Passive Diagnosis of Mental Health Disorders Incorporating an Empathic Dialogue System

Through the Use of Psycholinguistics to Predict Depression and Anxiety while Incorporating Emoji Tokens in a Dialogue System to Model Empathy

Master's thesis in Applied Data Science

Fionn Delahunty

MASTER'S THESIS 2019

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Fionn Delahunty

UNIVERSITY OF
GOTHENBURG

CHALMERS
UNIVERSITY OF TECHNOLOGY

Department of Computer Science and Engineering
CHALMERS UNIVERSITY OF TECHNOLOGY
UNIVERSITY OF GOTHENBURG
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Fionn Delahunty

Email: Fionnd@pm.me

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Supervisor: Robert Johansson

Department of Computer and Information Science, Linköping University / Department of Psychology, Stockholm University, Sweden.

Advisor: Mihael Arcan

Natural Language Processing Unit, Insight Centre for Data Analytics, Data Science Institute, NUI Galway, Ireland.

Examiner: Richard Johansson

Department of Computer Science and Engineering.

Master's Thesis 2019

Department of Computer Science and Engineering

Chalmers University of Technology and University of Gothenburg

SE-412 96 Gothenburg

Telephone +46 31 772 1000

Cover: Interface used for the dialogue system in our experimental framework.

Typeset in L^AT_EX

Gothenburg, Sweden 2019

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Abstract

Depression and anxiety are the two most prevalent mental health disorders worldwide, impacting the lives of millions of people each year. Current screening methods require individuals to manually complete psychometric questionnaires. In this work we develop a deep learning approach to predict psychometric scores given textual data through the use of psycholinguistics features. Data is collected via a dialogue system, where we develop and incorporate an approach to model empathy. Which aims to allow for appropriate use of these systems in a clinical setting. Following a public evaluation, we demonstrate that our approach to model empathy can outperform a similarly trained non empathic approach. Additionally, we show that our deep learning prediction approach performed well on evaluation data, but has difficulty generalizing to experimentally collected data. Limitations and implications as a result of this work are discussed.

Keywords: Clinical Psychology, Medicine, Depression, Anxiety, Psycholinguistics, Multidimensional Deep Learning, Dialogue systems, Empathy.

Acknowledgements

A thesis is an imperfect summary of the learning and experience gain over a short, albeit concentrated period of time. This work has challenged, excited and developed me over the last eight months. I would like to my extend my utmost thanks and gratitude to both my supervisors, Robert and Mihael for their unending support and encouragement over the course of this project, both personally and academically.

Additionally, to the Insight centre for supporting my work, and to all my colleagues in the NLP unit for their support and countless tea breaks.

Finally, to my friends and family. For the repeated reminder that a thesis is best done with a clear and relaxed mind.

This work has emanated from research conducted with the financial support of Science Foundation Ireland (SFI) under Grant Number SFI/12/RC/2289 (Insight).

Fionn Delahunty, Ireland, 2019

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Nomenclature

Medical

Anhedonia Inability to feel pleasure in normally pleasurable activities.

Aetiology The cause, set of causes, or manner of causation of a disease or condition.

1

Introduction

Over the last decade, two simultaneous trends have emerged. The first is a more publicly recognised mental health crisis, where, according to a Lancet Commission report the worldwide "quality of mental health services is routinely worse than the quality of those for physical health" [1]. Which, the World Health Organisation (WHO) estimates results in 800,000 avoidable deaths a year [2], and many more stark statistics could be included here.

However, due to massive technological advancements in the last 20 years, we are now living in a society categorised by previously impossible to imagine levels of data collection. This is the second trend, and undoubtedly has both positive and negatives consequences, however in the last two years a new potential convergence of these trends has offered an exciting new domain.

High-Performance Medicine is proposed as the merging of artificial intelligence (AI) and medicine [3]. Resulting in a new ability to make use of innovative data to complement human decision making in hopes of saving lives. Mental health is just one sub-discipline that this new domain may offer potentially groundbreaking work. This thesis explores once such application within this area.

1.1 Depression and Anxiety

Some of the earliest discoveries of modern medicine date back to the time of Leonardo da Vinci, who dissected various parts of the human body and recorded the contents. Unfortunately, there is no part of the human anatomy as intrinsically complicated as the brain. Simply dissecting and viewing it provides very little information regarding its method or processes. As a result, the field of psychiatry has long struggled with classifying behaviour as normal or abnormal, and what constitutes normal functioning and disorders of the brain. To provide some consensus between the research community and front line practice the Diagnostic and Statistical Manual of Mental Disorders (DSM) which was first published in the mid 20th century, and has positioned itself as a standardised summary of the large body of research work in the field. Almost every healthcare service in the western world subscribes to the classification and symptomology contained within the DSM. It provides a standardised understanding of behavioural symptoms across countries and cultures.

The most prevalent DSM disorder is major depressive disorder¹, with a lifetime prevalence rate between 15% and 17% of the population worldwide [4]. The WHO estimates 300 million people a year will suffer a depressive episode lasting a minimum

¹Hereafter referred to as simply depression.

of two weeks, making depression the largest cause of disability worldwide [5]. On a macro level, the disorder is characterised by a persistent period of low mood. More specifically however, the DSM requires either the presence of either persistent low mood or anhedonia to be impacting the functioning of an individual for at least two weeks before a positive diagnosis can be made.

Generalized anxiety disorder² is the second most prevalent mental disorder worldwide, with a lifetime prevalent rate around 5% of the population [6]. The disorder is characterised by either excessive anxiety or worries about life events, often manifesting in physical symptoms such as irritability, muscle tension or sleep disturbance [7].

As discussed in the related work (Section 3) of this thesis, there is a current reliance on psychometric questionnaires for initial screening of these disorders. These questionnaires suffer from limitations such as socially desirable responding, misunderstanding and are often time consuming to complete. Recent work from the machine learning research community has looked at alternative methods to screen disorders using predictive analysis on various different data modalities [8, 9, 10].

The patient health questionnaire (PHQ) is a short form psychometric screening questionnaire, as explained in more detail in Section 2, this is our chosen output of the psychometric classifier we develop.

1.2 Dialogue Systems

Dialogue systems³ are end-to-end technological systems designed to interact with users via text and they have seen successful application across various areas in the medical community over the last number of years [11, 12, 13]. These systems offer a range of advantages to the medical community, besides the ability to work in parallel with hundreds or thousands of patients at a single time, they have a low development and implement cost [14]. Additionally, they offer a high level of recording for clinical governance [15, 16].

