226	—																				
	p-value	0.372	< .001	0.407	0.567	0.002	—																				
7. negate	Pearson's	0.161	-0.3	-0.124	0.085	-0.128	-0.503	—																			
	p-value	0.026	< .001	0.09	0.246	0.079	< .001	—																			
8. affect	Pearson's	0.032	-0.284	0.094	0.078	-0.117	-0.443	0.223	—																		
	p-value	0.66	< .001	0.197	0.286	0.109	< .001	0.002	—																		
9. posemo	Pearson's	-0.124	-0.226	0.111	0.009	-0.085	-0.467	0.228	0.899	—																	
	p-value	0.089	0.002	0.13	0.903	0.244	< .001	0.002	< .001	—																	
10. negem	Pearson's	0.336	-0.175	-0.035	0.179	-0.075	-0.027	0.055	0.338	-0.101	—																
	p-value	< .001	0.016	0.637	0.014	0.308	0.71	0.449	< .001	0.168	—																
11. anx	Pearson's	0.175	-0.213	0.129	0.077	-0.135	-0.016	-0.062	0.271	0.058	0.497	—															
	p-value	0.016	0.003	0.077	0.291	0.063	0.83	0.398	< .001	0.426	< .001	—															
12. anger	Pearson's	0.221	-0.043	-0.167	0.161	-0.074	0.011	0.036	0.17	-0.13	0.661	0.119	—														
	p-value	0.002	0.56	0.022	0.027	0.312	0.882	0.622	0.019	0.076	< .001	0.103	—														
13. sad	Pearson's	0.343	-0.004	0.024	0.175	0.016	0.128	-0.081	-0.004	-0.205	0.446	0.039	0.042	—													
	p-value	< .001	0.953	0.74	0.016	0.824	0.078	0.271	0.958	0.005	< .001	0.591	0.562	—													
14. family	Pearson's	0.005	-0.143	0.146	0.082	0.214	0.005	-0.063	0.105	0.098	0.05	0.089	-0.002	0.084	—												
	p-value	0.948	0.05	0.045	0.259	0.003	0.951	0.386	0.151	0.181	0.493	0.225	0.974	0.251	—												
15. friend	Pearson's	-0.166	-0.06	0.027	-0.018	0.11	-0.07	-0.023	0.162	0.199	-0.059	-0.131	0.031	-0.068	-0.021	—											
	p-value	0.022	0.415	0.71	0.801	0.132	0.34	0.75	0.026	0.006	0.424	0.071	0.668	0.35	0.772	—											
16. insight	Pearson's	-0.068	0.109	-0.186	0.033	-0.192	-0.092	0.294	-0.11	-0.089	-0.052	-0.065	-0.066	-0.019	-0.252	-0.157	—										
	p-value	0.352	0.136	0.011	0.649	0.008	0.208	< .001	0.131	0.225	0.477	0.375	0.369	0.797	< .001	0.031	—										
17. cause	Pearson's	-0.119	0.09	0.056	0.02	-0.1	0.228	-0.147	-0.221	-0.223	-0.042	-0.031	-0.009	0.052	-0.065	-0.005	0.108	—									
	p-value	0.102	0.216	0.444	0.782	0.17	0.002	0.043	0.002	0.002	0.566	0.677	0.899	0.481	0.373	0.944	0.14	—									
18. differ	Pearson's	-0.029	0.203	-0.168	0.111	0.011	0.295	0.106	-0.092	-0.103	0.038	-0.002	0.103	-0.005	-0.057	-0.039	0.143	0.14	—								
	p-value	0.69	0.005	0.021	0.129	0.88	< .001	0.146	0.209	0.158	0.601	0.984	0.158	0.946	0.437	0.594	0.049	0.055	—								
19. feel	Pearson's	0.141	-0.031	-0.019	0.261	-0.104	0.009	-0.086	0.114	0.049	0.166	0.156	0.066	0.131	0.074	-0.019	0.104	0.048	0.024	—							
	p-value	0.053	0.67	0.792	< .001	0.155	0.906	0.24	0.12	0.504	0.022	0.032	0.368	0.072	0.309	0.79	0.153	0.516	0.747	—							
20. health	Pearson's	0.288	-0.078	0.135	0.091	0.02	0.126	-0.175	-0.084	-0.13	0.101	0.137	-0.023	0.211	0.03	-0.062	-0.242	0.104	-0.118	-0.044	—						
	p-value	< .001	0.287	0.063	0.211	0.787	0.085	0.016	0.249	0.075	0.166	0.061	0.751	0.004	0.679	0.396	< .001	0.152	0.106	0.551	—						
21. focusp	Pearson's	0.042	-0.017	-0.01	0.097	0.273	0.274	-0.143	-0.226	-0.28	0.09	-0.026	0.152	0.086	0.052	0.076	-0.29	-0.045	-0.031	-0.007	0.133	—					
	p-value	0.564	0.819	0.889	0.185	< .001	< .001	0.049	0.002	< .001	0.219	0.726	0.037	0.237	0.481	0.3	< .001	0.536	0.672	0.92	0.069	—					
22. focusp	Pearson's	0.102	0.09	-0.413	0.2	-0.119	-0.231	0.425	0.045	0.075	-0.04	-0.099	-0.004	-0.044	-0.192	-0.139	0.588	0.14	0.178	0.075	-0.227	-0.561	—				
	p-value	0.161	0.217	< .001	0.006	0.102	0.001	< .001	0.538	0.303	0.583	0.175	0.952	0.545	0.008	0.057	< .001	0.055	0.015	0.303	0.002	< .001	—				
23. time	Pearson's	0.033	-0.104	-0.012	-0.033	0.11	0.017	-0.034	-0.025	0.01	-0.105	0.012	-0.034	-0.078	0.102	0.065	-0.339	-0.109	-0.11	-0.061	-0.081	0.322	-0.232	—			
	p-value	0.653	0.154	0.869	0.65	0.132	0.814	0.646	0.728	0.89	0.151	0.865	0.641	0.286	0.162	0.373	< .001	0.136	0.132	0.408	0.268	< .001	0.001	—			
24. work	Pearson's	-0.093	-0.039	0.294	-0.084	-0.019	-0.128	-0.014	-0.043	0.036	-0.165	-0.008	-0.117	-0.035	0.059	-0.033	-0.191	-0.128	-0.166	-0.106	-0.105	-0.12	-0.078	0.069	—		
	p-value	0.202	0.591	< .001	0.252	0.8	0.08	0.846	0.557	0.622	0.024	0.912	0.109	0.634	0.418	0.654	0.009	0.079	0.023	0.147	0.151	0.101	0.287	0.344	—		
25. home	Pearson's	-0.055	-0.034	-0.028	-0.051	0.229	0.017	-0.074	-0.006	0.023	-0.052	-0.079	-0.046	-0.023	0.295	0.208	-0.289	-0.134	-0.175	0.028	0.024	0.068	-0.113	0.103	0.121	—	
	p-value	0.45	0.641	0.698	0.486	0.002	0.812	0.309	0.938	0.753	0.475	0.282	0.525	0.749	< .001	0.004	< .001	0.065	0.016	0.706	0.746	0.351	0.121	0.158	0.099	—	
26. death	Pearson's	0.079	0.026	0.073	0.101	-0.012	0.09	0.003	-0.148	-0.178	0.057	0.018	-0.009	0.139	0.046	-0.091	-0.015	0.108	-0.007	0.071	0.222	0.136	-0.004	0.007	-0.041	-0.125	—
	p-value	0.28	0.723	0.316	0.165	0.867	0.217	0.967	0.042	0.014	0.438	0.802	0.903	0.057	0.526	0.213	0.836	0.14	0.927	0.33	0.002	0.063	0.958	0.928	0.574	0.087	—

F. LIWC & depression correlations based on gender (Female)

Variable		PHQ-Score	WPS	Sixltr	i	we	conj	negate	affect	posemo	negemo	anx	anger	sad	family	friend	insight	cause	differ	feel	health	focuspast	focuspres	time	work	home	death
1. PHQ-Sc	Pearson's	—																									
	p-value	—																									
2. WPS	Pearson's	-0.179	—																								
	p-value	0.097	—																								
3. Sixltr	Pearson's	-0.105	-0.143	—																							
	p-value	0.333	0.187	—																							
4. i	Pearson's	0.229	-0.056	-0.334	—																						
	p-value	0.033	0.606	0.002	—																						
5. we	Pearson's	-0.07	0.113	-0.06	-0.152	—																					
	p-value	0.517	0.297	0.584	0.159	—																					
6. conj	Pearson's	-0.069	0.297	-0.158	-0.056	0.221	—																				
	p-value	0.527	0.005	0.143	0.608	0.04	—																				
7. negate	Pearson's	0.257	-0.391	-0.229	0.362	-0.023	-0.416	—																			
	p-value	0.016	< .001	0.033	< .001	0.832	< .001	—																			
8. affect	Pearson's	0.09	-0.29	-0.022	0.217	-0.118	-0.637	0.432	—																		
	p-value	0.408	0.006	0.837	0.044	0.276	< .001	< .001	—																		
9. posemc	Pearson's	-0.125	-0.157	-0.054	0.164	-0.057	-0.617	0.375	0.857	—																	
	p-value	0.25	0.147	0.618	0.129	0.598	< .001	< .001	< .001	—																	
10. negem	Pearson's	0.378	-0.314	0.034	0.176	-0.136	-0.237	0.247	0.537	0.03	—																
	p-value	< .001	0.003	0.755	0.103	0.208	0.027	0.021	< .001	0.781	—																
11. anx	Pearson's	0.148	-0.288	0.204	0.052	-0.154	-0.094	-0.047	0.3	-0.039	0.66	—															
	p-value	0.171	0.007	0.058	0.634	0.155	0.385	0.665	0.005	0.717	< .001	—															
12. anger	Pearson's	0.323	-0.165	-0.031	0.184	-0.077	-0.099	0.228	0.354	-0.038	0.743	0.387	—														
	p-value	0.002	0.127	0.774	0.089	0.479	0.362	0.033	< .001	0.728	< .001	< .001	—														
13. sad	Pearson's	0.444	-0.115	6.880e -4	0.183	-0.099	-0.017	0.093	0.205	-0.024	0.451	0.158	0.092	—													
	p-value	< .001	0.287	0.995	0.089	0.361	0.877	0.393	0.057	0.825	< .001	0.143	0.396	—													
14. family	Pearson's	-0.002	-0.13	0.081	0.046	0.24	-0.089	0.04	0.104	0.046	0.132	0.206	0.064	0.155	—												
	p-value	0.984	0.231	0.458	0.673	0.025	0.412	0.715	0.336	0.673	0.222	0.056	0.555	0.151	—												
15. friend	Pearson's	-0.12	-0.02	0.046	0.018	0.204	0.028	0.089	0.005	0.072	-0.123	-0.154	-0.067	-0.141	-0.062	—											
	p-value	0.268	0.856	0.671	0.868	0.057	0.798	0.411	0.962	0.507	0.257	0.155	0.538	0.192	0.568	—											
16. insight	Pearson's	-0.202	0.081	-0.092	-0.001	-0.272	0.094	-0.14	-0.113	-0.053	-0.116	0.039	-0.036	-0.146	-0.171	-0.286	—										
	p-value	0.061	0.458	0.399	0.989	0.011	0.384	0.197	0.296	0.625	0.285	0.718	0.743	0.177	0.112	0.007	—										
17. cause	Pearson's	-0.141	0.089	0.044	0.024	-0.08	0.151	0.011	-0.229	-0.222	-0.077	-0.029	-0.035	-0.148	-0.009	-0.126	0.155	—									
	p-value	0.191	0.411	0.685	0.827	0.46	0.162	0.919	0.033	0.038	0.477	0.79	0.749	0.172	0.937	0.244	0.151	—									
18. differ	Pearson's	-0.149	0.182	-0.192	0.12	-0.015	0.321	0.147	-0.042	-0.021	-0.029	-0.018	0.087	-0.123	-0.11	-0.025	0.248	0.202	—								
	p-value	0.168	0.091	0.075	0.269	0.887	0.002	0.175	0.696	0.846	0.79	0.872	0.422	0.255	0.311	0.82	0.021	0.06	—								
19. feel	Pearson's	0.282	-0.097	0.145	0.245	-0.19	-0.194	0.075	0.175	0.05	0.242	0.044	0.094	0.341	0.091	-0.006	-0.024	-0.117	-0.13	—							
	p-value	0.008	0.372	0.181	0.022	0.078	0.072	0.489	0.105	0.644	0.024	0.687	0.389	0.001	0.404	0.953	0.824	0.279	0.231	—							
20. health	Pearson's	0.355	-0.196	0.081	-0.064	0.031	0.05	-0.074	-0.166	-0.225	0.061	0.181	-0.11	0.194	0.085	-0.137	-0.161	0.026	-0.158	-0.038	—						
	p-value	< .001	0.069	0.453	0.555	0.777	0.642	0.497	0.125	0.036	0.572	0.093	0.311	0.073	0.435	0.206	0.135	0.811	0.143	0.724	—						
21. focusp	Pearson's	0.163	-0.098	0.03	0.012	0.315	0.345	-0.083	-0.271	-0.403	0.134	0.188	0.099	0.109	-0.091	0.171	-0.194	-0.03	-0.1	0.031	0.273	—					
	p-value	0.131	0.365	0.781	0.911	0.003	0.001	0.447	0.011	< .001	0.217	0.081	0.361	0.317	0.4	0.112	0.072	0.786	0.359	0.774	0.01	—					
22. focusp	Pearson's	0.058	0.167	-0.391	0.162	-0.176	-0.146	0.344	0.113	0.243	-0.158	-0.279	-0.012	-0.066	-0.073	-0.286	0.402	0.197	0.263	-0.102	-0.22	-0.597	—				
	p-value	0.596	0.122	< .001	0.134	0.103	0.178	0.001	0.299	0.023	0.143	0.009	0.914	0.543	0.5	0.007	< .001	0.067	0.014	0.349	0.04	< .001	—				
23. time	Pearson's	-0.033	0.022	0.035	-0.067	0.258	0.051	0.06	-0.09	-0.002	-0.185	-0.123	-0.175	-0.14	-0.004	0.094	-0.213	-0.122	-0.034	0.007	-0.14	0.201	-0.099	—			
	p-value	0.763	0.84	0.745	0.537	0.016	0.638	0.582	0.408	0.984	0.086	0.258	0.105	0.195	0.974	0.389	0.047	0.261	0.753	0.951	0.196	0.062	0.36	—			
24. work	Pearson's	-0.28	0.151	0.327	-4.240e -4	0.05	0.031	-0.13	-0.143	-0.04	-0.222	-0.116	-0.184	0.048	0.034	-0.004	-0.035	0.001	-0.21	0.096	-0.202	-0.098	-0.077	0.12	—		
	p-value	0.009	0.162	0.002	0.997	0.647	0.774	0.229	0.187	0.71	0.039	0.286	0.088	0.662	0.755	0.974	0.745	0.992	0.051	0.379	0.06	0.367	0.476	0.269	—		
25. home	Pearson's	0.045	-0.069	-0.076	-0.098	0.169	0.012	0.082	-0.093	-0.068	-0.07	-0.161	-0.085	0.024	0.208	0.241	-0.266	-0.205	-0.179	-0.003	0.038	-0.024	-0.056	0.145	-0.017	—	
	p-value	0.676	0.525	0.486	0.366	0.117	0.911	0.451	0.39	0.529	0.517	0.135	0.432	0.825	0.053	0.024	0.013	0.057	0.097	0.98	0.726	0.827	0.605	0.18	0.873	—	
26. death	Pearson's	0.139	-0.056	0.129	0.072	0.011	0.017	0.026	-0.213	-0.256	-0.002	0.044	-0.065	0.149	0.085	-0.061	-0.03	0.131	-0.056	0.078	0.28	0.236	-0.012	0.068	0.076	-0.119	—
	p-value	0.198	0.608	0.232	0.505	0.921	0.874	0.814	0.048	0.017	0.986	0.683	0.55	0.168	0.435	0.574	0.785	0.227	0.604	0.472	0.009	0.028	0.913	0.533	0.483	0.271	—