Despite the potential advantages, a range of problem currently exists which limit the widespread implementation of these systems. For automatically generated dialogue content, content which is written by a data-driven algorithm as opposite to handwritten by a human, ensuring a bedside manner or awareness of empathy is vital for safe human-computer interaction [17, 18]. A limited, but growing amount of work over the last two years has approached this nontrivial problem of developing data-driven models of empathy, which is a key requirement if these systems will ever see widespread use.

Within the mental health domain specifically, dialogue systems are already seeing widespread implementation [13], both for screening and treatment of disorders [3]. As an example, one charity in the United States (US) has processed over 109 billion text messages from US adolescents in the last six years alone and already experiments with automated data-driven replies.

Despite the limitations mentioned above, the demand for mental health support is

²Hereafter referred to as simply anxiety.

³Commonly known as chatbots.

increasing and non-profit organisations often must implement automated services without full assurance that these systems are ready for real life interactions [19, 20].

1.3 Research Challenges

To refine the above areas, the research challenges we explore is how textual data can be used to predict psychometric questionnaire scores for depression and anxiety. The aim is that by using predictive analysis, we can overcome some existing limitations with the administration of these questionnaires. We do this by employing a dialogue system as a data collection method. However, to achieve this we must explore how empathy can be incorporated into these systems. Based on our literature review in Section 3, these systems have been demonstrated to remove social desirability and thus allow for more honest responding to personal questions.

1.4 Hypotheses

We propose two hypotheses for study within this thesis.

- H_1 – That PHQ-4 scores can be predicted from textual data using psycholinguistic features and share a significant agreement with manually completing the same questionnaire.
- H_2 – That encoding emotional values into dialogue training can provide a more empathic aware system as measured by user performance.

1.5 Evaluation

We propose the following approach to evaluate Hypothesis 1. We recruited participants from the public domain who had a short conversation with our proposed empathic dialogue system. Their input into the conversations were analysed and PHQ-4 values predicted using our prediction model. Participants manually complete a PHQ-4 questionnaire, and limit of agreement tests were used to examine if predicted values are similar to self-reported values.

To evaluate Hypothesis 2, we randomly allocated recruited participants to have conversations with one of two dialogue systems. One system contains the empathic module described later in this text, while the other does not. We use self-reported evaluation questions adapted from [18] to measure if participants felt one system was more empathic than the other. These questions can be found in Table 4.5.

1.6 Sections Levels

The contents of this thesis are laid out in five sections, following the introduction, Section 2 lays out technical knowledge in both the psychology and dialogue system domains required to fully understand the problem space. Section 3, provides a literature review of the previous work in certain areas related to this thesis and

identification of the literature gaps we propose exploring. Section 4 which follows explains the process we employed to test our hypotheses, with the results presented in Section 5. The last section provides an overview of the whole thesis and identification of limitations and future work.

2

Background

Given the nature of a cross disciplinary thesis, in this section we provide an overview to various areas we have incorporated into the project. This should allow the reader to better understand the literature review in Section 3, and our contributions to the field outlined in sections 4 and 5.

2.1 Anxiety and Depression

The fields of psychiatry and psychology concern themselves with understanding how normal human behaviour can develop into aberrant or abnormal behaviour. A range of theories have been proposed to explain how the disorders of depression and anxiety can develop in a healthy human individual. The most prominent theory is Beck's cognitive model of depression [21]. The theory is based on the psychological concept of automatic thoughts, these are thought processes within our subconscious mind we are not explicitly aware of. We can generally classify these thought processes as either positive or negative. An example of a negative automatic thought might be a husband reacting with the thought "She does not respect me" when his wife did not respond to him. Beck and subsequent authors demonstrate that a variety of these thoughts processes are latent in varying degrees in all individuals [21, 22, 23].

The transition from latent state to an active state is often the result of the occurrence of a stressful life event [24]. In the case of a negative thought process becoming active, the situation is known as a *negative cognitive shift*. The result of this activation is that individuals begin to unconsciously filter out positive thoughts and focus on negative ones [21]. This results in the manifestation of the DSM-V symptom of "depressed mood most of the day, nearly every day".

Beck proposed that both anxiety and depression share the same negative cognitive shift. However, the trigger event in both disorders is different. In the case of anxiety, this event is often perceived by the individual to be a highly stressful life event, but objectively may not actually be. The automatic thought process here focuses more on the event itself such as catastrophizing, compared with depressed mood state where the focus is more on the long times negative outcomes of the event [21].

Over the early half of the 21st century, Beck's theory evolved into the *tripartite model of anxiety and depression* which was proposed by Clark and Weston [25]. As shown in Figure 2.1, this theory builds off the same concept that both disorders share a similar aetiology in the form of negative affect. However, they differ on the manifestation of this, either developing hyperarousal or anhedonia.

There is a duality reasoning as to why this understanding of the aetiology is im-

Figure 2.1: The tripartite theory: Negative affect is shared between depression and anxiety, whereas hyperarousal is unique to anxiety and anhedonia is unique to depression.

portant in the context of this thesis. Firstly, although depression and anxiety are listed as separate DSM-V disorders, clinicians will often investigate for both disorders simultaneously at the time of diagnosis. Establishing first if the negative affect is present and then which of the two unique aspects is present. Therefore, in the context of this work, it makes sense to approach the problem from a similar perspective. Secondly, an understanding of the aetiology is important to further understand why the DSM-V requires certain symptoms to be present for diagnose of depression or anxiety.

Of those existing applications of machine learning to the field of medicine, critics of these applications have argued that computer scientists and statisticians lack a true understanding of the medical aspects of the problem. Much of the existing published content comes from the perspective of a single domain, and therefore is often limited in its contributions to the overall field [3].

In Section 3 of this thesis, we will discuss a limitation of the existing work in this field with regards to how depression is always viewed as a binary occurrence. Although this makes sense from a statistical approach, it is rarely, if ever possible to fully categorise a person into such a narrow construct. Especially since many mental disorders are often considered to occur on a continuum. More recent work by the authors of [8] has looked at predicting depression on a symptomatic level instead, overcoming this limitation.

The most logical approach, in this case, is to focus on predicting the primary symptoms of each disorder. In a clinical setting, psychometric questionnaires are often employed as an initial screening tool in diagnosis. They are often short, standardised and allow for easy comparisons between patients.

2.2 Patient Health Questionnaire

A number of different questionnaires exist for depression and anxiety disorders, the most commonly employed type is the PHQ-4, which comes in a variety of different

forms depending on the disorder being investigated [26]. These questionnaires maintain both high sensitivity and specificity metrics, demonstrate high validity across languages and have been successfully administered across a broad range of medical settings [26]. All questionnaires are non-commercially licensed, meaning they can be easily employed in a variety of settings.

The 4-item version which was proposed in 2009 is designed as an ultra-brief screening scale for both depression and anxiety. Based on the DSM-V classification it assesses the severity over the last two weeks of the four key symptoms for anxiety and depression. Each question is matched to one of the following symptoms, anhedonia, depressed mood, excessive anxiety and uncontrollable worry [27]. The results of the questionnaire can be interpreted in three different ways. At a most basic level, the four questions can be viewed independently on a binary cut-off (symptom presence/absent). The presence of at least one symptom could identify a disorder. A more fine-grained view can be achieved by divide the questionnaire into two sections, composed of the two anxiety questions and the two depression questions. Combining the scores for each of the sections gives a value between 0 – 6. Finally combining all scores on the questionnaire gives an overall score between 0 – 12.

Despite their usefulness in many settings, psychometric questionnaires have a number of inherent limitations, one of which is social desirability impacting the honesty of responses [28]. Social desirability is the subconscious process of tailoring your behaviour in hopes of its becoming more socially acceptable [29]. In a patient-doctor setting, honesty of reporting is a vital requirement for a correct diagnosis, social desirability can result in individuals not providing full accounts to their doctors. Especially this is an issue in the case of taboo topics, such as drug use, suicide and safe sex practices [29, 30].

Therefore, there is a requirement to identify ways in which social desirability can be removed from the diagnosis setting. Recently, dialogue systems have been successfully applied in this domain [11, 13, 30]. This body of work demonstrates that individuals feel more comfortable discussing taboo issues when they are not required to do so in the physical presence of another individual. This can be achieved through telemedicine, wizard of oz style setups¹ or fully automated dialogue systems.

Considerable work has been published over the last ten years on the how technology can be applied to the discipline of clinical psychology, from prognosis and diagnosis [31] to automated counselling sessions, and to applications of therapeutic treatment through technology [32]. These systems are often highly scalable, low cost compared to a medical professional time commitment and available on instant demand [32]. Several national healthcare providers have already implemented various forms of these systems, and a growing number of private companies exist offering various products in this space.

Within the context of this work however, our focus is how technology can remove social desirability in the patient-doctor setting. The general trend in the field of dialogue systems has been to develop increasingly human-like systems, with the famous "Turing test" as the gold standard evaluation technique. However, the authors of [33] argue that in the context of reducing social desirability, the aim should not

¹Occurs when a participant interacts with a computer system that they believe to be autonomous, but is controlled by a unseen human being.

be to create system that are indistinguishable from humans. Rather, imperfection is required so people are always aware they are talking to a computer.

It has been further demonstrated that individuals react psychologically to dialogue systems, even when they know they are not human [33]. This leads to individuals being less fearful of self-disclosure and displaying more intense emotions in patient-computer conversations than would be expected. Despite the requirement that these systems maintain some characteristics of computer systems, authors of [8, 18, 33, 34] have all noted that these systems still need to maintain a certain level in empathy in all their interactions to fully be efficient in this space.

2.3 Empathy

Research on the construct of empathy originated from the field of medicine, generally in response to training new medical students [35]. The literature lacks a consistent definition. However, empathy is generally considered to be *"the ability to detect, understand and acknowledge the emotions of another individual without directly experiencing them in oneself"* [36]. Importantly, the literature consistently agrees that a key characteristic of empathy is a certain level of detachment from the emotions, which allows a clinician to maintain objectivity [36].

The importance of empathy throughout the entire medical process is repeatedly demonstrated [37, 38]. Higher levels of empathy have been shown to facilitate trust, improve disclosure and reduce anxiety between patients and doctors [36]. Many medical schools consider it vital to train students to be empathic [35]. Recent work from the field of neuropsychology has identified two biologically distinct empathic processes [39].

The primary or basic form of empathy is *affective empathy*, which consists of the ability to detect emotional states in others. A higher neurologically process is *cognitive empathy*, which is the ability to take the mental perspective of others, thus allowing inferences about their mental or emotional states [40]. A slightly alternative definition is provided by the authors of [41], where affective empathy is the ability "be sensitive to and vicariously experience the feelings of others", while cognitive empathy is "construct a working model of the emotional states of others".

Regardless, however, research has repeatably demonstrated a dual process by brain imaging and brain lesion studies in both animals and humans [42, 43]. In terms of psychopathology, it has been shown to manifest in psychiatric illnesses. Psychopaths and schizophrenics are characterised by deficits in the affective aspect, but not the cognitive aspect. While the reverse is true for autism, bipolar and borderline disorders [39, 44].

As we demonstrate in Section 3, much of the existing work from the field of natural language understanding has focused on affective empathy, examples of which include shared tasks where the object has been to detect certain emotional features from the text. However, very limited work has focused on cognitive empathy, where the aim is on the appropriate response in a given situation.

2.4 Passive Diagnosis

As the author of [3] state, "*Almost every type of clinician, ranging from specialty doctor to paramedic, will be using AI [artificial intelligence] technology, and in particular deep learning, in the future*". Even within the last five years, AI, machine learning and data science have become an increasingly common tool in the medical community. These tools have supported clinicians in fields such as radiology, cardiology, oncology and psychiatry [3]. This has prompted the food and drug administration in the US to begin the process of introducing legalization where machine learning systems are involved in medical admission or decision making [45].

The authors of [3] have proposed that this combination of medicine and AI falls under the term *High Performance Medicine*. The work undertaken as part of this thesis also falls generally within this domain, but more specifically within a category termed *Passive Diagnosis*, a term was coined by the authors of [8]. In comparison to the traditional concept of active diagnosis, where an individual suffering certain symptoms would actively seek out a medical diagnosis, this process can now be facilitated by adding a passive element. Unlike a medical professional who has limited time and resources, it is feasible to have machine learning algorithms constantly passively observe an individual's health. Once these algorithms detect certain changes in an individual's health that might be indicative of a disorder, the algorithm can inform the individual and an appropriate human professional for further investigation.