G. LIWC & depression correlations based on gender (Male)

Variable		PHQ-Scor	WPS	Sixltr	i	we	conj	negate	affect	posemo	negemo	anx	anger	sad	family	friend	insight	cause	differ	feel	health	focuspast	focuspres	time	work	home	death
1. PHQ-Sc	Pearson's	—																									
	p-value	—																									
2. WPS	Pearson's	-0.188	—																								
	p-value	0.058	—																								
3. Sixltr	Pearson's	-0.029	-0.217	—																							
	p-value	0.771	0.028	—																							
4. i	Pearson's	0.205	0.056	-0.386	—																						
	p-value	0.039	0.573	< .001	—																						
5. we	Pearson's	-0.118	0.176	-0.231	-0.023	—																					
	p-value	0.237	0.078	0.019	0.819	—																					
6. conj	Pearson's	-0.107	0.55	-0.034	0.054	0.226	—																				
	p-value	0.283	< .001	0.734	0.592	0.023	—																				
7. negate	Pearson's	0.182	-0.292	-0.086	0.044	-0.192	-0.544	—																			
	p-value	0.067	0.003	0.388	0.658	0.053	< .001	—																			
8. affect	Pearson's	-0.024	-0.289	0.179	-0.034	-0.123	-0.337	0.19	—																		
	p-value	0.808	0.003	0.071	0.737	0.218	< .001	0.056	—																		
9. posemc	Pearson's	-0.123	-0.274	0.222	-0.081	-0.111	-0.388	0.2	0.933	—																	
	p-value	0.219	0.005	0.025	0.419	0.265	< .001	0.044	< .001	—																	
10. negem	Pearson's	0.26	-0.059	-0.143	0.145	-0.005	0.111	0.025	0.138	-0.216	—																
	p-value	0.008	0.558	0.152	0.145	0.959	0.267	0.805	0.168	0.029	—																
11. anx	Pearson's	0.202	-0.149	0.06	0.096	-0.118	0.036	-0.072	0.246	0.132	0.304	—															
	p-value	0.042	0.135	0.547	0.34	0.239	0.717	0.47	0.013	0.187	0.002	—															
12. anger	Pearson's	0.114	0.061	-0.287	0.137	-0.076	0.081	-0.015	0.02	-0.192	0.583	-0.139	—														
	p-value	0.255	0.546	0.003	0.17	0.446	0.417	0.879	0.842	0.053	< .001	0.165	—														
13. sad	Pearson's	0.237	0.068	0.025	0.144	0.13	0.2	-0.124	-0.167	-0.319	0.437	-0.071	-0.005	—													
	p-value	0.017	0.498	0.803	0.148	0.194	0.044	0.215	0.093	0.001	< .001	0.477	0.963	—													
14. family	Pearson's	-0.02	-0.198	0.181	0.073	0.168	0.021	-0.079	0.103	0.152	-0.105	-0.04	-0.078	-0.009	—												
	p-value	0.845	0.046	0.069	0.468	0.092	0.836	0.428	0.305	0.128	0.294	0.693	0.438	0.93	—												
15. friend	Pearson's	-0.197	-0.075	0.028	-0.023	0.037	-0.105	-0.07	0.269	0.266	0.02	-0.114	0.108	-0.007	0.032	—											
	p-value	0.047	0.456	0.78	0.816	0.709	0.293	0.483	0.006	0.007	0.839	0.254	0.281	0.945	0.751	—											
16. insight	Pearson's	0.031	0.144	-0.234	0.071	-0.141	-0.169	0.393	-0.109	-0.109	0.01	-0.132	-0.083	0.063	-0.308	-0.102	—										
	p-value	0.761	0.149	0.018	0.476	0.157	0.089	< .001	0.277	0.276	0.92	0.184	0.407	0.528	0.002	0.307	—										
17. cause	Pearson's	-0.112	0.08	0.055	9.720e -4	-0.133	0.271	-0.202	-0.217	-0.223	-0.024	-0.035	0.009	0.199	-0.137	0.085	0.089	—									
	p-value	0.261	0.425	0.581	0.992	0.183	0.006	0.041	0.028	0.024	0.814	0.73	0.931	0.045	0.17	0.396	0.373	—									
18. differ	Pearson's	0.082	0.209	-0.166	0.081	0.032	0.262	0.128	-0.138	-0.16	0.097	0.011	0.114	0.085	-0.029	-0.04	0.092	0.078	—								
	p-value	0.41	0.035	0.096	0.416	0.746	0.008	0.2	0.165	0.109	0.332	0.914	0.253	0.397	0.775	0.689	0.359	0.438	—								
19. feel	Pearson's	-0.033	-0.023	-0.193	0.228	-0.042	0.078	-0.108	0.061	0.064	0.028	0.259	0.032	-0.075	1.440e -4	-0.002	0.209	0.163	0.134	—							
	p-value	0.742	0.82	0.052	0.021	0.677	0.436	0.28	0.542	0.524	0.783	0.008	0.749	0.457	0.999	0.983	0.035	0.101	0.179	—							
20. health	Pearson's	0.197	0.007	0.164	0.201	-0.011	0.147	-0.217	-0.019	-0.057	0.117	0.087	0.053	0.21	-0.065	0.011	-0.296	0.165	-0.099	-0.102	—						
	p-value	0.047	0.945	0.099	0.043	0.915	0.14	0.029	0.85	0.571	0.243	0.385	0.596	0.034	0.515	0.91	0.003	0.098	0.321	0.31	—						
21. focusp	Pearson's	-0.067	0.057	-0.037	0.173	0.24	0.246	-0.184	-0.191	-0.207	0.054	-0.213	0.198	0.074	0.191	0.009	-0.352	-0.055	0.032	-0.03	0.015	—					
	p-value	0.506	0.572	0.71	0.083	0.015	0.013	0.065	0.054	0.037	0.588	0.031	0.047	0.459	0.055	0.928	< .001	0.581	0.748	0.763	0.884	—					
22. focusp	Pearson's	0.139	0.033	-0.436	0.226	-0.076	-0.295	0.482	8.546e -4	-0.014	0.062	0.035	-1.449e -4	-0.033	-0.299	-0.052	0.683	0.101	0.115	0.197	-0.244	-0.54	—				
	p-value	0.162	0.739	< .001	0.022	0.445	0.003	< .001	0.993	0.887	0.533	0.726	0.999	0.74	0.002	0.605	< .001	0.314	0.251	0.048	0.013	< .001	—				
23. time	Pearson's	0.121	-0.171	-0.018	0.034	-0.007	0.053	-0.095	0.024	0.008	0.012	0.128	0.081	-0.009	0.242	0.03	-0.429	-0.086	-0.152	-0.056	-0.001	0.409	-0.313	—			
	p-value	0.225	0.085	0.858	0.732	0.945	0.598	0.344	0.811	0.935	0.903	0.198	0.421	0.93	0.014	0.766	< .001	0.388	0.128	0.579	0.991	< .001	0.001	—			
24. work	Pearson's	0.03	-0.149	0.289	-0.127	-0.069	-0.202	0.005	0.011	0.069	-0.133	0.06	-0.08	-0.077	0.087	-0.05	-0.256	-0.2	-0.143	-0.22	-0.044	-0.135	-0.078	0.039	—		
	p-value	0.763	0.134	0.003	0.202	0.488	0.042	0.959	0.915	0.492	0.182	0.549	0.424	0.44	0.382	0.616	0.009	0.044	0.152	0.026	0.664	0.175	0.436	0.694	—		
25. home	Pearson's	-0.19	-0.041	-0.021	-0.062	0.287	-0.038	-0.102	0.058	0.095	-0.086	-0.011	-0.023	-0.093	0.346	0.213	-0.3	-0.098	-0.202	-0.008	-0.027	0.151	-0.161	0.122	0.213	—	
	p-value	0.056	0.68	0.834	0.535	0.004	0.708	0.307	0.563	0.344	0.391	0.914	0.819	0.355	< .001	0.032	0.002	0.329	0.041	0.939	0.787	0.129	0.106	0.224	0.031	—	
26. death	Pearson's	0.012	0.085	0.021	0.112	-0.045	0.127	0.007	-0.1	-0.128	0.11	-0.008	0.036	0.122	-0.004	-0.106	-0.002	0.084	0.03	0.048	0.161	0.059	7.274e -5	-0.023	-0.106	-0.148	—
	p-value	0.907	0.394	0.838	0.26	0.653	0.204	0.944	0.316	0.201	0.273	0.94	0.72	0.221	0.97	0.288	0.985	0.4	0.765	0.629	0.107	0.553	0.999	0.817	0.289	0.138	—

H. Personality & depression correlations (Text)

Variable		PHQ8	i	we	conj	negate	affect	posemo	negemo	anx	anger	sad	family	friend	insight	cause	differ	feel	health	focuspast	focuspres	time	work	home	death
1. PHQ8	Pearson's r	—																							
	p-value	—																							
2. i	Pearson's r	0.166	—																						
	p-value	0.022	—																						
3. we	Pearson's r	-0.075	-0.079	—																					
	p-value	0.306	0.283	—																					
4. conj	Pearson's r	-0.012	0.042	0.226	—																				
	p-value	0.875	0.567	0.002	—																				
5. negate	Pearson's r	0.082	0.085	-0.128	-0.503	—																			
	p-value	0.259	0.246	0.079	< .001	—																			
6. affect	Pearson's r	-0.021	0.078	-0.117	-0.443	0.223	—																		
	p-value	0.777	0.286	0.109	< .001	0.002	—																		
7. posemo	Pearson's r	-0.144	0.009	-0.085	-0.467	0.228	0.899	—																	
	p-value	0.048	0.903	0.244	< .001	0.002	< .001	—																	
8. negemo	Pearson's r	0.261	0.179	-0.075	-0.027	0.055	0.338	-0.101	—																
	p-value	< .001	0.014	0.308	0.71	0.449	< .001	0.168	—																
9. anx	Pearson's r	0.194	0.077	-0.135	-0.016	-0.062	0.271	0.058	0.497	—															
	p-value	0.007	0.291	0.063	0.83	0.398	< .001	0.426	< .001	—															
10. anger	Pearson's r	0.181	0.161	-0.074	0.011	0.036	0.17	-0.13	0.661	0.119	—														
	p-value	0.013	0.027	0.312	0.882	0.622	0.019	0.076	< .001	0.103	—														
11. sad	Pearson's r	0.21	0.175	0.016	0.128	-0.081	-0.004	-0.205	0.446	0.039	0.042	—													
	p-value	0.004	0.016	0.824	0.078	0.271	0.958	0.005	< .001	0.591	0.562	—													
12. family	Pearson's r	0.008	0.082	0.214	0.005	-0.063	0.105	0.098	0.05	0.089	-0.002	0.084	—												
	p-value	0.917	0.259	0.003	0.951	0.386	0.151	0.181	0.493	0.225	0.974	0.251	—												
13. friend	Pearson's r	-0.204	-0.018	0.11	-0.07	-0.023	0.162	0.199	-0.059	-0.131	0.031	-0.068	-0.021	—											
	p-value	0.005	0.801	0.132	0.34	0.75	0.026	0.006	0.424	0.071	0.668	0.35	0.772	—											
14. insight	Pearson's r	-0.063	0.033	-0.192	-0.092	0.294	-0.11	-0.089	-0.052	-0.065	-0.066	-0.019	-0.252	-0.157	—										
	p-value	0.39	0.649	0.008	0.208	< .001	0.131	0.225	0.477	0.375	0.369	0.797	< .001	0.031	—										
15. cause	Pearson's r	-0.048	0.02	-0.1	0.228	-0.147	-0.221	-0.223	-0.042	-0.031	-0.009	0.052	-0.065	-0.005	0.108	—									
	p-value	0.515	0.782	0.17	0.002	0.043	0.002	0.002	0.566	0.677	0.899	0.481	0.373	0.944	0.14	—									
16. differ	Pearson's r	0.03	0.111	0.011	0.295	0.106	-0.092	-0.103	0.038	-0.002	0.103	-0.005	-0.057	-0.039	0.143	0.14	—								
	p-value	0.681	0.129	0.88	< .001	0.146	0.209	0.158	0.601	0.984	0.158	0.946	0.437	0.594	0.049	0.055	—								
17. feel	Pearson's r	0.051	0.261	-0.104	0.009	-0.086	0.114	0.049	0.166	0.156	0.066	0.131	0.074	-0.019	0.104	0.048	0.024	—							
	p-value	0.485	< .001	0.155	0.906	0.24	0.12	0.504	0.022	0.032	0.368	0.072	0.309	0.79	0.153	0.516	0.747	—							
18. health	Pearson's r	0.225	0.091	0.02	0.126	-0.175	-0.084	-0.13	0.101	0.137	-0.023	0.211	0.03	-0.062	-0.242	0.104	-0.118	-0.044	—						
	p-value	0.002	0.211	0.787	0.085	0.016	0.249	0.075	0.166	0.061	0.751	0.004	0.679	0.396	< .001	0.152	0.106	0.551	—						
19. focuspast	Pearson's r	0.034	0.097	0.273	0.274	-0.143	-0.226	-0.28	0.09	-0.026	0.152	0.086	0.052	0.076	-0.29	-0.045	-0.031	-0.007	0.133	—					
	p-value	0.639	0.185	< .001	< .001	0.049	0.002	< .001	0.219	0.726	0.037	0.237	0.481	0.3	< .001	0.536	0.672	0.92	0.069	—					
20. focuspresent	Pearson's r	0.096	0.2	-0.119	-0.231	0.425	0.045	0.075	-0.04	-0.099	-0.004	-0.044	-0.192	-0.139	0.588	0.14	0.178	0.075	-0.227	-0.561	—				
	p-value	0.191	0.006	0.102	0.001	< .001	0.538	0.303	0.583	0.175	0.952	0.545	0.008	0.057	< .001	0.055	0.015	0.303	0.002	< .001	—				
21. time	Pearson's r	0.071	-0.033	0.11	0.017	-0.034	-0.025	0.01	-0.105	0.012	-0.034	-0.078	0.102	0.065	-0.339	-0.109	-0.11	-0.061	-0.081	0.322	-0.232	—			
	p-value	0.332	0.65	0.132	0.814	0.646	0.728	0.89	0.151	0.865	0.641	0.286	0.162	0.373	< .001	0.136	0.132	0.408	0.268	< .001	0.001	—			
22. work	Pearson's r	-0.074	-0.084	-0.019	-0.128	-0.014	-0.043	0.036	-0.165	-0.008	-0.117	-0.035	0.059	-0.033	-0.191	-0.128	-0.166	-0.106	-0.105	-0.12	-0.078	0.069	—		
	p-value	0.312	0.252	0.8	0.08	0.846	0.557	0.622	0.024	0.912	0.109	0.634	0.418	0.654	0.009	0.079	0.023	0.147	0.151	0.101	0.287	0.344	—		
23. home	Pearson's r	-0.094	-0.051	0.229	0.017	-0.074	-0.006	0.023	-0.052	-0.079	-0.046	-0.023	0.295	0.208	-0.289	-0.134	-0.175	0.028	0.024	0.068	-0.113	0.103	0.121	—	
	p-value	0.197	0.486	0.002	0.812	0.309	0.938	0.753	0.475	0.282	0.525	0.749	< .001	0.004	< .001	0.065	0.016	0.706	0.746	0.351	0.121	0.158	0.099	—	
24. death	Pearson's r	0.136	0.101	-0.012	0.09	0.003	-0.148	-0.178	0.057	0.018	-0.009	0.139	0.046	-0.091	-0.015	0.108	-0.007	0.071	0.222	0.136	-0.004	0.007	-0.041	-0.125	—
	p-value	0.062	0.165	0.867	0.217	0.967	0.042	0.014	0.438	0.802	0.903	0.057	0.526	0.213	0.836	0.14	0.927	0.33	0.002	0.063	0.958	0.928	0.574	0.087	—

I. Personality & depression correlations based on gender (Text - Female)

Variable		PHQ8	i	we	conj	negate	affect	posemo	negemo	anx	anger	sad	family	friend	insight	cause	differ	feel	health	focuspast	focuspres	time	work	home	death
1. PHQ8	Pearson's r	—																							
	p-value	—																							
2. i	Pearson's r	0.165	—																						
	p-value	0.127	—																						
3. we	Pearson's r	-0.052	-0.152	—																					
	p-value	0.631	0.159	—																					
4. conj	Pearson's r	-0.05	-0.056	0.221	—																				
	p-value	0.647	0.608	0.04	—																				
5. negate	Pearson's r	0.203	0.362	-0.023	-0.416	—																			
	p-value	0.059	< .001	0.832	< .001	—																			
6. affect	Pearson's r	0.017	0.217	-0.118	-0.637	0.432	—																		
	p-value	0.874	0.044	0.276	< .001	< .001	—																		
7. posemo	Pearson's r	-0.122	0.164	-0.057	-0.617	0.375	0.857	—																	
	p-value	0.261	0.129	0.598	< .001	< .001	< .001	—																	
8. negemo	Pearson's r	0.244	0.176	-0.136	-0.237	0.247	0.537	0.03	—																
	p-value	0.023	0.103	0.208	0.027	0.021	< .001	0.781	—																
9. anx	Pearson's r	0.145	0.052	-0.154	-0.094	-0.047	0.3	-0.039	0.66	—															
	p-value	0.18	0.634	0.155	0.385	0.665	0.005	0.717	< .001	—															
10. anger	Pearson's r	0.25	0.184	-0.077	-0.099	0.228	0.354	-0.038	0.743	0.387	—														
	p-value	0.02	0.089	0.479	0.362	0.033	< .001	0.728	< .001	< .001	—														
11. sad	Pearson's r	0.207	0.183	-0.099	-0.017	0.093	0.205	-0.024	0.451	0.158	0.092	—													
	p-value	0.055	0.089	0.361	0.877	0.393	0.057	0.825	< .001	0.143	0.396	—													
12. family	Pearson's r	0.007	0.046	0.24	-0.089	0.04	0.104	0.046	0.132	0.206	0.064	0.155	—												
	p-value	0.946	0.673	0.025	0.412	0.715	0.336	0.673	0.222	0.056	0.555	0.151	—												
13. friend	Pearson's r	-0.154	0.018	0.204	0.028	0.089	0.005	0.072	-0.123	-0.154	-0.067	-0.141	-0.062	—											
	p-value	0.155	0.868	0.057	0.798	0.411	0.962	0.507	0.257	0.155	0.538	0.192	0.568	—											
14. insight	Pearson's r	-0.084	-0.001	-0.272	0.094	-0.14	-0.113	-0.053	-0.116	0.039	-0.036	-0.146	-0.171	-0.286	—										
	p-value	0.439	0.989	0.011	0.384	0.197	0.296	0.625	0.285	0.718	0.743	0.177	0.112	0.007	—										
15. cause	Pearson's r	0.009	0.024	-0.08	0.151	0.011	-0.229	-0.222	-0.077	-0.029	-0.035	-0.148	-0.009	-0.126	0.155	—									
	p-value	0.933	0.827	0.46	0.162	0.919	0.033	0.038	0.477	0.79	0.749	0.172	0.937	0.244	0.151	—									
16. differ	Pearson's r	-0.035	0.12	-0.015	0.321	0.147	-0.042	-0.021	-0.029	-0.018	0.087	-0.123	-0.11	-0.025	0.248	0.202	—								
	p-value	0.746	0.269	0.887	0.002	0.175	0.696	0.846	0.79	0.872	0.422	0.255	0.311	0.82	0.021	0.06	—								
17. feel	Pearson's r	0.157	0.245	-0.19	-0.194	0.075	0.175	0.05	0.242	0.044	0.094	0.341	0.091	-0.006	-0.024	-0.117	-0.13	—							
	p-value	0.146	0.022	0.078	0.072	0.489	0.105	0.644	0.024	0.687	0.389	0.001	0.404	0.953	0.824	0.279	0.231	—							
18. health	Pearson's r	0.343	-0.064	0.031	0.05	-0.074	-0.166	-0.225	0.061	0.181	-0.11	0.194	0.085	-0.137	-0.161	0.026	-0.158	-0.038	—						
	p-value	0.001	0.555	0.777	0.642	0.497	0.125	0.036	0.572	0.093	0.311	0.073	0.435	0.206	0.135	0.811	0.143	0.724	—						
19. focuspast	Pearson's r	0.101	0.012	0.315	0.345	-0.083	-0.271	-0.403	0.134	0.188	0.099	0.109	-0.091	0.171	-0.194	-0.03	-0.1	0.031	0.273	—					
	p-value	0.353	0.911	0.003	0.001	0.447	0.011	< .001	0.217	0.081	0.361	0.317	0.4	0.112	0.072	0.786	0.359	0.774	0.01	—					
20. focuspresen	Pearson's r	0.136	0.162	-0.176	-0.146	0.344	0.113	0.243	-0.158	-0.279	-0.012	-0.066	-0.073	-0.286	0.402	0.197	0.263	-0.102	-0.22	-0.597	—				
	p-value	0.21	0.134	0.103	0.178	0.001	0.299	0.023	0.143	0.009	0.914	0.543	0.5	0.007	< .001	0.067	0.014	0.349	0.04	< .001	—				
21. time	Pearson's r	0.057	-0.067	0.258	0.051	0.06	-0.09	-0.002	-0.185	-0.123	-0.175	-0.14	-0.004	0.094	-0.213	-0.122	-0.034	0.007	-0.14	0.201	-0.099	—			
	p-value	0.601	0.537	0.016	0.638	0.582	0.408	0.984	0.086	0.258	0.105	0.195	0.974	0.389	0.047	0.261	0.753	0.951	0.196	0.062	0.36	—			
22. work	Pearson's r	-0.297	-4.240e -4	0.05	0.031	-0.13	-0.143	-0.04	-0.222	-0.116	-0.184	0.048	0.034	-0.004	-0.035	0.001	-0.21	0.096	-0.202	-0.098	-0.077	0.12	—		
	p-value	0.005	0.997	0.647	0.774	0.229	0.187	0.71	0.039	0.286	0.088	0.662	0.755	0.974	0.745	0.992	0.051	0.379	0.06	0.367	0.476	0.269	—		
23. home	Pearson's r	-0.084	-0.098	0.169	0.012	0.082	-0.093	-0.068	-0.07	-0.161	-0.085	0.024	0.208	0.241	-0.266	-0.205	-0.179	-0.003	0.038	-0.024	-0.056	0.145	-0.017	—	
	p-value	0.439	0.366	0.117	0.911	0.451	0.39	0.529	0.517	0.135	0.432	0.825	0.053	0.024	0.013	0.057	0.097	0.98	0.726	0.827	0.605	0.18	0.873	—	
24. death	Pearson's r	0.161	0.072	0.011	0.017	0.026	-0.213	-0.256	-0.002	0.044	-0.065	0.149	0.085	-0.061	-0.03	0.131	-0.056	0.078	0.28	0.236	-0.012	0.068	0.076	-0.119	—
	p-value	0.136	0.505	0.921	0.874	0.814	0.048	0.017	0.986	0.683	0.55	0.168	0.435	0.574	0.785	0.227	0.604	0.472	0.009	0.028	0.913	0.533	0.483	0.271	—