This concept has been applied across both a range of medical disorders and data modalities [9, 46, 47]. Each type of modality offers potential advantages and disadvantages to completing the goal of passive diagnosis. There is an often a trade-off required between the availability and validity of data. The concept explored with Hypothesis one of this thesis is related to the this area.

2.5 Dialogue Algorithms

The question of designing systems to engage in human-computer interaction has long been a topical issue within the field of natural language processing. Dialogue systems (or conversational agents) are automatic computer systems intended to be able to converse with humans [48]. They can employ various modalities such as text, speech, haptics or gestures. Depending on their end-use application, these systems can either be considered to be task-oriented, focused around allowing the user to complete a certain task or non task-oriented systems focused on general nonspecific conversations [49, 50]. Within the context of the thesis, our focus is on non-task-oriented systems.

The development of non-task-oriented systems often relies on one of two approaches, data-driven neural generative models or retrieval-based methods [50]. Both approaches must balance the generalisability of the trained model and conversational features such as fluency in responses and appropriateness. Retrieval based system employs a pipeline approach, beginning with some form of natural language understanding, an input is reduced to analysis its semantic meaning. This is then queried

Figure 2.2: A sample single layer network, with an input layer, single hidden layer, and output layer.

against a database of prewritten possible responses. The closest matching or most appropriate response is then returned to the user.

Since all responses in these systems are prewritten by a human, these systems maintain high fluency and appropriateness provided their database contain a sufficient number of possible situations. However, expect for large systems, the generalisability of these systems can be limited, and they have no ability to scale outside of their prewritten areas. In contrast, neural generative models overcome this limitation by employing a data-driven approach in generating their own answers to inputs.

2.5.1 Neural Generative Models

These approaches originate from the field of statistical machine translation and are viewed as an extension of the attempt to translate a source language into a different target language. These methods work by developing a language model (LM), which is a trained probability distribution that assigns a probability likelihood to the next word in textual data given context for a sequence of previous words (Equation 2.1). Initial work demonstrated that neural networks offer high accuracy scores when used to train these LMs. Specifically, *recurrent neural networks* (RNNs) are applicable given their ability to model sequential data.

$$P(w_t | \text{context}) \forall t \in V \quad (2.1)$$

Feedforward neural networks, of which RNNs are a specific implementation are layered matrices composed of neurons and layers. At a minimum, an input layer, hidden layer and output layer are always present. The number of neurons in the input layer is equal to the number of features in the dataset. Data passes into each neuron on the input layer, if the neuron allows, the data will pass to the subsequent neuron in the next layer in a forward moving fashion.

For each neuron in an feed forward neural network (FNNs), it takes an input value x which is then multiplied by a weight value w . If the neuron accepts multiple inputs, each input follows the same process. All combined inputs and weights are then added to a bias term b . The sum of this equation is then compared against a threshold level (activation function f), to determine if the new value passes into the next neuron in the feed.

$$f(x * w + b) \quad (2.2)$$

Figure 2.3: A simple recurrent neural networks model, with a single hidden layer (context layer), credit from the authors of [51].

As mentioned previously, RNNs are a specific implementation of these networks. The main difference is present at the input of each layer, where we see the input to a specific node (x) is the concatenation of the current input x at time t with the previous output of that node formed at time $t - 1$. Such that we update the neuron formula to match equation 2.3, or as is demonstrated in Figure 2.3 [51].

$$f([x_{t-1}, x_t] * w + b) \quad (2.3)$$

For both FNNs and RNNs, weights (w), bias (b) and activation thresholds (f) all need to be set using a supervised learning approach. For RNNs this is achieved using an algorithm known as *backpropagation through time*. A gradient-based method that unfolds a network backwards across time to calculate the parameters. In certain cases, this lead to the conceptual problem known as vanishing gradient, which occurs when across the chain rule the gradient becomes so small the update to the weights is minimal which can result in the model halting the training procedure [51].

2.5.2 Long Short Term Memory

The solution to this problem is achieved by incorporating a *Long Short Term Memory* (LSTM) approach into the network. The network architecture is modified in such a way that the vanishing gradient problem is avoided, while the actual algorithm is left unchanged. The changes occur within the individual neurons of the model. Within the neuron, three *gates* are added. Ordered in the following sequence, the gates are titled the *forgot gate*, *storage gate* and *output gate*. The three gates are present within each cell in a model. Where we previously considered an FNNs to be composed of neurons within layers, we now consider the model to be composed of cells which store multiple neuron within layers.

Figure 2.4: A LSTM cell with input, storage and forget gates together.

The forget gate is a normal neuron wrapped in a sigmoid activation layer. For each state in the cell, the output of the neuron is confined to the bounds of 0 to 1, where 0 indicates that the whole contents of the cell should be forgotten, and 1 that it should be completely kept.

$$\text{Forget Gate} = \sigma(w * [x_{t-1}, x_t] + b) \quad (2.4)$$

The storage gate, which is affected by the content of the forget gate is next in the sequence. This gate contains two separate neurons, firstly another sigmoid activation neuron is used to determine which content the storage gate will update. The equation matches that of the forget gate. Following this, a $\tanh$ layer creates a new vector which will become the new cell state. We then multiple the contents of the input gate by the new cell state to determine which aspects of the cell should be updated. The contents of the forget gate is also multiple by the old cell state to record the new level of information required. We combine these two states to create a new cell state such as demonstrated in equation 2.6.

$$\text{New empty cell state} / c_t = \tanh(w * [x_{t-1}, x_t] + b) \quad (2.5)$$

$$c_t = \text{forget gate} * c_{t-1} + \text{input gate} * c_t \quad (2.6)$$

Now that a new cell state has been stored in the cell, the output must be passed to the next cell in the network. The cell is first passed through a sigmoid layer to determine what parts should be passed forward, and then through a tanh layer which bounds all values to -1 to 1 [52].

To further ensure that extremely long sequences contain long term information dependency, two LSTM layers can be used in opposite directions (bidirectional LSTMs) [53]. As demonstrated in Figure 2.5, a bi-RNNs employs at least two hidden layers, each layer feeds information in the opposite direction. The content of the layers are also not shared between each other. As outlined in greater detail in [53], the training method employs both forward and backward passes over the data. This insures that at any given time, both future and past information can be viewed by a neuron to aid in its training.

Figure 2.5: A bidirectional RNNs with two hidden layers feeding in opposite directions. Image credit from [54].

Figure 2.6: A sequence to sequence model composed of four encoders and four decoders. Source; <https://github.com/farizrahman4u/seq2seq>

2.5.3 Sequence to Sequence Models

Given the above possible architecture, sequence to sequence (seq2seq) models are a specific implementation of these networks designed to model one set of data into another. The basis of a seq2seq model is that it contains a set of encoder modules and decoder modules. Each module contains an RNNs style neural network. The number of modules on the encoder and decoder size is fixed. As demonstrated in Figure 2.6, each module on the encoder side accepts two forms of input. An input x from the input content, and a hidden state value x_{t-1} . The output of this module is known as a context vector, and become the hidden state value for the next module in the sequence.

For seq2seq models that accept textual data as inputs, the data is first converted to the vector representation of that text. This is achieved by mapping words into a vector space model, which is a high dimensional space where words that share similar semantic meaning are "closer" together. The basis of this is the distributional hypothesis, that words that appear in a similar context share semantic meaning [55]. An embedding space is developed by creating a neural probabilistic language model. By developing a prediction model which employs linguistic and localization parameters to predict word location in multidimensional space [56, 57].

Unlike traditional FNNs, the size of the input vector x can be of arbitrary length.

In many cases it is set to equal the size of the vocabulary V [51]. However, in larger text corpuses V can be set larger for a more reasonable model to be trained. Therefore, to improve both the generalizability of the model, and the computational training time, data compression algorithms are often employed.

One such approach is byte pair encoding, which begin by dividing the text corpus into character level tokens, while appended each word with a end character "<w>" to ensure word segmentation is maintained. A number of iterations is chosen, and character are combined to represent the most commonly occurring tokens. For example, if A followed by B is the most commonly occurring pair of tokens, these are replaced by the single token AB . The final token vocabulary size is equal to the size of the initial vocabulary, plus the number of merge operation. [54]. This provides better prediction for open vocabularies by reducing the occurrence of rare words.

In addition to an RNNs in an encoder, each module has a *self attention layer* where information is processed before being passed into the next RNNs. A self-attention layer is a specific vector transformer designed to model dependency of a long vector into a short vector input. For example, if an encoder module accepts a single word as an input, the purpose of the self-attention layer is to model how that word is affected by all the other words in the sentence.

For each word embedding, this is achieved by creating three new values vectors. A query (Q_x), key (K_x) and value (V_x). The content of these three vectors is a linear projection of the embeddings coming into the RNN. A score value is calculated by taking the dot product of Q_x and K_x and softmaxing the outputted value. The resulting score is then multiplied by the V_x vector, and the resulting vector (new word score) are passed to the next RNN [58].

3

Related Work

In this section, we expand the background concepts explained in section two, and move forward by referencing the latest research in each area.

3.1 Machine Learning Application to Mental Disorders

The field of health informatics has a long history of developing statistical models to perform prognosis or diagnosis of medical disorders. In general, these models would employ features extracted from biological tests, such as biopsies results being used to predict cancer growth [59]. This approach has seen very little application to mental disorders, due to the fact that many mental disorders have an incomplete aetiology and normally reside at a both a behavioural and more fundamental biological level. Hence, recent research has looked at other areas to detect the manifestation of mental disorders. One such area is psycholinguistics.

3.1.1 Psycholinguistics

As far back the 18th century Sigmund Freud proposed that the way in which humans use language reflected aspects of their cognitive processes. Various work over the last thirty years has demonstrated how different cognitive aspects of mental illnesses can manifest in linguistic characteristics. The authors of [60] demonstrated that individuals diagnosed with depression, anxiety and suicidal ideation used a statistically significantly higher percentage of absolutist words. The authors propose this as a manifestation of absolutist thinking, a cognitive component of all three disorders. Similarity, the authors of [61] have shown that those diagnosed with social anxiety disorders have unique linguistic manifestations, notable a higher count of positive words when asked to speak in public.

The largest contribution to this field has been from the author Pennebaker, who has completed a range of studies to demonstrate that individuals diagnosed with depression alter their use of function words compared to non-depressed individuals. This is seen by higher use of singular and personal pronouns, and lower future temporal words [62, 63, 64]. Pennebaker and colleagues propose these are manifestations of Beck's cognitive theory of depression. Concretely, one aspect of Beck's theory is the social integration and disengagement model of suicide, a form of latent thought process. This model proposes that those considering suicide view themselves as

detached from social life, and not integrated into society. This is manifested linguistically by their higher use of singular and personal pronouns [64].

As an extension of this work, Pennebaker began the process of categorizing various words into psychological constructs. This began the differentiation between content and function words. Function words account for about 0.05% of the English vocabulary but makeup about 55% of words used in day to day life. It has been demonstrated that function words reflect how people are communicating, whereas content words convey what they are saying and both types of categories are processed differently in the brain [65]. Pennebaker proceeded to categorise various function words into psychological constructs. A total of 104 constructs were formed, with high annotator agreement between all chosen words and categories [66]. This work formed the basis of LIWC, a psycholinguistic dictionary, which assigns certain words to various psychological constructs [66].

Based on the premise of this work, the research community began investigating the possibility of analysing text to perform prognosis or diagnosis of various mental illnesses. Much of this work focused on depression, but also bipolar disorder [67], anorexia [68], and suicide as a standalone disorder [69, 70, 71, 72]. A considerable percentage of the work in this area has originated from the CLEF conference eRisk (Early Risk Prediction on the Internet) workshop, which is in its third consecutive year. The workshop is formed around a shared task, aimed at predicting the presence of certain mental disorders (depression, anorexia, self-harm) based on social media data. Almost 50 proceedings have been published related to this workshop over the last three years. Occasionally other standalone work is published such as that by the authors [9, 73, 74], but the majority of what we discuss going forward has origination from the eRisk workshop.

3.1.2 Data

Data in this area needs to be balanced between two considerations, the size of the data, and the validity of the annotations. Since almost all the publications employ supervised learning, the data requires some form of annotation. The outcome of these tasks is to predict if an individual is diagnosed with an disorder, the data must be annotated in such a way that it is possible to differentiate between people with the disorder and those without it. One possibility is performing some form of standard clinical diagnosis or screening, often completed through individuals filling out a psychometric screening questionnaire and selecting a cutoff score as indicative of a disorder. This is often time-consuming and can result in smaller sample sizes. Alternative approaches often employ data mining, either of social media sites [75] or online forums [9]. Generally, the only validation for labelling provided here is making the naive assumption that if an individual talks about certain topics, they are clinically suffering those disorders. For example, much of the eRisk workshop assumes that social media users who post on Reddit forums focused on depression are always depressed, but those who post on forums focused on dogs are not [10]. Although this allows for quantifiability large amount of data to be extract for use in training, the inferences that can be made from this are quite limited.