J. Personality & depression correlations based on gender (Text - Male)

Variable		PHQ8	i	we	conj	negate	affect	posemo	negemo	anx	anger	sad	family	friend	insight	cause	differ	feel	health	focuspast	focuspres	time	work	home	death
1. PHQ8	Pearson's	—																							
	p-value	—																							
2. i	Pearson's	0.137	—																						
	p-value	0.171	—																						
3. we	Pearson's	-0.123	-0.023	—																					
	p-value	0.218	0.819	—																					
4. conj	Pearson's	-0.03	0.054	0.226	—																				
	p-value	0.768	0.592	0.023	—																				
5. negate	Pearson's	0.082	0.044	-0.192	-0.544	—																			
	p-value	0.412	0.658	0.053	< .001	—																			
6. affect	Pearson's	-0.06	-0.034	-0.123	-0.337	0.19	—																		
	p-value	0.552	0.737	0.218	< .001	0.056	—																		
7. posemo	Pearson's	-0.158	-0.081	-0.111	-0.388	0.2	0.933	—																	
	p-value	0.112	0.419	0.265	< .001	0.044	< .001	—																	
8. negemo	Pearson's	0.256	0.145	-0.005	0.111	0.025	0.138	-0.216	—																
	p-value	0.009	0.145	0.959	0.267	0.805	0.168	0.029	—																
9. anx	Pearson's	0.242	0.096	-0.118	0.036	-0.072	0.246	0.132	0.304	—															
	p-value	0.014	0.34	0.239	0.717	0.47	0.013	0.187	0.002	—															
10. anger	Pearson's	0.109	0.137	-0.076	0.081	-0.015	0.02	-0.192	0.583	-0.139	—														
	p-value	0.277	0.17	0.446	0.417	0.879	0.842	0.053	< .001	0.165	—														
11. sad	Pearson's	0.195	0.144	0.13	0.2	-0.124	-0.167	-0.319	0.437	-0.071	-0.005	—													
	p-value	0.05	0.148	0.194	0.044	0.215	0.093	0.001	< .001	0.477	0.963	—													
12. family	Pearson's	-0.031	0.073	0.168	0.021	-0.079	0.103	0.152	-0.105	-0.04	-0.078	-0.009	—												
	p-value	0.76	0.468	0.092	0.836	0.428	0.305	0.128	0.294	0.693	0.438	0.93	—												
13. friend	Pearson's	-0.234	-0.023	0.037	-0.105	-0.07	0.269	0.266	0.02	-0.114	0.108	-0.007	0.032	—											
	p-value	0.018	0.816	0.709	0.293	0.483	0.006	0.007	0.839	0.254	0.281	0.945	0.751	—											
14. insight	Pearson's	-0.04	0.071	-0.141	-0.169	0.393	-0.109	-0.109	0.01	-0.132	-0.083	0.063	-0.308	-0.102	—										
	p-value	0.693	0.476	0.157	0.089	< .001	0.277	0.276	0.92	0.184	0.407	0.528	0.002	0.307	—										
15. cause	Pearson's	-0.114	9.720e -4	-0.133	0.271	-0.202	-0.217	-0.223	-0.024	-0.035	0.009	0.199	-0.137	0.085	0.089	—									
	p-value	0.253	0.992	0.183	0.006	0.041	0.028	0.024	0.814	0.73	0.931	0.045	0.17	0.396	0.373	—									
16. differ	Pearson's	0.078	0.081	0.032	0.262	0.128	-0.138	-0.16	0.097	0.011	0.114	0.085	-0.029	-0.04	0.092	0.078	—								
	p-value	0.437	0.416	0.746	0.008	0.2	0.165	0.109	0.332	0.914	0.253	0.397	0.775	0.689	0.359	0.438	—								
17. feel	Pearson's	-0.098	0.228	-0.042	0.078	-0.108	0.061	0.064	0.028	0.259	0.032	-0.075	1.440e -4	-0.002	0.209	0.163	0.134	—							
	p-value	0.328	0.021	0.677	0.436	0.28	0.542	0.524	0.783	0.008	0.749	0.457	0.999	0.983	0.035	0.101	0.179	—							
18. health	Pearson's	0.077	0.201	-0.011	0.147	-0.217	-0.019	-0.057	0.117	0.087	0.053	0.21	-0.065	0.011	-0.296	0.165	-0.099	-0.102	—						
	p-value	0.44	0.043	0.915	0.14	0.029	0.85	0.571	0.243	0.385	0.596	0.034	0.515	0.91	0.003	0.098	0.321	0.31	—						
19. focuspast	Pearson's	-0.019	0.173	0.24	0.246	-0.184	-0.191	-0.207	0.054	-0.213	0.198	0.074	0.191	0.009	-0.352	-0.055	0.032	-0.03	0.015	—					
	p-value	0.846	0.083	0.015	0.013	0.065	0.054	0.037	0.588	0.031	0.047	0.459	0.055	0.928	< .001	0.581	0.748	0.763	0.884	—					
20. focuspresen	Pearson's	0.064	0.226	-0.076	-0.295	0.482	8.546e -4	-0.014	0.062	0.035	-1.449e -4	-0.033	-0.299	-0.052	0.683	0.101	0.115	0.197	-0.244	-0.54	—				
	p-value	0.522	0.022	0.445	0.003	< .001	0.993	0.887	0.533	0.726	0.999	0.74	0.002	0.605	< .001	0.314	0.251	0.048	0.013	< .001	—				
21. time	Pearson's	0.122	0.034	-0.007	0.053	-0.095	0.024	0.008	0.012	0.128	0.081	-0.009	0.242	0.03	-0.429	-0.086	-0.152	-0.056	-0.001	0.409	-0.313	—			
	p-value	0.223	0.732	0.945	0.598	0.344	0.811	0.935	0.903	0.198	0.421	0.93	0.014	0.766	< .001	0.388	0.128	0.579	0.991	< .001	0.001	—			
22. work	Pearson's	0.07	-0.127	-0.069	-0.202	0.005	0.011	0.069	-0.133	0.06	-0.08	-0.077	0.087	-0.05	-0.256	-0.2	-0.143	-0.22	-0.044	-0.135	-0.078	0.039	—		
	p-value	0.483	0.202	0.488	0.042	0.959	0.915	0.492	0.182	0.549	0.424	0.44	0.382	0.616	0.009	0.044	0.152	0.026	0.664	0.175	0.436	0.694	—		
23. home	Pearson's	-0.146	-0.062	0.287	-0.038	-0.102	0.058	0.095	-0.086	-0.011	-0.023	-0.093	0.346	0.213	-0.3	-0.098	-0.202	-0.008	-0.027	0.151	-0.161	0.122	0.213	—	
	p-value	0.142	0.535	0.004	0.708	0.307	0.563	0.344	0.391	0.914	0.819	0.355	< .001	0.032	0.002	0.329	0.041	0.939	0.787	0.129	0.106	0.224	0.031	—	
24. death	Pearson's	0.104	0.112	-0.045	0.127	0.007	-0.1	-0.128	0.11	-0.008	0.036	0.122	-0.004	-0.106	-0.002	0.084	0.03	0.048	0.161	0.059	7.274e -5	-0.023	-0.106	-0.148	—
	p-value	0.299	0.26	0.653	0.204	0.944	0.316	0.201	0.273	0.94	0.72	0.221	0.97	0.288	0.985	0.4	0.765	0.629	0.107	0.553	0.999	0.817	0.289	0.138	—

K. Audio features & depression correlations

Correlations	Coefficient	PHQ8
PHQ8	Pearson Correlation	1
	Sig. (2-tailed)	
	N	189
F0_mean	Pearson Correlation	0.126
	Sig. (2-tailed)	0.083
	N	189
NAQ_mean	Pearson Correlation	0.004
	Sig. (2-tailed)	0.958
	N	189
QOQ_mean	Pearson Correlation	0.019
	Sig. (2-tailed)	0.793
	N	189
H1_mean	Pearson Correlation	.156*
	Sig. (2-tailed)	0.032
	N	189
H2_mean	Pearson Correlation	0.101
	Sig. (2-tailed)	0.166
	N	189
PSP_mean	Pearson Correlation	0.105
	Sig. (2-tailed)	0.15
	N	189
MDQ_mean	Pearson Correlation	0.068
	Sig. (2-tailed)	0.356
	N	189
peakSlope_mean	Pearson Correlation	0.048
	Sig. (2-tailed)	0.512
	N	189
Rd_mean	Pearson Correlation	-0.052
	Sig. (2-tailed)	0.474
	N	189
F0_std	Pearson Correlation	0.099
	Sig. (2-tailed)	0.177
	N	189
NAQ_std	Pearson Correlation	.165*
	Sig. (2-tailed)	0.023
	N	189
QOQ_std	Pearson Correlation	.214**
	Sig. (2-tailed)	0.003
	N	189
H1_std	Pearson Correlation	0.111
	Sig. (2-tailed)	0.127

	N	189
H2_std	Pearson Correlation	0.117
	Sig. (2-tailed)	0.109
	N	189
PSP_std	Pearson Correlation	0.104
	Sig. (2-tailed)	0.154
	N	189
MDQ_std	Pearson Correlation	0.084
	Sig. (2-tailed)	0.249
	N	189
peakSlope_std	Pearson Correlation	0.114
	Sig. (2-tailed)	0.117
	N	189
Rd_std	Pearson Correlation	0.132
	Sig. (2-tailed)	0.07
	N	189
F0_min	Pearson Correlation	.157*
	Sig. (2-tailed)	0.031
	N	189
NAQ_min	Pearson Correlation	.c
	Sig. (2-tailed)	.
	N	189
QOQ_min	Pearson Correlation	.c
	Sig. (2-tailed)	.
	N	189
H1_min	Pearson Correlation	0.083
	Sig. (2-tailed)	0.256
	N	189
H2_min	Pearson Correlation	.c
	Sig. (2-tailed)	.
	N	189
PSP_min	Pearson Correlation	0.115
	Sig. (2-tailed)	0.114
	N	189
MDQ_min	Pearson Correlation	-0.008
	Sig. (2-tailed)	0.913
	N	189
peakSlope_min	Pearson Correlation	0.004
	Sig. (2-tailed)	0.962
	N	189
Rd_min	Pearson Correlation	-0.052
	Sig. (2-tailed)	0.479
	N	189
F0_max	Pearson Correlation	.169*

	Sig. (2-tailed)	0.02
	N	189
NAQ_max	Pearson Correlation	-0.031
	Sig. (2-tailed)	0.675
	N	189
QOQ_max	Pearson Correlation	0.119
	Sig. (2-tailed)	0.102
	N	189
H1_max	Pearson Correlation	0.133
	Sig. (2-tailed)	0.068
	N	189
H2_max	Pearson Correlation	0.032
	Sig. (2-tailed)	0.658
	N	189
PSP_max	Pearson Correlation	-0.094
	Sig. (2-tailed)	0.2
	N	189
MDQ_max	Pearson Correlation	-0.017
	Sig. (2-tailed)	0.818
	N	189
peakSlope_max	Pearson Correlation	0.124
	Sig. (2-tailed)	0.089
	N	189
Rd_max	Pearson Correlation	-0.03
	Sig. (2-tailed)	0.682
	N	189
F0_range	Pearson Correlation	.169*
	Sig. (2-tailed)	0.02
	N	189
NAQ_range	Pearson Correlation	-0.031
	Sig. (2-tailed)	0.675
	N	189
QOQ_range	Pearson Correlation	0.119
	Sig. (2-tailed)	0.102
	N	189
H1_range	Pearson Correlation	0.054
	Sig. (2-tailed)	0.463
	N	189
H2_range	Pearson Correlation	0.032
	Sig. (2-tailed)	0.658
	N	189
PSP_range	Pearson Correlation	-0.095
	Sig. (2-tailed)	0.195
	N	189

MDQ_range	Pearson Correlation	-0.015
	Sig. (2-tailed)	0.837
	N	189
peakSlope_range	Pearson Correlation	0.007
	Sig. (2-tailed)	0.929
	N	189
Rd_range	Pearson Correlation	0.03
	Sig. (2-tailed)	0.681
	N	189
HMPDD_0_mean	Pearson Correlation	-0.014
	Sig. (2-tailed)	0.849
	N	189
HMPDD_1_mean	Pearson Correlation	-0.09
	Sig. (2-tailed)	0.219
	N	189
HMPDD_10_mean	Pearson Correlation	0.112
	Sig. (2-tailed)	0.124
	N	189
HMPDD_11_mean	Pearson Correlation	0.124
	Sig. (2-tailed)	0.088
	N	189
HMPDD_12_mean	Pearson Correlation	0.115
	Sig. (2-tailed)	0.116
	N	189
HMPDD_2_mean	Pearson Correlation	-.149*
	Sig. (2-tailed)	0.041
	N	189
HMPDD_3_mean	Pearson Correlation	-0.131
	Sig. (2-tailed)	0.072
	N	189
HMPDD_4_mean	Pearson Correlation	-0.138
	Sig. (2-tailed)	0.058
	N	189
HMPDD_5_mean	Pearson Correlation	-.152*
	Sig. (2-tailed)	0.037
	N	189
HMPDD_6_mean	Pearson Correlation	-0.056
	Sig. (2-tailed)	0.442
	N	189
HMPDD_7_mean	Pearson Correlation	0.005
	Sig. (2-tailed)	0.943
	N	189
HMPDD_8_mean	Pearson Correlation	0.1
	Sig. (2-tailed)	0.17

	N	189
HMPDD_9_mean	Pearson Correlation	.143*
	Sig. (2-tailed)	0.049
	N	189
HMPDM_0_mean	Pearson Correlation	.b
	Sig. (2-tailed)	.
	N	189
HMPDM_1_mean	Pearson Correlation	.b
	Sig. (2-tailed)	.
	N	189
HMPDM_10_mean	Pearson Correlation	.154*
	Sig. (2-tailed)	0.035
	N	189
HMPDM_11_mean	Pearson Correlation	0.061
	Sig. (2-tailed)	0.407
	N	189
HMPDM_12_mean	Pearson Correlation	-0.067
	Sig. (2-tailed)	0.361
	N	189
HMPDM_13_mean	Pearson Correlation	-0.071
	Sig. (2-tailed)	0.329
	N	189
HMPDM_14_mean	Pearson Correlation	-0.029
	Sig. (2-tailed)	0.692
	N	189
HMPDM_15_mean	Pearson Correlation	0.002
	Sig. (2-tailed)	0.978
	N	189
HMPDM_16_mean	Pearson Correlation	-0.025
	Sig. (2-tailed)	0.733
	N	189
HMPDM_17_mean	Pearson Correlation	-0.028
	Sig. (2-tailed)	0.706
	N	189
HMPDM_18_mean	Pearson Correlation	-0.019
	Sig. (2-tailed)	0.792
	N	189
HMPDM_19_mean	Pearson Correlation	-0.007
	Sig. (2-tailed)	0.921
	N	189
HMPDM_2_mean	Pearson Correlation	.b
	Sig. (2-tailed)	.
	N	189
HMPDM_20_mean	Pearson Correlation	-0.01

	Sig. (2-tailed)	0.89
	N	189
HMPDM_21_mean	Pearson Correlation	-0.006
	Sig. (2-tailed)	0.93
	N	189
HMPDM_22_mean	Pearson Correlation	-0.033
	Sig. (2-tailed)	0.651
	N	189
HMPDM_23_mean	Pearson Correlation	0.085
	Sig. (2-tailed)	0.245
	N	189
HMPDM_24_mean	Pearson Correlation	0.001
	Sig. (2-tailed)	0.986
	N	189
HMPDM_3_mean	Pearson Correlation	.b
	Sig. (2-tailed)	.
	N	189
HMPDM_4_mean	Pearson Correlation	-0.039
	Sig. (2-tailed)	0.59
	N	189
HMPDM_5_mean	Pearson Correlation	-0.019
	Sig. (2-tailed)	0.796
	N	189
HMPDM_6_mean	Pearson Correlation	0.011
	Sig. (2-tailed)	0.879
	N	189
HMPDM_7_mean	Pearson Correlation	0.054
	Sig. (2-tailed)	0.459
	N	189
HMPDM_8_mean	Pearson Correlation	0.091
	Sig. (2-tailed)	0.213
	N	189
HMPDM_9_mean	Pearson Correlation	0.118
	Sig. (2-tailed)	0.106
	N	189
MCEP_0_mean	Pearson Correlation	-0.045
	Sig. (2-tailed)	0.538
	N	189
MCEP_1_mean	Pearson Correlation	-0.053
	Sig. (2-tailed)	0.47
	N	189
MCEP_10_mean	Pearson Correlation	0.029
	Sig. (2-tailed)	0.688
	N	189

MCEP_11_mean	Pearson Correlation	-.175*
	Sig. (2-tailed)	0.016
	N	189
MCEP_12_mean	Pearson Correlation	.151*
	Sig. (2-tailed)	0.038
	N	189
MCEP_13_mean	Pearson Correlation	0.058
	Sig. (2-tailed)	0.425
	N	189
MCEP_14_mean	Pearson Correlation	-0.039
	Sig. (2-tailed)	0.597
	N	189
MCEP_15_mean	Pearson Correlation	0.062
	Sig. (2-tailed)	0.399
	N	189
MCEP_16_mean	Pearson Correlation	-0.01
	Sig. (2-tailed)	0.891
	N	189
MCEP_17_mean	Pearson Correlation	-0.008
	Sig. (2-tailed)	0.917
	N	189
MCEP_18_mean	Pearson Correlation	-0.033
	Sig. (2-tailed)	0.649
	N	189
MCEP_19_mean	Pearson Correlation	-0.007
	Sig. (2-tailed)	0.919
	N	189
MCEP_2_mean	Pearson Correlation	0.016
	Sig. (2-tailed)	0.83
	N	189
MCEP_20_mean	Pearson Correlation	-0.112
	Sig. (2-tailed)	0.126
	N	189
MCEP_21_mean	Pearson Correlation	0.001
	Sig. (2-tailed)	0.992
	N	189
MCEP_22_mean	Pearson Correlation	-0.008
	Sig. (2-tailed)	0.914
	N	189
MCEP_23_mean	Pearson Correlation	0.012
	Sig. (2-tailed)	0.872
	N	189
MCEP_24_mean	Pearson Correlation	-0.012
	Sig. (2-tailed)	0.869

	N	189
MCEP_3_mean	Pearson Correlation	-0.012
	Sig. (2-tailed)	0.868
	N	189
MCEP_4_mean	Pearson Correlation	0.03
	Sig. (2-tailed)	0.685
	N	189
MCEP_5_mean	Pearson Correlation	.150*
	Sig. (2-tailed)	0.039
	N	189
MCEP_6_mean	Pearson Correlation	-0.059
	Sig. (2-tailed)	0.421
	N	189
MCEP_7_mean	Pearson Correlation	0.079
	Sig. (2-tailed)	0.28
	N	189
MCEP_8_mean	Pearson Correlation	0.031
	Sig. (2-tailed)	0.669
	N	189
MCEP_9_mean	Pearson Correlation	-0.11
	Sig. (2-tailed)	0.13
	N	189
Rd_conf_mean	Pearson Correlation	.b
	Sig. (2-tailed)	.
	N	189
HMPDD_0_std	Pearson Correlation	-0.031
	Sig. (2-tailed)	0.674
	N	189
HMPDD_1_std	Pearson Correlation	-0.069
	Sig. (2-tailed)	0.348
	N	189
HMPDD_10_std	Pearson Correlation	0.094
	Sig. (2-tailed)	0.199
	N	189
HMPDD_11_std	Pearson Correlation	0.116
	Sig. (2-tailed)	0.113
	N	189
HMPDD_12_std	Pearson Correlation	0.11
	Sig. (2-tailed)	0.134
	N	189
HMPDD_2_std	Pearson Correlation	0.068
	Sig. (2-tailed)	0.351
	N	189
HMPDD_3_std	Pearson Correlation	0.07

	Sig. (2-tailed)	0.341
	N	189
HMPDD_4_std	Pearson Correlation	0.071
	Sig. (2-tailed)	0.331
	N	189
HMPDD_5_std	Pearson Correlation	-0.08
	Sig. (2-tailed)	0.271
	N	189
HMPDD_6_std	Pearson Correlation	-0.007
	Sig. (2-tailed)	0.924
	N	189
HMPDD_7_std	Pearson Correlation	0.003
	Sig. (2-tailed)	0.963
	N	189
HMPDD_8_std	Pearson Correlation	0.053
	Sig. (2-tailed)	0.471
	N	189
HMPDD_9_std	Pearson Correlation	0.113
	Sig. (2-tailed)	0.122
	N	189
HMPDM_0_std	Pearson Correlation	.b
	Sig. (2-tailed)	.
	N	189
HMPDM_1_std	Pearson Correlation	.b
	Sig. (2-tailed)	.
	N	189
HMPDM_10_std	Pearson Correlation	-0.059
	Sig. (2-tailed)	0.42
	N	189
HMPDM_11_std	Pearson Correlation	-.158*
	Sig. (2-tailed)	0.03
	N	189
HMPDM_12_std	Pearson Correlation	-.185*
	Sig. (2-tailed)	0.011
	N	189
HMPDM_13_std	Pearson Correlation	-0.039
	Sig. (2-tailed)	0.596
	N	189
HMPDM_14_std	Pearson Correlation	-0.005
	Sig. (2-tailed)	0.949
	N	189
HMPDM_15_std	Pearson Correlation	-0.003
	Sig. (2-tailed)	0.967
	N	189

HMPDM_16_std	Pearson Correlation	-0.005
	Sig. (2-tailed)	0.946
	N	189
HMPDM_17_std	Pearson Correlation	0.013
	Sig. (2-tailed)	0.86
	N	189
HMPDM_18_std	Pearson Correlation	0.014
	Sig. (2-tailed)	0.848
	N	189
HMPDM_19_std	Pearson Correlation	-0.003
	Sig. (2-tailed)	0.968
	N	189
HMPDM_2_std	Pearson Correlation	.b
	Sig. (2-tailed)	.
	N	189
HMPDM_20_std	Pearson Correlation	0.014
	Sig. (2-tailed)	0.852
	N	189
HMPDM_21_std	Pearson Correlation	0.003
	Sig. (2-tailed)	0.963
	N	189
HMPDM_22_std	Pearson Correlation	0.041
	Sig. (2-tailed)	0.577
	N	189
HMPDM_23_std	Pearson Correlation	-0.074
	Sig. (2-tailed)	0.312
	N	189
HMPDM_24_std	Pearson Correlation	-0.034
	Sig. (2-tailed)	0.645
	N	189
HMPDM_3_std	Pearson Correlation	.b
	Sig. (2-tailed)	.
	N	189
HMPDM_4_std	Pearson Correlation	-0.101
	Sig. (2-tailed)	0.165
	N	189
HMPDM_5_std	Pearson Correlation	-0.094
	Sig. (2-tailed)	0.2
	N	189
HMPDM_6_std	Pearson Correlation	-0.087
	Sig. (2-tailed)	0.236
	N	189
HMPDM_7_std	Pearson Correlation	-0.089
	Sig. (2-tailed)	0.224

	N	189
HMPDM_8_std	Pearson Correlation	-0.074
	Sig. (2-tailed)	0.311
	N	189
HMPDM_9_std	Pearson Correlation	-0.056
	Sig. (2-tailed)	0.441
	N	189
MCEP_0_std	Pearson Correlation	0.027
	Sig. (2-tailed)	0.713
	N	189
MCEP_1_std	Pearson Correlation	-0.001
	Sig. (2-tailed)	0.989
	N	189
MCEP_10_std	Pearson Correlation	0.088
	Sig. (2-tailed)	0.227
	N	189
MCEP_11_std	Pearson Correlation	-0.081
	Sig. (2-tailed)	0.269
	N	189
MCEP_12_std	Pearson Correlation	-0.119
	Sig. (2-tailed)	0.103
	N	189
MCEP_13_std	Pearson Correlation	-0.092
	Sig. (2-tailed)	0.206
	N	189
MCEP_14_std	Pearson Correlation	-0.051
	Sig. (2-tailed)	0.484
	N	189
MCEP_15_std	Pearson Correlation	-0.128
	Sig. (2-tailed)	0.078
	N	189
MCEP_16_std	Pearson Correlation	-0.01
	Sig. (2-tailed)	0.896
	N	189
MCEP_17_std	Pearson Correlation	-0.025
	Sig. (2-tailed)	0.737
	N	189
MCEP_18_std	Pearson Correlation	-0.059
	Sig. (2-tailed)	0.423
	N	189
MCEP_19_std	Pearson Correlation	-0.046
	Sig. (2-tailed)	0.532
	N	189
MCEP_2_std	Pearson Correlation	-0.011

	Sig. (2-tailed)	0.881
	N	189
MCEP_20_std	Pearson Correlation	-0.09
	Sig. (2-tailed)	0.218
	N	189
MCEP_21_std	Pearson Correlation	-0.112
	Sig. (2-tailed)	0.125
	N	189
MCEP_22_std	Pearson Correlation	-0.123
	Sig. (2-tailed)	0.092
	N	189
MCEP_23_std	Pearson Correlation	-0.137
	Sig. (2-tailed)	0.06
	N	189
MCEP_24_std	Pearson Correlation	-0.092
	Sig. (2-tailed)	0.21
	N	189
MCEP_3_std	Pearson Correlation	0.022
	Sig. (2-tailed)	0.763
	N	189
MCEP_4_std	Pearson Correlation	0.052
	Sig. (2-tailed)	0.479
	N	189
MCEP_5_std	Pearson Correlation	-0.014
	Sig. (2-tailed)	0.853
	N	189
MCEP_6_std	Pearson Correlation	-0.033
	Sig. (2-tailed)	0.651
	N	189
MCEP_7_std	Pearson Correlation	0.032
	Sig. (2-tailed)	0.665
	N	189
MCEP_8_std	Pearson Correlation	0.01
	Sig. (2-tailed)	0.889
	N	189
MCEP_9_std	Pearson Correlation	-0.113
	Sig. (2-tailed)	0.122
	N	189
Rd_conf_std	Pearson Correlation	.a
	Sig. (2-tailed)	.
	N	189
HMPDD_0_min	Pearson Correlation	0.116
	Sig. (2-tailed)	0.113
	N	189

HMPDD_1_min	Pearson Correlation	-0.058
	Sig. (2-tailed)	0.428
	N	189
HMPDD_10_min	Pearson Correlation	0.01
	Sig. (2-tailed)	0.887
	N	189
HMPDD_11_min	Pearson Correlation	0.095
	Sig. (2-tailed)	0.194
	N	189
HMPDD_12_min	Pearson Correlation	-0.025
	Sig. (2-tailed)	0.729
	N	189
HMPDD_2_min	Pearson Correlation	-0.124
	Sig. (2-tailed)	0.089
	N	189
HMPDD_3_min	Pearson Correlation	-0.14
	Sig. (2-tailed)	0.055
	N	189
HMPDD_4_min	Pearson Correlation	-0.083
	Sig. (2-tailed)	0.255
	N	189
HMPDD_5_min	Pearson Correlation	-0.074
	Sig. (2-tailed)	0.311
	N	189
HMPDD_6_min	Pearson Correlation	-0.036
	Sig. (2-tailed)	0.621
	N	189
HMPDD_7_min	Pearson Correlation	-0.07
	Sig. (2-tailed)	0.339
	N	189
HMPDD_8_min	Pearson Correlation	0.031
	Sig. (2-tailed)	0.674
	N	189
HMPDD_9_min	Pearson Correlation	0.036
	Sig. (2-tailed)	0.626
	N	189
HMPDM_0_min	Pearson Correlation	.a
	Sig. (2-tailed)	.
	N	189
HMPDM_1_min	Pearson Correlation	.a
	Sig. (2-tailed)	.
	N	189
HMPDM_10_min	Pearson Correlation	0.07
	Sig. (2-tailed)	0.34

	N	189
HMPDM_11_min	Pearson Correlation	0.029
	Sig. (2-tailed)	0.688
	N	189
HMPDM_12_min	Pearson Correlation	0.039
	Sig. (2-tailed)	0.592
	N	189
HMPDM_13_min	Pearson Correlation	0.079
	Sig. (2-tailed)	0.277
	N	189
HMPDM_14_min	Pearson Correlation	-0.035
	Sig. (2-tailed)	0.632
	N	189
HMPDM_15_min	Pearson Correlation	-0.055
	Sig. (2-tailed)	0.453
	N	189
HMPDM_16_min	Pearson Correlation	0.012
	Sig. (2-tailed)	0.867
	N	189
HMPDM_17_min	Pearson Correlation	-0.019
	Sig. (2-tailed)	0.791
	N	189
HMPDM_18_min	Pearson Correlation	-0.044
	Sig. (2-tailed)	0.551
	N	189
HMPDM_19_min	Pearson Correlation	0.035
	Sig. (2-tailed)	0.628
	N	189
HMPDM_2_min	Pearson Correlation	.a
	Sig. (2-tailed)	.
	N	189
HMPDM_20_min	Pearson Correlation	0.073
	Sig. (2-tailed)	0.319
	N	189
HMPDM_21_min	Pearson Correlation	-0.057
	Sig. (2-tailed)	0.436
	N	189
HMPDM_22_min	Pearson Correlation	0.054
	Sig. (2-tailed)	0.461
	N	189
HMPDM_23_min	Pearson Correlation	-0.066
	Sig. (2-tailed)	0.364
	N	189
HMPDM_24_min	Pearson Correlation	0.011

	Sig. (2-tailed)	0.88
	N	189
HMPDM_3_min	Pearson Correlation	.a
	Sig. (2-tailed)	.
	N	189
HMPDM_4_min	Pearson Correlation	0.126
	Sig. (2-tailed)	0.083
	N	189
HMPDM_5_min	Pearson Correlation	0.105
	Sig. (2-tailed)	0.151
	N	189
HMPDM_6_min	Pearson Correlation	0.084
	Sig. (2-tailed)	0.249
	N	189
HMPDM_7_min	Pearson Correlation	0.095
	Sig. (2-tailed)	0.193
	N	189
HMPDM_8_min	Pearson Correlation	0.098
	Sig. (2-tailed)	0.181
	N	189
HMPDM_9_min	Pearson Correlation	0.026
	Sig. (2-tailed)	0.723
	N	189
MCEP_0_min	Pearson Correlation	-0.047
	Sig. (2-tailed)	0.521
	N	189
MCEP_1_min	Pearson Correlation	-0.053
	Sig. (2-tailed)	0.472
	N	189
MCEP_10_min	Pearson Correlation	-0.045
	Sig. (2-tailed)	0.538
	N	189
MCEP_11_min	Pearson Correlation	-0.079
	Sig. (2-tailed)	0.281
	N	189
MCEP_12_min	Pearson Correlation	0.082
	Sig. (2-tailed)	0.259
	N	189
MCEP_13_min	Pearson Correlation	-0.063
	Sig. (2-tailed)	0.386
	N	189
MCEP_14_min	Pearson Correlation	0.005
	Sig. (2-tailed)	0.945
	N	189

MCEP_15_min	Pearson Correlation	0.058
	Sig. (2-tailed)	0.43
	N	189
MCEP_16_min	Pearson Correlation	-0.027
	Sig. (2-tailed)	0.716
	N	189
MCEP_17_min	Pearson Correlation	0.032
	Sig. (2-tailed)	0.663
	N	189
MCEP_18_min	Pearson Correlation	-0.061
	Sig. (2-tailed)	0.408
	N	189
MCEP_19_min	Pearson Correlation	-0.069
	Sig. (2-tailed)	0.344
	N	189
MCEP_2_min	Pearson Correlation	-0.061
	Sig. (2-tailed)	0.407
	N	189
MCEP_20_min	Pearson Correlation	-0.103
	Sig. (2-tailed)	0.159
	N	189
MCEP_21_min	Pearson Correlation	0.115
	Sig. (2-tailed)	0.114
	N	189
MCEP_22_min	Pearson Correlation	0.058
	Sig. (2-tailed)	0.43
	N	189
MCEP_23_min	Pearson Correlation	0.115
	Sig. (2-tailed)	0.114
	N	189
MCEP_24_min	Pearson Correlation	-0.06
	Sig. (2-tailed)	0.415
	N	189
MCEP_3_min	Pearson Correlation	-0.021
	Sig. (2-tailed)	0.769
	N	189
MCEP_4_min	Pearson Correlation	-0.03
	Sig. (2-tailed)	0.677
	N	189
MCEP_5_min	Pearson Correlation	0.045
	Sig. (2-tailed)	0.538
	N	189
MCEP_6_min	Pearson Correlation	-.173*
	Sig. (2-tailed)	0.017

	N	189
MCEP_7_min	Pearson Correlation	0.033
	Sig. (2-tailed)	0.649
	N	189
MCEP_8_min	Pearson Correlation	-0.052
	Sig. (2-tailed)	0.475
	N	189
MCEP_9_min	Pearson Correlation	-0.092
	Sig. (2-tailed)	0.207
	N	189
Rd_conf_min	Pearson Correlation	.a
	Sig. (2-tailed)	.
	N	189
HMPDD_0_max	Pearson Correlation	-0.137
	Sig. (2-tailed)	0.06
	N	189
HMPDD_1_max	Pearson Correlation	-0.084
	Sig. (2-tailed)	0.248
	N	189
HMPDD_10_max	Pearson Correlation	0.127
	Sig. (2-tailed)	0.082
	N	189
HMPDD_11_max	Pearson Correlation	0.061
	Sig. (2-tailed)	0.407
	N	189
HMPDD_12_max	Pearson Correlation	0.075
	Sig. (2-tailed)	0.306
	N	189
HMPDD_2_max	Pearson Correlation	-0.08
	Sig. (2-tailed)	0.272
	N	189
HMPDD_3_max	Pearson Correlation	-0.008
	Sig. (2-tailed)	0.909
	N	189
HMPDD_4_max	Pearson Correlation	-0.063
	Sig. (2-tailed)	0.392
	N	189
HMPDD_5_max	Pearson Correlation	-0.052
	Sig. (2-tailed)	0.481
	N	189
HMPDD_6_max	Pearson Correlation	-0.012
	Sig. (2-tailed)	0.868
	N	189
HMPDD_7_max	Pearson Correlation	0.028

	Sig. (2-tailed)	0.698
	N	189
HMPDD_8_max	Pearson Correlation	0.069
	Sig. (2-tailed)	0.348
	N	189
HMPDD_9_max	Pearson Correlation	0.117
	Sig. (2-tailed)	0.11
	N	189
HMPDM_0_max	Pearson Correlation	.a
	Sig. (2-tailed)	.
	N	189
HMPDM_1_max	Pearson Correlation	.a
	Sig. (2-tailed)	.
	N	189
HMPDM_10_max	Pearson Correlation	-0.062
	Sig. (2-tailed)	0.399
	N	189
HMPDM_11_max	Pearson Correlation	-0.025
	Sig. (2-tailed)	0.729
	N	189
HMPDM_12_max	Pearson Correlation	0.047
	Sig. (2-tailed)	0.522
	N	189
HMPDM_13_max	Pearson Correlation	0.018
	Sig. (2-tailed)	0.808
	N	189
HMPDM_14_max	Pearson Correlation	0.029
	Sig. (2-tailed)	0.697
	N	189
HMPDM_15_max	Pearson Correlation	0.005
	Sig. (2-tailed)	0.943
	N	189
HMPDM_16_max	Pearson Correlation	0.045
	Sig. (2-tailed)	0.54
	N	189
HMPDM_17_max	Pearson Correlation	-0.066
	Sig. (2-tailed)	0.369
	N	189
HMPDM_18_max	Pearson Correlation	0.086
	Sig. (2-tailed)	0.242
	N	189
HMPDM_19_max	Pearson Correlation	-0.007
	Sig. (2-tailed)	0.925
	N	189

HMPDM_2_max	Pearson Correlation	.a
	Sig. (2-tailed)	.
	N	189
HMPDM_20_max	Pearson Correlation	-0.033
	Sig. (2-tailed)	0.655
	N	189
HMPDM_21_max	Pearson Correlation	0.07
	Sig. (2-tailed)	0.339
	N	189
HMPDM_22_max	Pearson Correlation	0.057
	Sig. (2-tailed)	0.436
	N	189
HMPDM_23_max	Pearson Correlation	0.009
	Sig. (2-tailed)	0.902
	N	189
HMPDM_24_max	Pearson Correlation	-0.121
	Sig. (2-tailed)	0.097
	N	189
HMPDM_3_max	Pearson Correlation	.a
	Sig. (2-tailed)	.
	N	189
HMPDM_4_max	Pearson Correlation	-0.093
	Sig. (2-tailed)	0.205
	N	189
HMPDM_5_max	Pearson Correlation	-0.092
	Sig. (2-tailed)	0.206
	N	189
HMPDM_6_max	Pearson Correlation	-0.06
	Sig. (2-tailed)	0.41
	N	189
HMPDM_7_max	Pearson Correlation	-0.073
	Sig. (2-tailed)	0.318
	N	189
HMPDM_8_max	Pearson Correlation	-0.028
	Sig. (2-tailed)	0.699
	N	189
HMPDM_9_max	Pearson Correlation	-0.025
	Sig. (2-tailed)	0.728
	N	189
MCEP_0_max	Pearson Correlation	0.026
	Sig. (2-tailed)	0.723
	N	189
MCEP_1_max	Pearson Correlation	0.024
	Sig. (2-tailed)	0.745

	N	189
MCEP_10_max	Pearson Correlation	0.125
	Sig. (2-tailed)	0.087
	N	189
MCEP_11_max	Pearson Correlation	-0.122
	Sig. (2-tailed)	0.093
	N	189
MCEP_12_max	Pearson Correlation	0.028
	Sig. (2-tailed)	0.699
	N	189
MCEP_13_max	Pearson Correlation	0.076
	Sig. (2-tailed)	0.298
	N	189
MCEP_14_max	Pearson Correlation	-0.025
	Sig. (2-tailed)	0.728
	N	189
MCEP_15_max	Pearson Correlation	-0.064
	Sig. (2-tailed)	0.382
	N	189
MCEP_16_max	Pearson Correlation	-0.122
	Sig. (2-tailed)	0.095
	N	189
MCEP_17_max	Pearson Correlation	0.056
	Sig. (2-tailed)	0.443
	N	189
MCEP_18_max	Pearson Correlation	-0.07
	Sig. (2-tailed)	0.337
	N	189
MCEP_19_max	Pearson Correlation	-0.021
	Sig. (2-tailed)	0.774
	N	189
MCEP_2_max	Pearson Correlation	0.057
	Sig. (2-tailed)	0.434
	N	189
MCEP_20_max	Pearson Correlation	-0.067
	Sig. (2-tailed)	0.358
	N	189
MCEP_21_max	Pearson Correlation	-0.032
	Sig. (2-tailed)	0.666
	N	189
MCEP_22_max	Pearson Correlation	-0.045
	Sig. (2-tailed)	0.538
	N	189
MCEP_23_max	Pearson Correlation	-0.101

	Sig. (2-tailed)	0.167
	N	189
MCEP_24_max	Pearson Correlation	0.062
	Sig. (2-tailed)	0.395
	N	189
MCEP_3_max	Pearson Correlation	0.098
	Sig. (2-tailed)	0.178
	N	189
MCEP_4_max	Pearson Correlation	0.008
	Sig. (2-tailed)	0.91
	N	189
MCEP_5_max	Pearson Correlation	0.103
	Sig. (2-tailed)	0.159
	N	189
MCEP_6_max	Pearson Correlation	-.163*
	Sig. (2-tailed)	0.025
	N	189
MCEP_7_max	Pearson Correlation	0.088
	Sig. (2-tailed)	0.228
	N	189
MCEP_8_max	Pearson Correlation	0.086
	Sig. (2-tailed)	0.237
	N	189
MCEP_9_max	Pearson Correlation	0.016
	Sig. (2-tailed)	0.831
	N	189
Rd_conf_max	Pearson Correlation	.a
	Sig. (2-tailed)	.
	N	189
HMPDD_0_range	Pearson Correlation	-0.12
	Sig. (2-tailed)	0.099
	N	189
HMPDD_1_range	Pearson Correlation	-0.021
	Sig. (2-tailed)	0.777
	N	189
HMPDD_10_range	Pearson Correlation	0.121
	Sig. (2-tailed)	0.098
	N	189
HMPDD_11_range	Pearson Correlation	0.025
	Sig. (2-tailed)	0.735
	N	189
HMPDD_12_range	Pearson Correlation	0.094
	Sig. (2-tailed)	0.199
	N	189

HMPDD_2_range	Pearson Correlation	0.061
	Sig. (2-tailed)	0.405
	N	189
HMPDD_3_range	Pearson Correlation	0.083
	Sig. (2-tailed)	0.256
	N	189
HMPDD_4_range	Pearson Correlation	-0.01
	Sig. (2-tailed)	0.895
	N	189
HMPDD_5_range	Pearson Correlation	-0.018
	Sig. (2-tailed)	0.811
	N	189
HMPDD_6_range	Pearson Correlation	0.004
	Sig. (2-tailed)	0.955
	N	189
HMPDD_7_range	Pearson Correlation	0.05
	Sig. (2-tailed)	0.498
	N	189
HMPDD_8_range	Pearson Correlation	0.051
	Sig. (2-tailed)	0.486
	N	189
HMPDD_9_range	Pearson Correlation	0.105
	Sig. (2-tailed)	0.151
	N	189
HMPDM_0_range	Pearson Correlation	.a
	Sig. (2-tailed)	.
	N	189
HMPDM_1_range	Pearson Correlation	.a
	Sig. (2-tailed)	.
	N	189
HMPDM_10_range	Pearson Correlation	-0.068
	Sig. (2-tailed)	0.35
	N	189
HMPDM_11_range	Pearson Correlation	-0.028
	Sig. (2-tailed)	0.701
	N	189
HMPDM_12_range	Pearson Correlation	0.035
	Sig. (2-tailed)	0.629
	N	189
HMPDM_13_range	Pearson Correlation	-0.004
	Sig. (2-tailed)	0.958
	N	189
HMPDM_14_range	Pearson Correlation	0.036
	Sig. (2-tailed)	0.627