The majority of these datasets, notable those employed in the eRisk workshop [10]

and those extracted from twitter [9, 74] consider each individual as belonging to either a binary group, suffering the disorder or not. As the authors of [8] mention, this is a considerable limitation of the resulting work since mental disorders are almost always viewed on a spectrum and binary classification is often considered far to limiting [76].

3.1.3 Features

In order to incorporate psycholinguistics into prediction models, the LIWC is almost always employed as a feature extractor, in most cases, all 104 constructs are included [77, 78]. Occasionally feature selection or reduction will be employed before the training stage which can reduce the number of constructs in certain cases [79]. This collection of psycholinguistic features can be complemented by including additional linguistic measures. Notable features that are repeatedly included are reading scores [8, 78], part of speech tagging [80], occasions of drug word usage [81] and sentiment or valence measures [78].

This feature set is then often complemented by a form of text embedding, which is a general attempt at creating a numerical representation of the meaning of words and sentences. This is an active research area within the NLP community, and new state of the art methods are released on an increasingly regular basis. The earliest work in this area made use of unigram or bigram counting approaches [9], which can provide good accuracy despite suffering from the independence problem [82]. To overcome this, more recent approaches often make use of text embedding, which incorporates the distributional hypothesis. The idea that when analysing written text, words that are used and occur in the same contexts tend to have similar semantic meanings [83]. This led to several publications developing their embedding spaces specific to their own datasets, often by employing the Word2vec or Doc2vec algorithms [8, 84], which again improved accuracy scores [78]. The most recent publications have drawn on the latest state of the art methods which incorporate transfer learning. The demonstration that when models are trained on a large corpus and refined on a smaller domain-specific corpus, highest results can be achieved [85]. In this case, commonly used models include ELMO, BERT and the universal sentence encoder [76, 86, 87].

Many publications will consider the temporal aspect of these disorders in some form, which can either be achieved at an algorithm level or a feature extraction level. Work that makes use of specific data types often employs metadata as features, such as user profile scores, number of previous messages, comment replies etc. At an algorithmic level, time-series approaches have been employed [73].

3.1.4 Algorithms

Once a feature space has been created, various algorithmic approaches can be employed. The majority of these approaches employ unsupervised learning [77, 78]. With a limited number of approaches investigating supervised learning such as k-Means Clustering algorithm [88]. Supervised learning often ranges in complexity, from marketability simple models such as Naive Bayes and support vector machines

(SVM), to deep machine learning approaches. Logistic regression is a popular choice given that the output is easily interpretable [8, 79, 81, 89]. As per the general trend in machine learning, the most recent publications often make use of deep learning architecture [76, 78, 80]. These approaches trade-off interpretability and training time for better accuracy scores.

3.1.5 Evaluation

Within the context of the eRisk workshop specifically, the authors [10] propose a specific evaluation measure that balances accuracy of the prediction against the time taken to make the prediction, rewarding decisions made sooner and penalizing later decisions. This is often reported alongside more traditional evaluations metrics such as precision, recall, accuracy and F1-scores. Certain publications has also computed sensitivity and specificity metrics [8, 76].

3.2 Empathic Module

As mentioned previously, we can consider empathy as two separate constructs, *(i)* the ability to detect emotions in others and *(ii)* the ability to respond to others given knowledge of those emotions. Work in the retrieval field achieves this by hard-coding certain responses that were deemed to be empathic by human experts [11]. However, these systems have no ability to scale and are often time-consuming to develop. The interest, therefore, turns to if empathy could be integrated into neural generation models.

For the purpose of this thesis, we have identified five existing publications in this area to review [18, 34, 90, 91, 92]. There are three levels at which a neural generation approach can be adapted to incorporate empathy, *input, training level or output stages*. All these approaches attempt various different alternations to the input stage, with two publications altering the training level and only one the output.

In all cases, the authors attempt to incorporate some degree of emotional understanding within the input stage. This is achieved by one of our two approaches, hard-coded labelling or emotional embedding. The authors of [18, 91] use various methods to extract hard-coded labels, often choosing six or eight major emotional classes and annotating each input against a class. The embedding of these classes (often just a one-hot encoded vector) is concatenated against the embedding of the input sentence and fed into a standard training model.

An alternate approach attempts to employ more complex forms of embeddings. The authors of [34] make use of the DeepMoji framework, to creating a 64^2 embedding space composed of a specific emoticon for each label in the space. Again employing a concatenating approach onto the input sentence. Only the authors of [90] attempt to make adjustments to the training stage and output stage to account for the additional emotional vectors. They follow all other authors by concatenating the standard text embedding with a valence arousal dominance model (VAL) composed of the sum of all words in a pre-written VAL dictionary. The standard cross-entropy loss was adjusted to minimize VAL scores in term of Euclidean distance between the response and output.

4

Methods

To provide a cohesive overview of the thesis, the section first provides an overview to the development of the psycholinguistic classifier, followed by the development of the empathetic dialogue system and finally the combination of both systems into the experimental protocol.

4.1 Machine Learning Classifier

As per Hypothesis 1, this section aims to develop a machine learning classifier that given a text input, or sequence of text inputs can predict PHQ-4 scores. This involves predicting ordinal scores (0 – 3) for each of the four questions on the form.

PHQ-4				
Over the <u>last 2 weeks</u> , how often have you been bothered by the following problems? (Use “✓” to indicate your answer)	Not at all	Several days	More than half the days	Nearly every day
1. Feeling nervous, anxious or on edge	0	1	2	3
2. Not being able to stop or control worrying	0	1	2	3
3. Little interest or pleasure in doing things	0	1	2	3
4. Feeling down, depressed, or hopeless	0	1	2	3

Figure 4.1: Patient Health Questionnaire (PHQ-4), four item version.

4.1.1 Data

As mentioned in Section 3, there is an ongoing challenge between finding sufficiently sized and appropriately annotated datasets. For the purpose of this thesis, we were provided with permission to use the DAIC-WOZ dataset [47]. The dataset is composed of transcribed clinical interviews collected through a Wizard-of-Oz approach¹

¹Human talking to a computer program which is controlled in realtime by another human being

Wizard-of-Oz

Ellie Who's someone that's been a positive influence in your life?

Participant Uh my father.

Ellie Can you tell me about that?

Participant Yeah, he is a uh

Participant He's a very he's a man of few words

Participant And uh he's very calm

Participant Slow to anger

Participant And um very warm very loving man

Participant Responsible

Participant And uh he's a gentleman has a great sense of style and he's a great cook.

Ellie Uh huh

Ellie What are you most proud of in your life?

Figure 4.2: An extract of the DAIC-WOZ dataset, image credit from [47]

for 142 patients. For all interviews, the topics of the conversations were general nonspecific topics and all were collected within the United States.

In addition to the transcripts from each patient, PHQ-8 questionnaires were administered at the same time as the interviews and these results were provided. For the purpose of our task, we combined all statements across all patients into a single dataset, furthermore, all non-patient statements (from the Wizard-of-Oz system) were removed leaving a total of 23,726 text statements.

This dataset is the largest publicly available dataset that contains PHQ scores matched against text transcripts, based on the literature review in Section 3, we feel it is best to place emphasize on valid annotation compared to possible increased data sizes that could be found in social media data.

As hypothesis one states, the outcome of our prediction system is PHQ-4 scores. The PHQ-8 and PHQ-4 share two questions, thus we can directly select these from the data provided in the DAIC-WOZ dataset. However, two PHQ-4 scores are missing, these two questions and corresponding scores concern anxiety, and are commonly referred to as the GAD-2 questions ²

As outlined in Section 2.1, both anxiety and depression share the same fundamental aetiology only differentiating in the trigger activation of certain symptoms. With such a strongly defined comorbidity and underlying shared aetiology, we proposed investigating if GAD-2 scores could be predicted from answers to the PHQ-8 scale.

4.1.2 Predicting GAD-2 from the PHQ-8

To achieve this, we were provided with a dataset from [93] containing 1,307 PHQ-8 and GAD-2 scores from a national Swedish sample. The distribution of the scores within this sample matched previous population samples.

²GAD abbreviation stands for generalized anxiety disorder.

Table 4.1: Distribution of values for GAD 1 and GAD 2 questions within the dataset

	0	1	2	3
GAD 1	657	497	81	72
GAD 2	1,042	196	38	31

We approach this task as a classic prediction problem, given a set of PHQ-8 scores, predict GAD 1 and GAD 2 scores. PHQ and GAD are ordinally encoded, and therefore it makes sense to consider the values 0,1,2 and 3 as independent classes. Our first approach focused on multi-class algorithms, however as per Table 4.1 shows, there is an uneven class balance among both datasets. A range of approaches have been proposed within the literature to deal with uneven class balance specifically within psychometric datasets [94, 95]. For the purpose of this project, we decided to approach the problem as a three-step pipeline.

During exploratory data analysis, we observed that in 87% and 92% of cases, if all PHQ-4 values were equal to zero, both GAD scores were equal to zero as well. We considered this to be a sufficiently high accuracy score that we could re-code all GAD 1 and 2 scores as zero if the above case was present. This was the *first step* in our classification pipeline.

To balance the uneven class problem, we recorded the four classes as one of two classes. Either 0 or (1,2,3). This provides a more even distribution closer to a 50/50 split, (*step two*). In the situations where our classifier predicts the (1,2,3) score, an optional *third step* was applied to predict which of these classes (1 or 2, or 3) are appropriate. In total four classification models were required to be trained to complete these three steps across two questions.

Listing 4.1: Pseudo-code for prediction pipeline

```
# Complete for both GAD_1 and GAD_2
if sum(PHQ) == 0:
    GAD_1 = 0
else:
    #Binary model, possible outputs 0 or (1,2,3)
    pred = First_model.predict(PHQ)
    if pred == 0:
        GAD_1 = 0
    else:
        #Possible outputs 1, 2 or 3
        pred = Second_model.predict(PHQ)
        GAD_1 = pred
```

To match the above pipeline, we removed all cases where PHQ scores and GAD scores equal zero from the dataset. The resulting dataset was then recoded with all cases of 1,2 and 3 being relabeled as a single value. A second dataset was created of just those observations which had a score of 1, 2 or 3. Both datasets were divided into 80% cut for training, 10% for testing and a final 10% for evaluation.

For both datasets, we chose to employ a multi-layer perceptron classifier, hyperparameters were set using a grid search technique on the first of our classification problems. The following hyperparameters were set, $\alpha = 0.00001$, *number of hidden layers* = 11, *activation function* = relu, *learning rate* = constant. For each

Table 4.2: Features for each GAD classification problem, features are numbered PHQ-8 questions

Classifier	Features
GAD 1 / 0 or (1,2,3)	2, 3, 5, 6
GAD 1 / 1,2 or 3	4, 7, 8
GAD 2 / 0 or (1,2,3)	2,3,4,6,7
GAD 2 / 1,2 or 3	1, 7

Table 4.3: Accuracy results of each of the four classifiers.

	<div style="display: flex; justify-content: space-around; text-align: center;"> <div>GAD 1 / 0 or (1,2,3)</div> <div>GAD 1 / 1,2 or 3</div> <div>GAD 2 / 0 or (1,2,3)</div> <div>GAD 2 / 1,2 or 3</div> </div>			
Majority class baseline	0.63	0.77	0.73	0.66
Overall accuracy score	0.71	0.80	0.84	0.70
Class 1 accuracy score	0.70	0.95	0.93	0.98
Class 2 accuracy score	0.72	0.19	0.62	0.12
Class 3 accuracy score		0.38		0.15

classification problem, we optimized the feature selection by performing an exhaustive search for all combinations of eight input features and selecting the combination that returned the highest accuracy score.

The following combination of features was selected for each of the four classifiers (Table 4.2). Results of the four classifiers on the evaluation set are presented in Table 4.3.

This three step approach described above was then applied to the DAIC-WOZ dataset to predict GAD-2 scores for each participant in the study.

4.1.3 Feature development

Given the DAIC-WOZ text data, and matching PHQ-4 scores. The following subsections describes the feature processing completed on the data. We employed three distinct methods to create our feature space.