	N	189
HMPDM_15_range	Pearson Correlation	0.038
	Sig. (2-tailed)	0.603
	N	189
HMPDM_16_range	Pearson Correlation	0.033
	Sig. (2-tailed)	0.653
	N	189
HMPDM_17_range	Pearson Correlation	-0.027
	Sig. (2-tailed)	0.709
	N	189
HMPDM_18_range	Pearson Correlation	0.071
	Sig. (2-tailed)	0.329
	N	189
HMPDM_19_range	Pearson Correlation	-0.022
	Sig. (2-tailed)	0.767
	N	189
HMPDM_2_range	Pearson Correlation	.a
	Sig. (2-tailed)	.
	N	189
HMPDM_20_range	Pearson Correlation	-0.055
	Sig. (2-tailed)	0.456
	N	189
HMPDM_21_range	Pearson Correlation	0.073
	Sig. (2-tailed)	0.321
	N	189
HMPDM_22_range	Pearson Correlation	-0.014
	Sig. (2-tailed)	0.853
	N	189
HMPDM_23_range	Pearson Correlation	0.04
	Sig. (2-tailed)	0.581
	N	189
HMPDM_24_range	Pearson Correlation	-0.078
	Sig. (2-tailed)	0.287
	N	189
HMPDM_3_range	Pearson Correlation	.a
	Sig. (2-tailed)	.
	N	189
HMPDM_4_range	Pearson Correlation	-0.117
	Sig. (2-tailed)	0.108
	N	189
HMPDM_5_range	Pearson Correlation	-0.109
	Sig. (2-tailed)	0.136
	N	189
HMPDM_6_range	Pearson Correlation	-0.078

	Sig. (2-tailed)	0.288
	N	189
HMPDM_7_range	Pearson Correlation	-0.091
	Sig. (2-tailed)	0.211
	N	189
HMPDM_8_range	Pearson Correlation	-0.068
	Sig. (2-tailed)	0.349
	N	189
HMPDM_9_range	Pearson Correlation	-0.027
	Sig. (2-tailed)	0.712
	N	189
MCEP_0_range	Pearson Correlation	0.035
	Sig. (2-tailed)	0.632
	N	189
MCEP_1_range	Pearson Correlation	0.057
	Sig. (2-tailed)	0.438
	N	189
MCEP_10_range	Pearson Correlation	0.124
	Sig. (2-tailed)	0.09
	N	189
MCEP_11_range	Pearson Correlation	-0.031
	Sig. (2-tailed)	0.675
	N	189
MCEP_12_range	Pearson Correlation	-0.05
	Sig. (2-tailed)	0.496
	N	189
MCEP_13_range	Pearson Correlation	0.102
	Sig. (2-tailed)	0.16
	N	189
MCEP_14_range	Pearson Correlation	-0.021
	Sig. (2-tailed)	0.773
	N	189
MCEP_15_range	Pearson Correlation	-0.079
	Sig. (2-tailed)	0.278
	N	189
MCEP_16_range	Pearson Correlation	-0.065
	Sig. (2-tailed)	0.377
	N	189
MCEP_17_range	Pearson Correlation	0.016
	Sig. (2-tailed)	0.83
	N	189
MCEP_18_range	Pearson Correlation	-0.008
	Sig. (2-tailed)	0.918
	N	189

MCEP_19_range	Pearson Correlation	0.037
	Sig. (2-tailed)	0.61
	N	189
MCEP_2_range	Pearson Correlation	0.075
	Sig. (2-tailed)	0.305
	N	189
MCEP_20_range	Pearson Correlation	0.008
	Sig. (2-tailed)	0.912
	N	189
MCEP_21_range	Pearson Correlation	-0.095
	Sig. (2-tailed)	0.192
	N	189
MCEP_22_range	Pearson Correlation	-0.066
	Sig. (2-tailed)	0.366
	N	189
MCEP_23_range	Pearson Correlation	-0.136
	Sig. (2-tailed)	0.061
	N	189
MCEP_24_range	Pearson Correlation	0.076
	Sig. (2-tailed)	0.299
	N	189
MCEP_3_range	Pearson Correlation	0.082
	Sig. (2-tailed)	0.264
	N	189
MCEP_4_range	Pearson Correlation	0.028
	Sig. (2-tailed)	0.698
	N	189
MCEP_5_range	Pearson Correlation	0.036
	Sig. (2-tailed)	0.623
	N	189
MCEP_6_range	Pearson Correlation	-0.006
	Sig. (2-tailed)	0.936
	N	189
MCEP_7_range	Pearson Correlation	0.036
	Sig. (2-tailed)	0.62
	N	189
MCEP_8_range	Pearson Correlation	0.102
	Sig. (2-tailed)	0.162
	N	189
MCEP_9_range	Pearson Correlation	0.076
	Sig. (2-tailed)	0.3
	N	189
Rd_conf_range	Pearson Correlation	.a
	Sig. (2-tailed)	.

	N	189

L. Audio features & depression correlations based on gender (Female – Male)

Correlations	Coefficient	FEMALE	MALE
F0_mean	Pearson Correlation	0.074	-0.002
	Sig. (2-tailed)	0.496	0.98
	N	87	102
NAQ_mean	Pearson Correlation	-0.054	0.034
	Sig. (2-tailed)	0.619	0.736
	N	87	102
QOQ_mean	Pearson Correlation	-0.097	0.094
	Sig. (2-tailed)	0.373	0.35
	N	87	102
H1_mean	Pearson Correlation	0.142	0.089
	Sig. (2-tailed)	0.189	0.373
	N	87	102
H2_mean	Pearson Correlation	0.114	-0.004
	Sig. (2-tailed)	0.292	0.967
	N	87	102
PSP_mean	Pearson Correlation	0.121	0.021
	Sig. (2-tailed)	0.264	0.83
	N	87	102
MDQ_mean	Pearson Correlation	0.065	-0.082
	Sig. (2-tailed)	0.552	0.415
	N	87	102
peakSlope_mean	Pearson Correlation	0.032	0.017
	Sig. (2-tailed)	0.767	0.868
	N	87	102
Rd_mean	Pearson Correlation	-0.043	-0.012
	Sig. (2-tailed)	0.693	0.906
	N	87	102
F0_std	Pearson Correlation	-0.018	0.032
	Sig. (2-tailed)	0.865	0.75
	N	87	102
NAQ_std	Pearson Correlation	.240*	0.063
	Sig. (2-tailed)	0.025	0.532
	N	87	102
QOQ_std	Pearson Correlation	.241*	0.146
	Sig. (2-tailed)	0.024	0.142
	N	87	102
H1_std	Pearson Correlation	0.054	0.068
	Sig. (2-tailed)	0.622	0.495

	N	87	102
H2_std	Pearson Correlation	0.197	-0.051
	Sig. (2-tailed)	0.067	0.612
	N	87	102
PSP_std	Pearson Correlation	0.176	-0.038
	Sig. (2-tailed)	0.103	0.708
	N	87	102
MDQ_std	Pearson Correlation	0.058	-0.059
	Sig. (2-tailed)	0.595	0.554
	N	87	102
peakSlope_std	Pearson Correlation	0.114	0.12
	Sig. (2-tailed)	0.292	0.229
	N	87	102
Rd_std	Pearson Correlation	0.161	0.045
	Sig. (2-tailed)	0.137	0.655
	N	87	102
F0_min	Pearson Correlation	0.107	0.11
	Sig. (2-tailed)	0.323	0.273
	N	87	102
NAQ_min	Pearson Correlation	.b	.b
	Sig. (2-tailed)	.	.
	N	87	102
QOQ_min	Pearson Correlation	.b	.b
	Sig. (2-tailed)	.	.
	N	87	102
H1_min	Pearson Correlation	0.109	-0.014
	Sig. (2-tailed)	0.315	0.887
	N	87	102
H2_min	Pearson Correlation	.b	.b
	Sig. (2-tailed)	.	.
	N	87	102
PSP_min	Pearson Correlation	0.166	-0.014
	Sig. (2-tailed)	0.124	0.891
	N	87	102
MDQ_min	Pearson Correlation	-0.064	-0.061
	Sig. (2-tailed)	0.557	0.539
	N	87	102
peakSlope_min	Pearson Correlation	0.077	0.01
	Sig. (2-tailed)	0.48	0.923
	N	87	102
Rd_min	Pearson Correlation	-0.079	0.005
	Sig. (2-tailed)	0.468	0.957
	N	87	102
F0_max	Pearson Correlation	0.082	0.165

	Sig. (2-tailed)	0.45	0.097
	N	87	102
NAQ_max	Pearson Correlation	-0.189	0.024
	Sig. (2-tailed)	0.079	0.812
	N	87	102
QOQ_max	Pearson Correlation	0.178	-0.007
	Sig. (2-tailed)	0.099	0.941
	N	87	102
H1_max	Pearson Correlation	0.162	0.023
	Sig. (2-tailed)	0.135	0.822
	N	87	102
H2_max	Pearson Correlation	0.023	-0.025
	Sig. (2-tailed)	0.831	0.807
	N	87	102
PSP_max	Pearson Correlation	-0.187	-0.051
	Sig. (2-tailed)	0.083	0.613
	N	87	102
MDQ_max	Pearson Correlation	0.043	-0.154
	Sig. (2-tailed)	0.693	0.121
	N	87	102
peakSlope_max	Pearson Correlation	0.108	0.108
	Sig. (2-tailed)	0.319	0.28
	N	87	102
Rd_max	Pearson Correlation	-0.026	0.003
	Sig. (2-tailed)	0.809	0.98
	N	87	102
F0_range	Pearson Correlation	0.071	0.163
	Sig. (2-tailed)	0.511	0.102
	N	87	102
NAQ_range	Pearson Correlation	-0.189	0.024
	Sig. (2-tailed)	0.079	0.812
	N	87	102
QOQ_range	Pearson Correlation	0.178	-0.007
	Sig. (2-tailed)	0.099	0.941
	N	87	102
H1_range	Pearson Correlation	0.045	0.026
	Sig. (2-tailed)	0.679	0.798
	N	87	102
H2_range	Pearson Correlation	0.023	-0.025
	Sig. (2-tailed)	0.831	0.807
	N	87	102
PSP_range	Pearson Correlation	-0.189	-0.05
	Sig. (2-tailed)	0.08	0.614
	N	87	102

MDQ_range	Pearson Correlation	0.061	-0.136
	Sig. (2-tailed)	0.575	0.172
	N	87	102
peakSlope_range	Pearson Correlation	-0.041	-0.002
	Sig. (2-tailed)	0.703	0.982
	N	87	102
Rd_range	Pearson Correlation	0.051	-0.004
	Sig. (2-tailed)	0.639	0.968
	N	87	102
HMPDD_0_mean	Pearson Correlation	-.221*	-.289**
	Sig. (2-tailed)	0.04	0.003
	N	87	102
HMPDD_1_mean	Pearson Correlation	0	-0.188
	Sig. (2-tailed)	0.999	0.059
	N	87	102
HMPDD_10_mean	Pearson Correlation	-.219*	0.068
	Sig. (2-tailed)	0.041	0.499
	N	87	102
HMPDD_11_mean	Pearson Correlation	-0.205	-0.01
	Sig. (2-tailed)	0.057	0.924
	N	87	102
HMPDD_12_mean	Pearson Correlation	-0.206	0.117
	Sig. (2-tailed)	0.056	0.242
	N	87	102
HMPDD_2_mean	Pearson Correlation	.363**	0.037
	Sig. (2-tailed)	0.001	0.714
	N	87	102
HMPDD_3_mean	Pearson Correlation	.370**	-0.137
	Sig. (2-tailed)	0	0.169
	N	87	102
HMPDD_4_mean	Pearson Correlation	.425**	-0.05
	Sig. (2-tailed)	0	0.619
	N	87	102
HMPDD_5_mean	Pearson Correlation	.467**	-0.08
	Sig. (2-tailed)	0	0.426
	N	87	102
HMPDD_6_mean	Pearson Correlation	.321**	-0.013
	Sig. (2-tailed)	0.002	0.893
	N	87	102
HMPDD_7_mean	Pearson Correlation	-0.034	0.083
	Sig. (2-tailed)	0.756	0.404
	N	87	102
HMPDD_8_mean	Pearson Correlation	-0.13	0.054
	Sig. (2-tailed)	0.23	0.587

	N	87	102
HMPDD_9_mean	Pearson Correlation	-0.192	0.135
	Sig. (2-tailed)	0.075	0.177
	N	87	102
HMPDM_0_mean	Pearson Correlation	.c	.c
	Sig. (2-tailed)	.	.
	N	87	102
HMPDM_1_mean	Pearson Correlation	.c	.c
	Sig. (2-tailed)	.	.
	N	87	102
HMPDM_10_mean	Pearson Correlation	-.296**	-.288**
	Sig. (2-tailed)	0.005	0.003
	N	87	102
HMPDM_11_mean	Pearson Correlation	-.215*	-0.157
	Sig. (2-tailed)	0.045	0.115
	N	87	102
HMPDM_12_mean	Pearson Correlation	-0.001	-0.006
	Sig. (2-tailed)	0.996	0.953
	N	87	102
HMPDM_13_mean	Pearson Correlation	0.099	0.063
	Sig. (2-tailed)	0.36	0.528
	N	87	102
HMPDM_14_mean	Pearson Correlation	.226*	0.127
	Sig. (2-tailed)	0.035	0.202
	N	87	102
HMPDM_15_mean	Pearson Correlation	.285**	0.116
	Sig. (2-tailed)	0.007	0.244
	N	87	102
HMPDM_16_mean	Pearson Correlation	.280**	0.163
	Sig. (2-tailed)	0.009	0.101
	N	87	102
HMPDM_17_mean	Pearson Correlation	.323**	0.163
	Sig. (2-tailed)	0.002	0.101
	N	87	102
HMPDM_18_mean	Pearson Correlation	.326**	0.162
	Sig. (2-tailed)	0.002	0.104
	N	87	102
HMPDM_19_mean	Pearson Correlation	.319**	0.157
	Sig. (2-tailed)	0.003	0.114
	N	87	102
HMPDM_2_mean	Pearson Correlation	.c	.c
	Sig. (2-tailed)	.	.
	N	87	102
HMPDM_20_mean	Pearson Correlation	.328**	0.135

	Sig. (2-tailed)	0.002	0.177
	N	87	102
HMPDM_21_mean	Pearson Correlation	.313**	0.128
	Sig. (2-tailed)	0.003	0.201
	N	87	102
HMPDM_22_mean	Pearson Correlation	.330**	.202*
	Sig. (2-tailed)	0.002	0.042
	N	87	102
HMPDM_23_mean	Pearson Correlation	.275**	0.056
	Sig. (2-tailed)	0.01	0.577
	N	87	102
HMPDM_24_mean	Pearson Correlation	.257*	-0.071
	Sig. (2-tailed)	0.016	0.479
	N	87	102
HMPDM_3_mean	Pearson Correlation	.c	.c
	Sig. (2-tailed)	.	.
	N	87	102
HMPDM_4_mean	Pearson Correlation	.c	0.052
	Sig. (2-tailed)	.	0.604
	N	87	102
HMPDM_5_mean	Pearson Correlation	0.079	0.07
	Sig. (2-tailed)	0.466	0.484
	N	87	102
HMPDM_6_mean	Pearson Correlation	0.042	0.046
	Sig. (2-tailed)	0.702	0.646
	N	87	102
HMPDM_7_mean	Pearson Correlation	-0.031	0.002
	Sig. (2-tailed)	0.774	0.988
	N	87	102
HMPDM_8_mean	Pearson Correlation	-0.191	-0.046
	Sig. (2-tailed)	0.077	0.647
	N	87	102
HMPDM_9_mean	Pearson Correlation	-.313**	-0.12
	Sig. (2-tailed)	0.003	0.228
	N	87	102
MCEP_0_mean	Pearson Correlation	-.297**	-.229*
	Sig. (2-tailed)	0.005	0.02
	N	87	102
MCEP_1_mean	Pearson Correlation	0.009	0.009
	Sig. (2-tailed)	0.934	0.931
	N	87	102
MCEP_10_mean	Pearson Correlation	0.008	0.001
	Sig. (2-tailed)	0.94	0.992
	N	87	102

MCEP_11_mean	Pearson Correlation	0.064	.204*
	Sig. (2-tailed)	0.554	0.04
	N	87	102
MCEP_12_mean	Pearson Correlation	-0.109	-0.179
	Sig. (2-tailed)	0.317	0.072
	N	87	102
MCEP_13_mean	Pearson Correlation	0.092	0.056
	Sig. (2-tailed)	0.398	0.573
	N	87	102
MCEP_14_mean	Pearson Correlation	-0.094	0.094
	Sig. (2-tailed)	0.388	0.348
	N	87	102
MCEP_15_mean	Pearson Correlation	0.004	-0.129
	Sig. (2-tailed)	0.973	0.198
	N	87	102
MCEP_16_mean	Pearson Correlation	0.064	0.126
	Sig. (2-tailed)	0.554	0.207
	N	87	102
MCEP_17_mean	Pearson Correlation	0.036	-0.034
	Sig. (2-tailed)	0.742	0.737
	N	87	102
MCEP_18_mean	Pearson Correlation	-0.067	0.087
	Sig. (2-tailed)	0.539	0.385
	N	87	102
MCEP_19_mean	Pearson Correlation	0.17	-0.047
	Sig. (2-tailed)	0.115	0.641
	N	87	102
MCEP_2_mean	Pearson Correlation	0.178	-0.073
	Sig. (2-tailed)	0.1	0.464
	N	87	102
MCEP_20_mean	Pearson Correlation	-0.097	-0.047
	Sig. (2-tailed)	0.37	0.641
	N	87	102
MCEP_21_mean	Pearson Correlation	-0.012	0.054
	Sig. (2-tailed)	0.91	0.593
	N	87	102
MCEP_22_mean	Pearson Correlation	-0.082	0.005
	Sig. (2-tailed)	0.453	0.959
	N	87	102
MCEP_23_mean	Pearson Correlation	.221*	-0.023
	Sig. (2-tailed)	0.04	0.818
	N	87	102
MCEP_24_mean	Pearson Correlation	-0.201	0.057
	Sig. (2-tailed)	0.061	0.566

	N	87	102
MCEP_3_mean	Pearson Correlation	-0.019	-0.097
	Sig. (2-tailed)	0.863	0.334
	N	87	102
MCEP_4_mean	Pearson Correlation	0.01	-0.193
	Sig. (2-tailed)	0.926	0.052
	N	87	102
MCEP_5_mean	Pearson Correlation	-0.18	0.04
	Sig. (2-tailed)	0.096	0.688
	N	87	102
MCEP_6_mean	Pearson Correlation	-0.132	-.215*
	Sig. (2-tailed)	0.223	0.03
	N	87	102
MCEP_7_mean	Pearson Correlation	0.06	-0.113
	Sig. (2-tailed)	0.579	0.26
	N	87	102
MCEP_8_mean	Pearson Correlation	-0.136	0.024
	Sig. (2-tailed)	0.209	0.814
	N	87	102
MCEP_9_mean	Pearson Correlation	0.119	-0.072
	Sig. (2-tailed)	0.27	0.474
	N	87	102
Rd_conf_mean	Pearson Correlation	.c	.c
	Sig. (2-tailed)	.	.
	N	87	102
HMPDD_0_std	Pearson Correlation	.309**	.208*
	Sig. (2-tailed)	0.004	0.036
	N	87	102
HMPDD_1_std	Pearson Correlation	.346**	-0.015
	Sig. (2-tailed)	0.001	0.882
	N	87	102
HMPDD_10_std	Pearson Correlation	-0.072	0.067
	Sig. (2-tailed)	0.507	0.506
	N	87	102
HMPDD_11_std	Pearson Correlation	-0.081	-0.044
	Sig. (2-tailed)	0.457	0.663
	N	87	102
HMPDD_12_std	Pearson Correlation	-0.042	0.076
	Sig. (2-tailed)	0.702	0.451
	N	87	102
HMPDD_2_std	Pearson Correlation	0.048	0.126
	Sig. (2-tailed)	0.659	0.208
	N	87	102
HMPDD_3_std	Pearson Correlation	0.136	-0.062

	Sig. (2-tailed)	0.211	0.533
	N	87	102
HMPDD_4_std	Pearson Correlation	0.152	0.046
	Sig. (2-tailed)	0.159	0.645
	N	87	102
HMPDD_5_std	Pearson Correlation	.302**	0.025
	Sig. (2-tailed)	0.005	0.804
	N	87	102
HMPDD_6_std	Pearson Correlation	.231*	0.141
	Sig. (2-tailed)	0.031	0.156
	N	87	102
HMPDD_7_std	Pearson Correlation	0.032	.197*
	Sig. (2-tailed)	0.771	0.047
	N	87	102
HMPDD_8_std	Pearson Correlation	-0.008	0.103
	Sig. (2-tailed)	0.944	0.303
	N	87	102
HMPDD_9_std	Pearson Correlation	-0.083	0.104
	Sig. (2-tailed)	0.446	0.299
	N	87	102
HMPDM_0_std	Pearson Correlation	.c	.c
	Sig. (2-tailed)	.	.
	N	87	102
HMPDM_1_std	Pearson Correlation	.c	.c
	Sig. (2-tailed)	.	.
	N	87	102
HMPDM_10_std	Pearson Correlation	.281**	-0.083
	Sig. (2-tailed)	0.008	0.404
	N	87	102
HMPDM_11_std	Pearson Correlation	.294**	0.178
	Sig. (2-tailed)	0.006	0.074
	N	87	102
HMPDM_12_std	Pearson Correlation	.407**	.198*
	Sig. (2-tailed)	0	0.046
	N	87	102
HMPDM_13_std	Pearson Correlation	.286**	0.193
	Sig. (2-tailed)	0.007	0.052
	N	87	102
HMPDM_14_std	Pearson Correlation	0.057	0.16
	Sig. (2-tailed)	0.598	0.108
	N	87	102
HMPDM_15_std	Pearson Correlation	-0.062	0.176
	Sig. (2-tailed)	0.57	0.076
	N	87	102

HMPDM_16_std	Pearson Correlation	-0.052	0.155
	Sig. (2-tailed)	0.629	0.12
	N	87	102
HMPDM_17_std	Pearson Correlation	-0.121	0.145
	Sig. (2-tailed)	0.266	0.145
	N	87	102
HMPDM_18_std	Pearson Correlation	-0.133	0.135
	Sig. (2-tailed)	0.219	0.178
	N	87	102
HMPDM_19_std	Pearson Correlation	-0.144	0.138
	Sig. (2-tailed)	0.182	0.168
	N	87	102
HMPDM_2_std	Pearson Correlation	.c	.c
	Sig. (2-tailed)	.	.
	N	87	102
HMPDM_20_std	Pearson Correlation	-0.13	0.138
	Sig. (2-tailed)	0.229	0.166
	N	87	102
HMPDM_21_std	Pearson Correlation	-0.075	0.153
	Sig. (2-tailed)	0.49	0.125
	N	87	102
HMPDM_22_std	Pearson Correlation	-0.096	0.117
	Sig. (2-tailed)	0.375	0.241
	N	87	102
HMPDM_23_std	Pearson Correlation	-0.051	.219*
	Sig. (2-tailed)	0.642	0.027
	N	87	102
HMPDM_24_std	Pearson Correlation	-0.035	.291**
	Sig. (2-tailed)	0.747	0.003
	N	87	102
HMPDM_3_std	Pearson Correlation	.c	.c
	Sig. (2-tailed)	.	.
	N	87	102
HMPDM_4_std	Pearson Correlation	.c	0.003
	Sig. (2-tailed)	.	0.974
	N	87	102
HMPDM_5_std	Pearson Correlation	0.152	-0.067
	Sig. (2-tailed)	0.16	0.505
	N	87	102
HMPDM_6_std	Pearson Correlation	.298**	-0.085
	Sig. (2-tailed)	0.005	0.396
	N	87	102
HMPDM_7_std	Pearson Correlation	.329**	-0.1
	Sig. (2-tailed)	0.002	0.316

	N	87	102
HMPDM_8_std	Pearson Correlation	.310**	-0.13
	Sig. (2-tailed)	0.003	0.194
	N	87	102
HMPDM_9_std	Pearson Correlation	.309**	-0.168
	Sig. (2-tailed)	0.004	0.091
	N	87	102
MCEP_0_std	Pearson Correlation	-0.046	-0.18
	Sig. (2-tailed)	0.675	0.07
	N	87	102
MCEP_1_std	Pearson Correlation	.335**	0.102
	Sig. (2-tailed)	0.002	0.306
	N	87	102
MCEP_10_std	Pearson Correlation	0.201	0.156
	Sig. (2-tailed)	0.063	0.118
	N	87	102
MCEP_11_std	Pearson Correlation	0.204	0.056
	Sig. (2-tailed)	0.059	0.574
	N	87	102
MCEP_12_std	Pearson Correlation	.277**	0.171
	Sig. (2-tailed)	0.009	0.086
	N	87	102
MCEP_13_std	Pearson Correlation	.242*	0.191
	Sig. (2-tailed)	0.024	0.055
	N	87	102
MCEP_14_std	Pearson Correlation	.311**	0.111
	Sig. (2-tailed)	0.003	0.265
	N	87	102
MCEP_15_std	Pearson Correlation	0.206	0.099
	Sig. (2-tailed)	0.055	0.324
	N	87	102
MCEP_16_std	Pearson Correlation	-0.076	0.17
	Sig. (2-tailed)	0.487	0.087
	N	87	102
MCEP_17_std	Pearson Correlation	-0.017	0.089
	Sig. (2-tailed)	0.872	0.375
	N	87	102
MCEP_18_std	Pearson Correlation	-0.043	0.03
	Sig. (2-tailed)	0.694	0.768
	N	87	102
MCEP_19_std	Pearson Correlation	-0.062	0.074
	Sig. (2-tailed)	0.568	0.459
	N	87	102
MCEP_2_std	Pearson Correlation	-0.063	-0.063

	Sig. (2-tailed)	0.562	0.531
	N	87	102
MCEP_20_std	Pearson Correlation	-0.091	0.01
	Sig. (2-tailed)	0.404	0.918
	N	87	102
MCEP_21_std	Pearson Correlation	-0.067	-0.046
	Sig. (2-tailed)	0.535	0.644
	N	87	102
MCEP_22_std	Pearson Correlation	-0.108	-0.033
	Sig. (2-tailed)	0.32	0.743
	N	87	102
MCEP_23_std	Pearson Correlation	-0.097	-0.073
	Sig. (2-tailed)	0.37	0.466
	N	87	102
MCEP_24_std	Pearson Correlation	-0.063	0.011
	Sig. (2-tailed)	0.56	0.911
	N	87	102
MCEP_3_std	Pearson Correlation	-0.099	0.095
	Sig. (2-tailed)	0.361	0.341
	N	87	102
MCEP_4_std	Pearson Correlation	0.138	-0.091
	Sig. (2-tailed)	0.202	0.362
	N	87	102
MCEP_5_std	Pearson Correlation	-0.121	0.02
	Sig. (2-tailed)	0.266	0.844
	N	87	102
MCEP_6_std	Pearson Correlation	-0.048	0.009
	Sig. (2-tailed)	0.656	0.929
	N	87	102
MCEP_7_std	Pearson Correlation	0.082	-0.007
	Sig. (2-tailed)	0.453	0.941
	N	87	102
MCEP_8_std	Pearson Correlation	0.002	0.014
	Sig. (2-tailed)	0.986	0.889
	N	87	102
MCEP_9_std	Pearson Correlation	0.045	-0.128
	Sig. (2-tailed)	0.682	0.201
	N	87	102
Rd_conf_std	Pearson Correlation	.a	.a
	Sig. (2-tailed)	.	.
	N	87	102
HMPDD_0_min	Pearson Correlation	0.165	0.089
	Sig. (2-tailed)	0.127	0.375
	N	87	102

HMPDD_1_min	Pearson Correlation	0.089	-0.003
	Sig. (2-tailed)	0.414	0.976
	N	87	102
HMPDD_10_min	Pearson Correlation	0.05	-0.064
	Sig. (2-tailed)	0.643	0.526
	N	87	102
HMPDD_11_min	Pearson Correlation	0.054	0.033
	Sig. (2-tailed)	0.621	0.74
	N	87	102
HMPDD_12_min	Pearson Correlation	-0.077	-0.105
	Sig. (2-tailed)	0.479	0.295
	N	87	102
HMPDD_2_min	Pearson Correlation	-0.034	-0.053
	Sig. (2-tailed)	0.753	0.598
	N	87	102
HMPDD_3_min	Pearson Correlation	-0.054	-0.091
	Sig. (2-tailed)	0.619	0.365
	N	87	102
HMPDD_4_min	Pearson Correlation	0.024	-0.044
	Sig. (2-tailed)	0.825	0.659
	N	87	102
HMPDD_5_min	Pearson Correlation	-0.061	0.067
	Sig. (2-tailed)	0.576	0.502
	N	87	102
HMPDD_6_min	Pearson Correlation	0.083	-0.016
	Sig. (2-tailed)	0.444	0.873
	N	87	102
HMPDD_7_min	Pearson Correlation	-0.02	0.011
	Sig. (2-tailed)	0.853	0.916
	N	87	102
HMPDD_8_min	Pearson Correlation	0.076	0.085
	Sig. (2-tailed)	0.485	0.397
	N	87	102
HMPDD_9_min	Pearson Correlation	0.03	0.032
	Sig. (2-tailed)	0.784	0.753
	N	87	102
HMPDM_0_min	Pearson Correlation	.a	.a
	Sig. (2-tailed)	.	.
	N	87	102
HMPDM_1_min	Pearson Correlation	.a	.a
	Sig. (2-tailed)	.	.
	N	87	102
HMPDM_10_min	Pearson Correlation	-0.007	0.106
	Sig. (2-tailed)	0.948	0.291

	N	87	102
HMPDM_11_min	Pearson Correlation	0.008	.241*
	Sig. (2-tailed)	0.941	0.015
	N	87	102
HMPDM_12_min	Pearson Correlation	0.107	0.063
	Sig. (2-tailed)	0.325	0.53
	N	87	102
HMPDM_13_min	Pearson Correlation	0.209	0.109
	Sig. (2-tailed)	0.052	0.274
	N	87	102
HMPDM_14_min	Pearson Correlation	0.045	-0.036
	Sig. (2-tailed)	0.677	0.72
	N	87	102
HMPDM_15_min	Pearson Correlation	-0.093	-0.049
	Sig. (2-tailed)	0.391	0.624
	N	87	102
HMPDM_16_min	Pearson Correlation	-0.178	0.168
	Sig. (2-tailed)	0.1	0.091
	N	87	102
HMPDM_17_min	Pearson Correlation	0.042	-0.025
	Sig. (2-tailed)	0.702	0.799
	N	87	102
HMPDM_18_min	Pearson Correlation	-0.04	-0.032
	Sig. (2-tailed)	0.714	0.749
	N	87	102
HMPDM_19_min	Pearson Correlation	-0.078	0.107
	Sig. (2-tailed)	0.471	0.282
	N	87	102
HMPDM_2_min	Pearson Correlation	.a	.a
	Sig. (2-tailed)	.	.
	N	87	102
HMPDM_20_min	Pearson Correlation	-0.066	0.153
	Sig. (2-tailed)	0.546	0.124
	N	87	102
HMPDM_21_min	Pearson Correlation	-0.104	-0.031
	Sig. (2-tailed)	0.339	0.758
	N	87	102
HMPDM_22_min	Pearson Correlation	0.004	0.102
	Sig. (2-tailed)	0.968	0.31
	N	87	102
HMPDM_23_min	Pearson Correlation	-0.149	0.01
	Sig. (2-tailed)	0.167	0.921
	N	87	102
HMPDM_24_min	Pearson Correlation	-0.022	0.019

	Sig. (2-tailed)	0.838	0.846
	N	87	102
HMPDM_3_min	Pearson Correlation	.a	.a
	Sig. (2-tailed)	.	.
	N	87	102
HMPDM_4_min	Pearson Correlation	.a	0.096
	Sig. (2-tailed)	.	0.337
	N	87	102
HMPDM_5_min	Pearson Correlation	0.022	0.043
	Sig. (2-tailed)	0.842	0.666
	N	87	102
HMPDM_6_min	Pearson Correlation	0.072	0.011
	Sig. (2-tailed)	0.506	0.914
	N	87	102
HMPDM_7_min	Pearson Correlation	0.027	0.033
	Sig. (2-tailed)	0.803	0.742
	N	87	102
HMPDM_8_min	Pearson Correlation	-0.039	0.053
	Sig. (2-tailed)	0.72	0.597
	N	87	102
HMPDM_9_min	Pearson Correlation	-0.165	0.053
	Sig. (2-tailed)	0.126	0.595
	N	87	102
MCEP_0_min	Pearson Correlation	-0.059	-0.107
	Sig. (2-tailed)	0.584	0.285
	N	87	102
MCEP_1_min	Pearson Correlation	-0.026	-0.059
	Sig. (2-tailed)	0.814	0.558
	N	87	102
MCEP_10_min	Pearson Correlation	-0.089	0.016
	Sig. (2-tailed)	0.412	0.87
	N	87	102
MCEP_11_min	Pearson Correlation	0.011	-0.126
	Sig. (2-tailed)	0.92	0.206
	N	87	102
MCEP_12_min	Pearson Correlation	0.07	0.013
	Sig. (2-tailed)	0.522	0.897
	N	87	102
MCEP_13_min	Pearson Correlation	-0.147	-0.087
	Sig. (2-tailed)	0.173	0.385
	N	87	102
MCEP_14_min	Pearson Correlation	-0.075	0.142
	Sig. (2-tailed)	0.489	0.155
	N	87	102

MCEP_15_min	Pearson Correlation	-0.061	0.07
	Sig. (2-tailed)	0.577	0.483
	N	87	102
MCEP_16_min	Pearson Correlation	0.084	-.215*
	Sig. (2-tailed)	0.437	0.03
	N	87	102
MCEP_17_min	Pearson Correlation	0.007	0.054
	Sig. (2-tailed)	0.947	0.59
	N	87	102
MCEP_18_min	Pearson Correlation	-0.008	-0.113
	Sig. (2-tailed)	0.943	0.259
	N	87	102
MCEP_19_min	Pearson Correlation	-0.051	-0.181
	Sig. (2-tailed)	0.637	0.069
	N	87	102
MCEP_2_min	Pearson Correlation	-0.031	-0.008
	Sig. (2-tailed)	0.779	0.938
	N	87	102
MCEP_20_min	Pearson Correlation	-0.026	-0.161
	Sig. (2-tailed)	0.808	0.106
	N	87	102
MCEP_21_min	Pearson Correlation	0.085	0.054
	Sig. (2-tailed)	0.436	0.593
	N	87	102
MCEP_22_min	Pearson Correlation	0.116	-0.04
	Sig. (2-tailed)	0.283	0.69
	N	87	102
MCEP_23_min	Pearson Correlation	0.058	0.105
	Sig. (2-tailed)	0.596	0.296
	N	87	102
MCEP_24_min	Pearson Correlation	-0.029	-0.171
	Sig. (2-tailed)	0.79	0.085
	N	87	102
MCEP_3_min	Pearson Correlation	0.154	-0.064
	Sig. (2-tailed)	0.153	0.525
	N	87	102
MCEP_4_min	Pearson Correlation	-0.076	0.055
	Sig. (2-tailed)	0.485	0.586
	N	87	102
MCEP_5_min	Pearson Correlation	0.182	-0.013
	Sig. (2-tailed)	0.091	0.897
	N	87	102
MCEP_6_min	Pearson Correlation	-.218*	-0.105
	Sig. (2-tailed)	0.043	0.295

	N	87	102
MCEP_7_min	Pearson Correlation	0.043	0.009
	Sig. (2-tailed)	0.695	0.926
	N	87	102
MCEP_8_min	Pearson Correlation	-0.152	-0.004
	Sig. (2-tailed)	0.159	0.967
	N	87	102
MCEP_9_min	Pearson Correlation	-0.075	-0.087
	Sig. (2-tailed)	0.49	0.383
	N	87	102
Rd_conf_min	Pearson Correlation	.a	.a
	Sig. (2-tailed)	.	.
	N	87	102
HMPDD_0_max	Pearson Correlation	-0.14	0.012
	Sig. (2-tailed)	0.197	0.902
	N	87	102
HMPDD_1_max	Pearson Correlation	-0.064	-0.146
	Sig. (2-tailed)	0.553	0.142
	N	87	102
HMPDD_10_max	Pearson Correlation	0.13	0.009
	Sig. (2-tailed)	0.228	0.931
	N	87	102
HMPDD_11_max	Pearson Correlation	-0.1	0.006
	Sig. (2-tailed)	0.356	0.956
	N	87	102
HMPDD_12_max	Pearson Correlation	-0.089	0.033
	Sig. (2-tailed)	0.414	0.74
	N	87	102
HMPDD_2_max	Pearson Correlation	-0.1	-0.062
	Sig. (2-tailed)	0.357	0.534
	N	87	102
HMPDD_3_max	Pearson Correlation	-0.076	0.039
	Sig. (2-tailed)	0.485	0.697
	N	87	102
HMPDD_4_max	Pearson Correlation	-0.179	0.01
	Sig. (2-tailed)	0.096	0.918
	N	87	102
HMPDD_5_max	Pearson Correlation	-0.1	-0.022
	Sig. (2-tailed)	0.355	0.825
	N	87	102
HMPDD_6_max	Pearson Correlation	-0.183	0.06
	Sig. (2-tailed)	0.089	0.547
	N	87	102
HMPDD_7_max	Pearson Correlation	-0.023	-0.037

	Sig. (2-tailed)	0.832	0.713
	N	87	102
HMPDD_8_max	Pearson Correlation	0	-0.044
	Sig. (2-tailed)	0.998	0.66
	N	87	102
HMPDD_9_max	Pearson Correlation	0.08	0.01
	Sig. (2-tailed)	0.461	0.923
	N	87	102
HMPDM_0_max	Pearson Correlation	.a	.a
	Sig. (2-tailed)	.	.
	N	87	102
HMPDM_1_max	Pearson Correlation	.a	.a
	Sig. (2-tailed)	.	.
	N	87	102
HMPDM_10_max	Pearson Correlation	0.038	-0.151
	Sig. (2-tailed)	0.729	0.131
	N	87	102
HMPDM_11_max	Pearson Correlation	-0.003	-.249*
	Sig. (2-tailed)	0.976	0.012
	N	87	102
HMPDM_12_max	Pearson Correlation	-.283**	0.06
	Sig. (2-tailed)	0.008	0.546
	N	87	102
HMPDM_13_max	Pearson Correlation	-0.123	0.016
	Sig. (2-tailed)	0.257	0.873
	N	87	102
HMPDM_14_max	Pearson Correlation	0.094	-0.017
	Sig. (2-tailed)	0.388	0.865
	N	87	102
HMPDM_15_max	Pearson Correlation	0.128	-0.047
	Sig. (2-tailed)	0.237	0.639
	N	87	102
HMPDM_16_max	Pearson Correlation	0.161	0.022
	Sig. (2-tailed)	0.137	0.83
	N	87	102
HMPDM_17_max	Pearson Correlation	0.102	-0.167
	Sig. (2-tailed)	0.349	0.093
	N	87	102
HMPDM_18_max	Pearson Correlation	0.102	0.076
	Sig. (2-tailed)	0.345	0.447
	N	87	102
HMPDM_19_max	Pearson Correlation	0.056	-0.057
	Sig. (2-tailed)	0.605	0.57
	N	87	102

HMPDM_2_max	Pearson Correlation	.a	.a
	Sig. (2-tailed)	.	.
	N	87	102
HMPDM_20_max	Pearson Correlation	0.067	-0.096
	Sig. (2-tailed)	0.537	0.339
	N	87	102
HMPDM_21_max	Pearson Correlation	0.083	0.067
	Sig. (2-tailed)	0.444	0.501
	N	87	102
MCEP_16_std	Pearson Correlation	-0.076	0.07
	Sig. (2-tailed)	0.487	0.486
	N	87	102
MCEP_17_std	Pearson Correlation	-0.017	-.251*
	Sig. (2-tailed)	0.872	0.011
	N	87	102
MCEP_18_std	Pearson Correlation	-0.043	-0.151
	Sig. (2-tailed)	0.694	0.129
	N	87	102
MCEP_19_std	Pearson Correlation	-0.062	.a
	Sig. (2-tailed)	0.568	.
	N	87	102
MCEP_2_std	Pearson Correlation	-0.063	-0.048
	Sig. (2-tailed)	0.562	0.634
	N	87	102
MCEP_20_std	Pearson Correlation	-0.091	-0.028
	Sig. (2-tailed)	0.404	0.777
	N	87	102
MCEP_21_std	Pearson Correlation	-0.067	0.022
	Sig. (2-tailed)	0.535	0.824
	N	87	102
MCEP_22_std	Pearson Correlation	-0.108	-0.02
	Sig. (2-tailed)	0.32	0.841
	N	87	102
MCEP_23_std	Pearson Correlation	-0.097	0.02
	Sig. (2-tailed)	0.37	0.845
	N	87	102
MCEP_24_std	Pearson Correlation	-0.063	-0.009
	Sig. (2-tailed)	0.56	0.927
	N	87	102
MCEP_3_std	Pearson Correlation	-0.099	-0.113
	Sig. (2-tailed)	0.361	0.259
	N	87	102
MCEP_4_std	Pearson Correlation	0.138	-0.006
	Sig. (2-tailed)	0.202	0.955

	N	87	102
MCEP_5_std	Pearson Correlation	-0.121	0.144
	Sig. (2-tailed)	0.266	0.15
	N	87	102
MCEP_6_std	Pearson Correlation	-0.048	-0.052
	Sig. (2-tailed)	0.656	0.605
	N	87	102
MCEP_7_std	Pearson Correlation	0.082	0.006
	Sig. (2-tailed)	0.453	0.956
	N	87	102
MCEP_8_std	Pearson Correlation	0.002	-0.037
	Sig. (2-tailed)	0.986	0.71
	N	87	102
MCEP_9_std	Pearson Correlation	0.045	0.002
	Sig. (2-tailed)	0.682	0.988
	N	87	102
Rd_conf_std	Pearson Correlation	.a	-0.029
	Sig. (2-tailed)	.	0.773
	N	87	102
HMPDD_0_min	Pearson Correlation	0.165	-0.185
	Sig. (2-tailed)	0.127	0.062
	N	87	102
HMPDD_1_min	Pearson Correlation	0.089	0.144
	Sig. (2-tailed)	0.414	0.149
	N	87	102
HMPDD_10_min	Pearson Correlation	0.05	-0.041
	Sig. (2-tailed)	0.643	0.686
	N	87	102
HMPDD_11_min	Pearson Correlation	0.054	-0.007
	Sig. (2-tailed)	0.621	0.943
	N	87	102
HMPDD_12_min	Pearson Correlation	-0.077	-0.064
	Sig. (2-tailed)	0.479	0.521
	N	87	102
HMPDD_2_min	Pearson Correlation	-0.034	0.003
	Sig. (2-tailed)	0.753	0.979
	N	87	102
HMPDD_3_min	Pearson Correlation	-0.054	-0.017
	Sig. (2-tailed)	0.619	0.868
	N	87	102
HMPDD_4_min	Pearson Correlation	0.024	0.051
	Sig. (2-tailed)	0.825	0.61
	N	87	102
HMPDD_5_min	Pearson Correlation	-0.061	0.047

	Sig. (2-tailed)	0.576	0.641
	N	87	102
HMPDD_6_min	Pearson Correlation	0.083	0.084
	Sig. (2-tailed)	0.444	0.399
	N	87	102
HMPDD_7_min	Pearson Correlation	-0.02	0.106
	Sig. (2-tailed)	0.853	0.291
	N	87	102
HMPDD_8_min	Pearson Correlation	0.076	0.036
	Sig. (2-tailed)	0.485	0.721
	N	87	102
HMPDD_9_min	Pearson Correlation	0.03	0.09
	Sig. (2-tailed)	0.784	0.366
	N	87	102
HMPDM_0_min	Pearson Correlation	.a	-0.135
	Sig. (2-tailed)	.	0.175
	N	87	102
HMPDM_1_min	Pearson Correlation	.a	0.073
	Sig. (2-tailed)	.	0.467
	N	87	102
HMPDM_10_min	Pearson Correlation	-0.007	0.076
	Sig. (2-tailed)	0.948	0.449
	N	87	102
HMPDM_11_min	Pearson Correlation	0.008	-0.057
	Sig. (2-tailed)	0.941	0.571
	N	87	102
HMPDM_12_min	Pearson Correlation	0.107	.a
	Sig. (2-tailed)	0.325	.
	N	87	102
HMPDM_13_min	Pearson Correlation	0.209	-0.089
	Sig. (2-tailed)	0.052	0.375
	N	87	102
HMPDM_14_min	Pearson Correlation	0.045	-0.113
	Sig. (2-tailed)	0.677	0.258
	N	87	102
HMPDM_15_min	Pearson Correlation	-0.093	0.03
	Sig. (2-tailed)	0.391	0.766
	N	87	102
HMPDM_16_min	Pearson Correlation	-0.178	-0.008
	Sig. (2-tailed)	0.1	0.937
	N	87	102
HMPDM_17_min	Pearson Correlation	0.042	0.078
	Sig. (2-tailed)	0.702	0.434
	N	87	102

HMPDM_18_min	Pearson Correlation	-0.04	-0.008
	Sig. (2-tailed)	0.714	0.934
	N	87	102
HMPDM_19_min	Pearson Correlation	-0.078	0.084
	Sig. (2-tailed)	0.471	0.403
	N	87	102
HMPDM_2_min	Pearson Correlation	.a	0.03
	Sig. (2-tailed)	.	0.762
	N	87	102
HMPDM_20_min	Pearson Correlation	-0.066	-0.043
	Sig. (2-tailed)	0.546	0.669
	N	87	102
HMPDM_21_min	Pearson Correlation	-0.104	0.06
	Sig. (2-tailed)	0.339	0.549
	N	87	102
HMPDM_22_min	Pearson Correlation	0.004	-0.039
	Sig. (2-tailed)	0.968	0.7
	N	87	102
HMPDM_23_min	Pearson Correlation	-0.149	-0.072
	Sig. (2-tailed)	0.167	0.471
	N	87	102
HMPDM_24_min	Pearson Correlation	-0.022	-0.001
	Sig. (2-tailed)	0.838	0.995
	N	87	102
HMPDM_3_min	Pearson Correlation	.a	.a
	Sig. (2-tailed)	.	.
	N	87	102
HMPDM_4_min	Pearson Correlation	.a	.a
	Sig. (2-tailed)	.	.
	N	87	102
HMPDM_5_min	Pearson Correlation	0.022	-0.139
	Sig. (2-tailed)	0.842	0.163
	N	87	102
HMPDM_6_min	Pearson Correlation	0.072	-.292**
	Sig. (2-tailed)	0.506	0.003
	N	87	102
HMPDM_7_min	Pearson Correlation	0.027	0.044
	Sig. (2-tailed)	0.803	0.66
	N	87	102
HMPDM_8_min	Pearson Correlation	-0.039	-0.012
	Sig. (2-tailed)	0.72	0.906
	N	87	102
HMPDM_9_min	Pearson Correlation	-0.165	0.027
	Sig. (2-tailed)	0.126	0.786

	N	87	102
MCEP_0_min	Pearson Correlation	-0.059	0.016
	Sig. (2-tailed)	0.584	0.872
	N	87	102
MCEP_1_min	Pearson Correlation	-0.026	-0.036
	Sig. (2-tailed)	0.814	0.718
	N	87	102
MCEP_10_min	Pearson Correlation	-0.089	-0.086
	Sig. (2-tailed)	0.412	0.391
	N	87	102
MCEP_11_min	Pearson Correlation	0.011	0.054
	Sig. (2-tailed)	0.92	0.589
	N	87	102
MCEP_12_min	Pearson Correlation	0.07	-0.089
	Sig. (2-tailed)	0.522	0.376
	N	87	102
MCEP_13_min	Pearson Correlation	-0.147	.a
	Sig. (2-tailed)	0.173	.
	N	87	102
MCEP_14_min	Pearson Correlation	-0.075	-0.13
	Sig. (2-tailed)	0.489	0.194
	N	87	102
MCEP_15_min	Pearson Correlation	-0.061	0.057
	Sig. (2-tailed)	0.577	0.572
	N	87	102
MCEP_16_min	Pearson Correlation	0.084	-0.06
	Sig. (2-tailed)	0.437	0.547
	N	87	102
MCEP_17_min	Pearson Correlation	0.007	-0.171
	Sig. (2-tailed)	0.947	0.086
	N	87	102
MCEP_18_min	Pearson Correlation	-0.008	-0.092
	Sig. (2-tailed)	0.943	0.36
	N	87	102
MCEP_19_min	Pearson Correlation	-0.051	.a
	Sig. (2-tailed)	0.637	.
	N	87	102
MCEP_2_min	Pearson Correlation	-0.031	-0.078
	Sig. (2-tailed)	0.779	0.438
	N	87	102
MCEP_20_min	Pearson Correlation	-0.026	-0.043
	Sig. (2-tailed)	0.808	0.67
	N	87	102
MCEP_21_min	Pearson Correlation	0.085	0.007

	Sig. (2-tailed)	0.436	0.945
	N	87	102
MCEP_22_min	Pearson Correlation	0.116	-0.03
	Sig. (2-tailed)	0.283	0.768
	N	87	102
MCEP_23_min	Pearson Correlation	0.058	-0.015
	Sig. (2-tailed)	0.596	0.878
	N	87	102
MCEP_24_min	Pearson Correlation	-0.029	-0.029
	Sig. (2-tailed)	0.79	0.771
	N	87	102
MCEP_3_min	Pearson Correlation	0.154	-0.095
	Sig. (2-tailed)	0.153	0.34
	N	87	102
MCEP_4_min	Pearson Correlation	-0.076	0.042
	Sig. (2-tailed)	0.485	0.674
	N	87	102
MCEP_5_min	Pearson Correlation	0.182	0.088
	Sig. (2-tailed)	0.091	0.38
	N	87	102
MCEP_6_min	Pearson Correlation	-.218*	0.051
	Sig. (2-tailed)	0.043	0.611
	N	87	102
MCEP_7_min	Pearson Correlation	0.043	-0.006
	Sig. (2-tailed)	0.695	0.949
	N	87	102
MCEP_8_min	Pearson Correlation	-0.152	0.039
	Sig. (2-tailed)	0.159	0.695
	N	87	102
MCEP_9_min	Pearson Correlation	-0.075	-0.09
	Sig. (2-tailed)	0.49	0.366
	N	87	102
Rd_conf_min	Pearson Correlation	.a	-0.061
	Sig. (2-tailed)	.	0.545
	N	87	102
HMPDD_0_max	Pearson Correlation	-0.14	-0.003
	Sig. (2-tailed)	0.197	0.977
	N	87	102
HMPDD_1_max	Pearson Correlation	-0.064	0.058
	Sig. (2-tailed)	0.553	0.561
	N	87	102
HMPDD_10_max	Pearson Correlation	0.13	0.042
	Sig. (2-tailed)	0.228	0.678
	N	87	102

HMPDD_11_max	Pearson Correlation	-0.1	0.127
	Sig. (2-tailed)	0.356	0.203
	N	87	102
HMPDD_12_max	Pearson Correlation	-0.089	-0.03
	Sig. (2-tailed)	0.414	0.763
	N	87	102
HMPDD_2_max	Pearson Correlation	-0.1	0.085
	Sig. (2-tailed)	0.357	0.397
	N	87	102
HMPDD_3_max	Pearson Correlation	-0.076	-0.047
	Sig. (2-tailed)	0.485	0.641
	N	87	102
HMPDD_4_max	Pearson Correlation	-0.179	0.063
	Sig. (2-tailed)	0.096	0.532
	N	87	102
HMPDD_5_max	Pearson Correlation	-0.1	-0.037
	Sig. (2-tailed)	0.355	0.714
	N	87	102
HMPDD_6_max	Pearson Correlation	-0.183	0.171
	Sig. (2-tailed)	0.089	0.086
	N	87	102
HMPDD_7_max	Pearson Correlation	-0.023	0.112
	Sig. (2-tailed)	0.832	0.262
	N	87	102
HMPDD_8_max	Pearson Correlation	0	-0.032
	Sig. (2-tailed)	0.998	0.749
	N	87	102
HMPDD_9_max	Pearson Correlation	0.08	0.063
	Sig. (2-tailed)	0.461	0.527
	N	87	102
HMPDM_0_max	Pearson Correlation	.a	-0.03
	Sig. (2-tailed)	.	0.766
	N	87	102
HMPDM_1_max	Pearson Correlation	.a	0.04
	Sig. (2-tailed)	.	0.689
	N	87	102
HMPDM_10_max	Pearson Correlation	0.038	0.054
	Sig. (2-tailed)	0.729	0.592
	N	87	102
HMPDM_11_max	Pearson Correlation	-0.003	0.019
	Sig. (2-tailed)	0.976	0.849
	N	87	102
HMPDM_12_max	Pearson Correlation	-.283**	.a
	Sig. (2-tailed)	0.008	.

	N	87	102
HMPDM_13_max	Pearson Correlation	-0.123	0.109
	Sig. (2-tailed)	0.257	0.274
	N	87	102
HMPDM_14_max	Pearson Correlation	0.094	-0.036
	Sig. (2-tailed)	0.388	0.72
	N	87	102
HMPDM_15_max	Pearson Correlation	0.128	-0.049
	Sig. (2-tailed)	0.237	0.624
	N	87	102
HMPDM_16_max	Pearson Correlation	0.161	0.168
	Sig. (2-tailed)	0.137	0.091
	N	87	102
HMPDM_17_max	Pearson Correlation	0.102	-0.025
	Sig. (2-tailed)	0.349	0.799
	N	87	102
HMPDM_18_max	Pearson Correlation	0.102	-0.032
	Sig. (2-tailed)	0.345	0.749
	N	87	102
HMPDM_19_max	Pearson Correlation	0.056	0.107
	Sig. (2-tailed)	0.605	0.282
	N	87	102
HMPDM_2_max	Pearson Correlation	.a	.a
	Sig. (2-tailed)	.	.
	N	87	102
HMPDM_20_max	Pearson Correlation	0.067	0.153
	Sig. (2-tailed)	0.537	0.124
	N	87	102
HMPDM_21_max	Pearson Correlation	0.083	-0.031
	Sig. (2-tailed)	0.444	0.758
	N	87	102
HMPDM_22_max	Pearson Correlation	0.069	0.102
	Sig. (2-tailed)	0.528	0.31
	N	87	102
HMPDM_23_max	Pearson Correlation	0.166	0.01
	Sig. (2-tailed)	0.123	0.921
	N	87	102
HMPDM_24_max	Pearson Correlation	-0.081	0.019
	Sig. (2-tailed)	0.454	0.846
	N	87	102
HMPDM_3_max	Pearson Correlation	.a	.a
	Sig. (2-tailed)	.	.
	N	87	102
HMPDM_4_max	Pearson Correlation	.a	0.096

	Sig. (2-tailed)	.	0.337
	N	87	102
HMPDM_5_max	Pearson Correlation	-0.025	0.043
	Sig. (2-tailed)	0.817	0.666
	N	87	102
HMPDM_6_max	Pearson Correlation	-0.068	0.011
	Sig. (2-tailed)	0.53	0.914
	N	87	102
HMPDM_7_max	Pearson Correlation	-0.006	0.033
	Sig. (2-tailed)	0.958	0.742
	N	87	102
HMPDM_8_max	Pearson Correlation	0.057	0.053
	Sig. (2-tailed)	0.599	0.597
	N	87	102
HMPDM_9_max	Pearson Correlation	0.085	0.053
	Sig. (2-tailed)	0.436	0.595
	N	87	102
MCEP_0_max	Pearson Correlation	0.15	-0.107
	Sig. (2-tailed)	0.165	0.285
	N	87	102
MCEP_1_max	Pearson Correlation	0.094	-0.059
	Sig. (2-tailed)	0.385	0.558
	N	87	102
MCEP_10_max	Pearson Correlation	0.066	0.016
	Sig. (2-tailed)	0.543	0.87
	N	87	102
MCEP_11_max	Pearson Correlation	-0.135	-0.126
	Sig. (2-tailed)	0.211	0.206
	N	87	102
MCEP_12_max	Pearson Correlation	0.018	0.013
	Sig. (2-tailed)	0.867	0.897
	N	87	102
MCEP_13_max	Pearson Correlation	0.136	-0.087
	Sig. (2-tailed)	0.209	0.385
	N	87	102
MCEP_14_max	Pearson Correlation	0.012	0.142
	Sig. (2-tailed)	0.91	0.155
	N	87	102
MCEP_15_max	Pearson Correlation	-0.099	0.07
	Sig. (2-tailed)	0.363	0.483
	N	87	102
MCEP_16_max	Pearson Correlation	-0.024	-.215*
	Sig. (2-tailed)	0.822	0.03
	N	87	102

MCEP_17_max	Pearson Correlation	0.026	0.054
	Sig. (2-tailed)	0.809	0.59
	N	87	102
MCEP_18_max	Pearson Correlation	-0.037	-0.113
	Sig. (2-tailed)	0.735	0.259
	N	87	102
MCEP_19_max	Pearson Correlation	-0.057	-0.181
	Sig. (2-tailed)	0.598	0.069
	N	87	102
MCEP_2_max	Pearson Correlation	0.075	-0.008
	Sig. (2-tailed)	0.489	0.938
	N	87	102
MCEP_20_max	Pearson Correlation	-0.034	-0.161
	Sig. (2-tailed)	0.752	0.106
	N	87	102
MCEP_21_max	Pearson Correlation	-0.004	0.054
	Sig. (2-tailed)	0.97	0.593
	N	87	102
MCEP_22_max	Pearson Correlation	-0.062	-0.04
	Sig. (2-tailed)	0.565	0.69
	N	87	102
MCEP_23_max	Pearson Correlation	-0.191	0.105
	Sig. (2-tailed)	0.076	0.296
	N	87	102
MCEP_24_max	Pearson Correlation	0.124	-0.171
	Sig. (2-tailed)	0.252	0.085
	N	87	102
MCEP_3_max	Pearson Correlation	0.138	-0.064
	Sig. (2-tailed)	0.203	0.525
	N	87	102
MCEP_4_max	Pearson Correlation	-0.061	0.055
	Sig. (2-tailed)	0.575	0.586
	N	87	102
MCEP_5_max	Pearson Correlation	0.058	-0.013
	Sig. (2-tailed)	0.593	0.897
	N	87	102
MCEP_6_max	Pearson Correlation	-.250*	-0.105
	Sig. (2-tailed)	0.019	0.295
	N	87	102
MCEP_7_max	Pearson Correlation	0.051	0.009
	Sig. (2-tailed)	0.642	0.926
	N	87	102
MCEP_8_max	Pearson Correlation	0	-0.004
	Sig. (2-tailed)	0.999	0.967

	N	87	102
MCEP_9_max	Pearson Correlation	0.188	-0.087
	Sig. (2-tailed)	0.081	0.383
	N	87	102
Rd_conf_max	Pearson Correlation	.a	.a
	Sig. (2-tailed)	.	.
	N	87	102
HMPDD_0_range	Pearson Correlation	-0.168	0.012
	Sig. (2-tailed)	0.121	0.902
	N	87	102
HMPDD_1_range	Pearson Correlation	-0.092	-0.146
	Sig. (2-tailed)	0.398	0.142
	N	87	102
HMPDD_10_range	Pearson Correlation	0.089	0.009
	Sig. (2-tailed)	0.411	0.931
	N	87	102
HMPDD_11_range	Pearson Correlation	-0.119	0.006
	Sig. (2-tailed)	0.272	0.956
	N	87	102
HMPDD_12_range	Pearson Correlation	-0.041	0.033
	Sig. (2-tailed)	0.708	0.74
	N	87	102
HMPDD_2_range	Pearson Correlation	-0.058	-0.062
	Sig. (2-tailed)	0.596	0.534
	N	87	102
HMPDD_3_range	Pearson Correlation	-0.045	0.039
	Sig. (2-tailed)	0.681	0.697
	N	87	102
HMPDD_4_range	Pearson Correlation	-0.163	0.01
	Sig. (2-tailed)	0.13	0.918
	N	87	102
HMPDD_5_range	Pearson Correlation	-0.068	-0.022
	Sig. (2-tailed)	0.532	0.825
	N	87	102
HMPDD_6_range	Pearson Correlation	-0.192	0.06
	Sig. (2-tailed)	0.075	0.547
	N	87	102
HMPDD_7_range	Pearson Correlation	-0.012	-0.037
	Sig. (2-tailed)	0.911	0.713
	N	87	102
HMPDD_8_range	Pearson Correlation	-0.035	-0.044
	Sig. (2-tailed)	0.746	0.66
	N	87	102
HMPDD_9_range	Pearson Correlation	0.064	0.01

	Sig. (2-tailed)	0.558	0.923
	N	87	102
HMPDM_0_range	Pearson Correlation	.a	.a
	Sig. (2-tailed)	.	.
	N	87	102
HMPDM_1_range	Pearson Correlation	.a	.a
	Sig. (2-tailed)	.	.
	N	87	102
HMPDM_10_range	Pearson Correlation	0.027	-0.151
	Sig. (2-tailed)	0.806	0.131
	N	87	102
HMPDM_11_range	Pearson Correlation	-0.006	-.249*
	Sig. (2-tailed)	0.959	0.012
	N	87	102
HMPDM_12_range	Pearson Correlation	-.222*	0.06
	Sig. (2-tailed)	0.039	0.546
	N	87	102
HMPDM_13_range	Pearson Correlation	-0.185	0.016
	Sig. (2-tailed)	0.086	0.873
	N	87	102
HMPDM_14_range	Pearson Correlation	0.023	-0.017
	Sig. (2-tailed)	0.836	0.865
	N	87	102
HMPDM_15_range	Pearson Correlation	0.119	-0.047
	Sig. (2-tailed)	0.273	0.639
	N	87	102
HMPDM_16_range	Pearson Correlation	0.198	0.022
	Sig. (2-tailed)	0.066	0.83
	N	87	102
HMPDM_17_range	Pearson Correlation	0.025	-0.167
	Sig. (2-tailed)	0.816	0.093
	N	87	102
HMPDM_18_range	Pearson Correlation	0.093	0.076
	Sig. (2-tailed)	0.391	0.447
	N	87	102
HMPDM_19_range	Pearson Correlation	0.071	-0.057
	Sig. (2-tailed)	0.516	0.57
	N	87	102
HMPDM_2_range	Pearson Correlation	.a	.a
	Sig. (2-tailed)	.	.
	N	87	102
HMPDM_20_range	Pearson Correlation	0.085	-0.096
	Sig. (2-tailed)	0.433	0.339
	N	87	102

HMPDM_21_range	Pearson Correlation	0.121	0.067
	Sig. (2-tailed)	0.266	0.501
	N	87	102
HMPDM_22_range	Pearson Correlation	0.052	0.07
	Sig. (2-tailed)	0.63	0.486
	N	87	102
HMPDM_23_range	Pearson Correlation	0.194	-.251*
	Sig. (2-tailed)	0.072	0.011
	N	87	102
HMPDM_24_range	Pearson Correlation	-0.046	-0.151
	Sig. (2-tailed)	0.675	0.129
	N	87	102
HMPDM_3_range	Pearson Correlation	.a	.a
	Sig. (2-tailed)	.	.
	N	87	102
HMPDM_4_range	Pearson Correlation	.a	-0.048
	Sig. (2-tailed)	.	0.634
	N	87	102
HMPDM_5_range	Pearson Correlation	-0.025	-0.028
	Sig. (2-tailed)	0.82	0.777
	N	87	102
HMPDM_6_range	Pearson Correlation	-0.077	0.022
	Sig. (2-tailed)	0.481	0.824
	N	87	102
HMPDM_7_range	Pearson Correlation	-0.017	-0.02
	Sig. (2-tailed)	0.874	0.841
	N	87	102
HMPDM_8_range	Pearson Correlation	0.055	0.02
	Sig. (2-tailed)	0.61	0.845
	N	87	102
HMPDM_9_range	Pearson Correlation	0.134	-0.009
	Sig. (2-tailed)	0.215	0.927
	N	87	102
MCEP_0_range	Pearson Correlation	0.161	-0.113
	Sig. (2-tailed)	0.137	0.259
	N	87	102
MCEP_1_range	Pearson Correlation	0.073	-0.006
	Sig. (2-tailed)	0.502	0.955
	N	87	102
MCEP_10_range	Pearson Correlation	0.114	0.144
	Sig. (2-tailed)	0.294	0.15
	N	87	102
MCEP_11_range	Pearson Correlation	-0.098	-0.052
	Sig. (2-tailed)	0.365	0.605

	N	87	102
MCEP_12_range	Pearson Correlation	-0.045	0.006
	Sig. (2-tailed)	0.681	0.956
	N	87	102
MCEP_13_range	Pearson Correlation	0.192	-0.037
	Sig. (2-tailed)	0.075	0.71
	N	87	102
MCEP_14_range	Pearson Correlation	0.057	0.002
	Sig. (2-tailed)	0.6	0.988
	N	87	102
MCEP_15_range	Pearson Correlation	-0.022	-0.029
	Sig. (2-tailed)	0.838	0.773
	N	87	102
MCEP_16_range	Pearson Correlation	-0.072	-0.185
	Sig. (2-tailed)	0.505	0.062
	N	87	102
MCEP_17_range	Pearson Correlation	0.012	0.144
	Sig. (2-tailed)	0.911	0.149
	N	87	102
MCEP_18_range	Pearson Correlation	-0.016	-0.041
	Sig. (2-tailed)	0.882	0.686
	N	87	102
MCEP_19_range	Pearson Correlation	-0.004	-0.007
	Sig. (2-tailed)	0.968	0.943
	N	87	102
MCEP_2_range	Pearson Correlation	0.07	-0.064
	Sig. (2-tailed)	0.517	0.521
	N	87	102
MCEP_20_range	Pearson Correlation	-0.005	0.003
	Sig. (2-tailed)	0.964	0.979
	N	87	102
MCEP_21_range	Pearson Correlation	-0.052	-0.017
	Sig. (2-tailed)	0.631	0.868
	N	87	102
MCEP_22_range	Pearson Correlation	-0.118	0.051
	Sig. (2-tailed)	0.277	0.61
	N	87	102
MCEP_23_range	Pearson Correlation	-0.164	0.047
	Sig. (2-tailed)	0.128	0.641
	N	87	102
MCEP_24_range	Pearson Correlation	0.09	0.084
	Sig. (2-tailed)	0.405	0.399
	N	87	102
MCEP_3_range	Pearson Correlation	-0.029	0.106

	Sig. (2-tailed)	0.788	0.291
	N	87	102
MCEP_4_range	Pearson Correlation	0.025	0.036
	Sig. (2-tailed)	0.815	0.721
	N	87	102
MCEP_5_range	Pearson Correlation	-0.069	0.09
	Sig. (2-tailed)	0.528	0.366
	N	87	102
MCEP_6_range	Pearson Correlation	-0.057	-0.135
	Sig. (2-tailed)	0.598	0.175
	N	87	102
MCEP_7_range	Pearson Correlation	0.005	0.073
	Sig. (2-tailed)	0.965	0.467
	N	87	102
MCEP_8_range	Pearson Correlation	0.092	0.076
	Sig. (2-tailed)	0.399	0.449
	N	87	102
MCEP_9_range	Pearson Correlation	0.176	-0.057
	Sig. (2-tailed)	0.103	0.571
	N	87	102
Rd_conf_range	Pearson Correlation	.a	.a
	Sig. (2-tailed)	.	.
	N	87	102

M. Mapping Personality for each Participant

Source (A)	PHQ-8	PHQ-Score	Gender	O	C	E	A	N
0	0	2	1	0	0	0	0	0
1	0	3	1	1	0	0	0	0
2	0	4	1	0	0	1	0	0
3	0	0	0	0	0	0	1	0
4	0	6	0	0	0	1	0	0
5	0	7	1	0	0	0	0	1
6	0	0	0	0	0	0	0	1
7	0	4	0	0	0	0	1	0
8	1	22	0	0	1	0	0	0
9	1	15	1	0	0	0	1	0
10	0	4	1	0	0	0	1	0
11	1	21	0	0	0	0	0	1
12	0	2	1	0	0	0	0	0
13	0	7	1	0	0	0	0	1
14	0	1	0	0	0	1	0	0
15	0	2	1	0	0	1	0	0

16	0	6	1	0	0	1	0	0
17	0	8	1	0	0	0	0	1
18	0	3	1	0	0	0	1	0
19	1	13	1	1	0	0	0	0
20	1	11	0	0	0	0	1	0
21	1	20	0	0	0	0	0	1
22	0	5	1	0	0	1	0	0
23	0	1	0	0	0	0	1	0
24	0	5	1	0	0	0	1	0
25	1	10	0	0	0	0	0	1
26	0	2	1	0	1	0	0	0
27	0	4	0	0	0	0	0	1
28	0	4	1	0	0	0	1	0
29	0	1	1	0	0	0	0	1
30	1	12	1	1	0	0	0	0
31	0	8	1	0	0	0	0	1
32	1	18	0	0	0	0	1	0
33	0	5	1	1	0	0	0	0
34	0	5	1	0	1	0	0	0
35	1	12	0	0	0	0	1	0
36	0	7	1	0	0	0	1	0
37	1	10	0	0	1	0	0	0
38	1	15	0	0	0	0	1	0
39	1	11	1	0	0	0	0	1
40	0	1	1	1	0	0	0	0
41	0	7	0	0	0	0	0	1
42	0	9	1	0	0	0	1	0
43	1	11	1	0	0	0	0	1
44	1	15	0	0	0	0	0	1
45	1	23	0	0	0	0	0	1
46	1	16	1	0	0	0	0	1
47	1	20	0	0	0	1	0	0
48	0	5	1	0	1	0	0	0
49	1	11	0	0	0	0	1	0
50	1	14	0	1	0	0	0	0
51	1	10	0	0	0	0	0	1
52	1	11	0	0	0	0	0	1
53	1	18	1	0	0	0	1	0
54	1	10	1	0	1	0	0	0
55	1	10	1	0	0	0	0	1
56	0	7	1	1	0	0	0	0
57	0	7	1	0	0	1	0	0
58	1	13	1	0	0	0	1	0
59	0	4	0	1	0	0	0	0

TU Delft

60	0	0	1	1	0	0	0	0
61	1	20	0	1	0	0	0	0
62	0	0	1	0	0	0	0	1
63	0	0	1	0	0	0	1	0
64	1	12	1	0	0	0	0	1
65	0	0	1	1	0	0	0	0
66	1	19	1	0	0	0	0	1
67	0	7	1	0	0	0	0	1
68	0	0	0	0	0	0	1	0
69	0	0	1	0	1	0	0	0
70	0	9	1	0	0	1	0	0
71	1	13	0	0	0	0	0	1
72	0	9	1	0	0	0	0	1
73	0	2	0	0	0	0	0	1
74	0	5	1	0	0	0	1	0
75	1	12	0	0	0	0	0	1
76	1	16	0	0	0	0	1	0
77	0	1	0	0	0	0	0	1
78	0	2	1	1	0	0	0	0
79	1	10	1	0	0	0	1	0
80	1	16	1	1	0	0	0	0
81	0	0	1	0	0	0	1	0
82	0	7	1	1	0	0	0	0
83	1	15	1	0	0	0	0	1
84	0	8	1	0	0	0	0	0
85	1	11	0	1	0	0	0	0
86	0	2	1	0	0	1	0	0
87	1	17	1	0	1	0	0	0
88	1	14	1	0	0	0	0	1
89	0	9	1	1	0	0	0	0
90	0	9	0	0	0	0	0	0
91	0	1	0	0	1	0	0	0
92	0	2	1	0	0	1	0	0
93	0	7	0	0	0	0	0	1
94	0	5	1	0	0	0	1	0
95	0	5	1	0	0	1	0	0
96	0	7	0	0	0	0	0	1
97	0	7	1	0	0	0	0	1
98	0	9	0	0	0	1	0	0
99	1	11	0	1	0	0	0	0
100	0	0	0	0	0	1	0	0
101	0	0	1	1	0	0	0	0
102	1	17	0	0	0	1	0	0
103	0	2	0	1	0	0	0	0

104	0	3	1	0	0	0	0	1
105	0	0	0	0	0	0	1	0
106	0	10	1	0	0	0	0	1
107	1	12	0	0	0	1	0	0
108	0	0	0	0	0	0	1	0
109	1	12	1	0	0	1	0	0
110	1	10	0	0	0	0	1	0
111	1	16	0	0	0	0	0	1
112	0	3	0	0	0	0	1	0
113	0	3	1	0	0	0	1	0
114	0	7	0	0	0	0	0	1
115	1	10	0	0	0	0	0	1
116	0	3	0	0	0	1	0	0
117	0	3	1	0	0	0	1	0
118	1	10	0	0	0	0	1	0
119	1	12	0	1	0	0	0	0
120	0	0	0	0	0	0	0	1
121	0	3	0	0	1	0	0	0
122	0	6	0	0	1	0	0	0
123	1	20	1	0	0	0	1	0
124	0	5	0	0	0	0	0	1
125	0	0	1	0	0	1	0	0
126	0	1	1	0	0	0	0	1
127	0	3	1	0	0	1	0	0
128	0	2	0	0	0	1	0	0
129	0	1	1	0	0	0	0	1
130	1	10	1	0	0	0	1	0
131	0	2	1	0	0	0	1	0
132	0	8	0	0	0	0	0	1
133	0	0	1	0	1	0	0	0
134	0	0	1	1	0	0	0	0
135	0	2	0	0	0	0	1	0
136	0	1	0	0	0	1	0	0
137	1	19	0	0	0	0	1	0
138	1	18	0	0	0	0	0	1
139	0	6	1	0	0	0	0	1
140	0	1	1	1	0	0	0	0
141	0	7	0	0	0	0	0	1
142	0	1	1	0	1	0	0	0
143	0	0	0	0	0	0	1	0
144	0	1	1	0	0	0	0	1
145	1	18	1	0	0	1	0	0
146	0	2	0	0	0	1	0	0
147	0	9	0	0	0	0	0	1

148	0	4	0	0	0	0	0	1
149	0	1	0	1	0	0	0	0
150	1	17	1	0	0	0	0	1
151	0	1	0	0	0	1	0	0
152	0	1	0	1	0	0	0	0
153	0	6	0	0	0	0	1	0
154	0	3	1	0	0	1	0	0
155	0	5	0	0	0	0	1	0
156	1	16	1	0	0	0	0	1
157	1	17	1	0	0	0	0	1
158	0	9	0	0	0	0	0	1
159	0	0	1	0	0	0	0	1
160	0	0	1	0	0	0	0	1
161	0	2	1	0	0	0	0	1
162	0	9	0	0	0	0	0	1
163	0	0	1	1	0	0	0	0
164	0	4	1	0	0	0	0	0
165	0	3	0	0	0	1	0	0
166	0	3	0	0	0	1	0	0
167	0	0	1	0	1	0	0	0
168	0	3	0	0	0	0	0	1
169	0	0	0	1	0	0	0	0
170	0	4	1	0	0	0	1	0
171	0	6	1	0	0	0	1	0
172	0	3	1	1	0	0	0	0
173	0	2	0	0	0	1	0	0
174	0	1	0	0	0	0	0	1
175	0	7	1	0	0	0	0	1
176	0	1	1	0	0	1	0	0
177	0	7	1	0	0	0	0	1
178	0	1	1	0	0	0	1	0
179	1	15	1	0	1	0	0	0
180	0	9	0	0	0	0	0	1
181	0	2	1	0	0	0	0	1
182	0	4	0	0	0	1	0	0
183	0	0	0	1	0	0	0	0
184	0	0	0	0	0	0	0	1
185	0	3	1	1	0	0	0	0
186	0	2	1	0	0	0	1	0
187	0	8	0	0	0	1	0	0
188	0	0	0	0	0	0	1	0

N. Mapping Audio Features for Big-Five

Big Five Traits	Audio Features	Pearsons r
Openness	H2_mean	-0.181*
	H2_std	-0.145*
	H1_min	0.2**
	QOQ_max	0.152*
	QOQ_range	0.152*
	H1_range	-0.195**
	HMPDM_8_mean	-.150*
	HMPDM_9_mean	-.143*
	HMPDM_20_std	.143*
	HMPDM_21_std	.163*
	HMPDM_22_std	.147*
	HMPDM_23_std	.158*
	HMPDM_24_std	.164*
	HMPDM_4_std	.184*
	HMPDM_5_std	.172*
	HMPDM_6_std	.164*
	HMPDM_7_std	.153*
	HMPDD_0_min	.157*
	HMPDM_17_min	-.158*
	HMPDM_4_min	-.147*
	HMPDM_5_min	-.212**
	HMPDM_6_min	-.200**
	MCEP_11_min	.154*
	HMPDD_1_max	-.186*
	HMPDD_4_max	-.185*
	HMPDD_5_max	-.187*
	MCEP_2_max	-.143*
	HMPDD_0_range	-.155*
	HMPDD_4_range	-.215**
	HMPDD_5_range	-.202**
	HMPDM_4_range	.153*
	HMPDM_5_range	.177*
	HMPDM_6_range	.160*
Consciousness	NAQ_mean	0.148*
	peakSlope_mean	0.171*
	HMPDM_11_mean	.152*
	MCEP_21_mean	-.180*
	HMPDD_1_std	-.171*
	HMPDM_12_std	-.209**
	HMPDM_13_std	-.192**

	HMPDM_14_std	-.160*
	HMPDM_18_std	-.149*
	HMPDM_20_std	-.158*
	HMPDM_21_std	-.157*
	HMPDM_22_std	-.144*
	MCEP_0_std	-.159*
	MCEP_1_std	-.145*
	HMPDM_12_min	.185*
	HMPDM_16_min	.178*
	HMPDM_20_min	.150*
	HMPDM_14_max	-.225**
	MCEP_0_max	-.181*
	MCEP_0_range	-.190**
Extraversion	H2_mean	0.162*
	MCEP_11_mean	-.146*
	MCEP_2_mean	.165*
	MCEP_7_mean	.187*
	MCEP_8_mean	-.266**
	HMPDM_24_std	-.174*
	HMPDD_5_min	-.147*
	HMPDM_24_min	.182*
	HMPDM_23_max	-.165*
	HMPDM_19_range	-.154*
	HMPDM_24_range	-.153*
Agreeableness	H1_min	-0.205**
	PSP_max	0.162*
	PSP_range	0.162*
	HMPDD_8_min	-.166*
Neuroticism	MCEP_7_mean	-.145*
	MCEP_8_mean	.256**
	MCEP_22_std	-.146*
	MCEP_23_std	-.145*
	MCEP_23_max	-.169*
	MCEP_5_max	.155*

0. Data Reduction words

[al]	<laughter>	<sharp inhale>	<abo>	<energi>
[laughter]	<yester>	<ma>	<bef>	<t>
[syncing]	<cha>	<deep breath>	<he>	<s>
[exhales]	<sigh>	<ag>	<argu>	<f>
[real]	<yawn>	<cough>	<disci>	<wh>
[ang]	<curr>	<sniffle>	<so>	<tr>
[clears throat]	<d>	<amo>	<difft>	<lo>
<coll>	<clears throat>	<fo>	<dec>	<e>
<wa>	<go>	<per>	<situatio>	<inv>
<th>	<spa>	<fi>	<tea>	<peop>
<litt>	<fantas>	<exhaling>	<m>	<makes sound with mouth>
<whi>	<sh>	<st>	<l>	<lo>
<ch>	<ha>	<mu>	<m>	<ss noise>
<psh psh>	<sniffle>	<psychia>	<sharp exhale>	<wou>
<so>	<fe>	<ss>	xxx	“
<see>	<ne>	<si>	<sl>	<j>
<cha>	<rea>	<motiv>	<to>	<i>
<o>		<n>	<ss>	<go>
<hou>	<le>	<be>	<cu>	<res>