4.1.3.1 Text Embedding

Text embedding was employed using a pre-trained implementation of the universal sentence encoder (USE). The USE approach is designed for longer strings compared to other pretrained models which work on a single word or token level. A transformer architecture is applied to each string to model dependence across the length of the string and compute a context aware word representations. The authors of the paper release a pre-trained implementation trained on a large body of generic data strings

[96]³.

We chose to make use of USE for two reasons, firstly that the format of the DAIC-WOZ is mostly in single sentences. Our desire was to capture the whole semantic meaning of the utterances, and sentence level representing was felt preferable to combining single word level. Secondly, given the small nature of the DAIC-WOZ, using a pre-trained model allowed for better generalisability of the model to unseen new data. Each of the patient statements was passed into the pre-trained model and a statement-level representation vector of shape 512 was returned.

4.1.3.2 Psycholinguistics

To model psycholinguistic features we employed the LIWC library, which is a psycholinguistic dictionary containing 94 psychological trait dimensions and over 2,000 words related to these dimensions [63]. A percentage count of the number of words in the text related to each dimension is computed. To identify an optimal subset of the number of relevant dimensions, we reviewed all proceedings from the CLEF *eRisk* workshop 2017 and 2018. For each proceeding that employed LIWC, the list of dimensions included was taken. An intersection of these lists was then taken to create a subset of 22 relevant dimensions, which resulted in the following features being included in our model: *word count, analytical thinking, authentic, emotional tone, function words, pronoun, personal pronouns, 1st person singular, 1st person plural, 2nd person, 3rd person singular, articles, auxiliary verbs, conjunctions, negations, regular verbs, negative emotions, social words, cognitive processes, past focus, present focus, future focus*.

4.1.3.3 Psychometric similarity

Recent work has seen success in comparing word embeddings in terms of semantic similarity [97, 98], where the distance between embeddings in a x^N dimensional space is considered equal to their likeness in terms of the semantic content. Since USE creates sentence level embeddings and is trained on a large cross-domain corpus, it allows us the ability to compare sentences in terms of similarity. We employed this approach by comparing the semantic similarity of patient statements with responses from psychometric questionnaires. The principle was that if a patient statement reflected the same content of a psychometric test it should have a higher similarity score compared with a random statement.

Four questionnaires were identified by choosing cognitive theories relevant to the aetiology of each of the four PHQ-4 symptoms. Explanation of this is provided in Section 2 of this thesis, and in Table 4.4. The concatenation of questions across all four questionnaires amounted to 102 questions. For each patient statement, a 512 embedding dimension was computed with the USE pre-trained model, along with this, embeddings for each of the 102 patient questions were computed.

Distance between vectors in the embedding space was measured using *cosine similarity* (CS), where two vectors are compared from a single starting point in space in terms of angle. A CS of 0 indicates orthogonality of the two vectors, and

³The model was extracted from Tensorflow hub on the 10/04/2019 <https://tfhub.dev/google/universal-sentence-encoder/2>.

Figure 4.3: Demonstration of semantic similarity using a heat map. Sentence 1,2 and 3 are extracted from psychometric questionnaires. Sentence 4,5 are highly similar to these questions, while 6 is not.

Table 4.4: Summary of aetiology theories and assessment tools

PHQ-4 Symptom	Theory	Assessment tool
Feeling nervous or anxious	Intolerance of uncertainty [23]	Intolerance of Uncertainty Scale
Uncontrollable worry	Positive belief about worry [23]	Penn State Worry Questionnaire
Anhedonia	Avoidance behaviour [23]	Cognitive-Behavioural Avoidance Scale
Depressed mood	Negative triad [21]	Beck's depression inventory

therefore little relation between them. Figure 4.3 shows a heat map demonstration of CS scores across related and unrelated vectors.

4.1.3.4 Feature space

The resulting dataset was composed of 636 features. All features were scaled by removing the mean and scaling to unit variance within the bounds of -1 and 1.

4.1.4 Algorithm identification

As mentioned previously, the desired output of the prediction system is to be able to predict an ordinal value for each of the four separate symptoms on the PHQ-4. Previous work has demonstrated that a single deep neural network (DNN) can model the interconnectivity of a problem space better than separate individual classifiers [99].

For each patient statement, the neural network needs to be able to output an ordinal value score for each question. This requires that the network outputs both multi-label (four symptoms) and multilabel (ordinal score). This architecture is regarded as multi-dimensional or multi-targeted classification, where the output is assigned both a set of labels $y = (y_0, \dots, y_d)$, and for each label y an ordinal value in the range of 0 to d [100].

For the purpose of this work, we proposed a two-step approach. We begin by training a multilabel algorithm, the specific architecture of which is described in the following subsection. However, in order to ensure the model appropriately deals with multi-label classes, a *sigmoid cross-entropy loss function* is applied⁴. This is a modification of a normal cross-entropy loss function, as shown as in equation 4.2, where values are first passed through a sigmoid function (as per equation 4.1)

$$f(s_i) = \frac{1}{1 + e^{-s_i}} \quad (4.1)$$

$$\text{Cross-entropy} = - \sum_{i=1}^{C'=2} t_i \log(f(s_i)) = -t_1 \log(f(s_1)) - (1 - t_1) \log(1 - f(s_1)) \quad (4.2)$$

⁴Also known as binary cross-entropy loss.

where t = Ground truth
 s = Predicted score

The above set up is computed independently for each class c_i , furthermore, the problem is divided into x binary comparisons between all classes. The loss is summed up over the different binary problems, while the gradients are summed to backpropagate the whole process [80, 101, 102, 103].

The final output of the above algorithm is a sigmoid score for each of the four possible symptoms. We manually assign three threshold levels, to classify the output score in terms of ordinal values. The following threshold levels were employed; if the outcome of the *sigmoid* function is less than 0.25, an ordinal score of 1 is applied, if the *Sigmoid* score is between 0.25 and 0.50, 2 is applied, between 0.50 and 0.75 3 is applied, if the *Sigmoid* score is larger than 0.75 a score of 4 is applied.

To compare our approach against a simpler model architecture, and determine if a DNN architecture is appropriate, we also trained a random forest classifier which is equally able to model multi-label outputs [104].

4.1.5 Evolutionary tuning

Tuning possible hyperparameters (HPs) is a vital aspect for achieving a model that correctly fits the problem space. Given training time, and the number of possible unique HP combinations, its computationally inefficient to perform an exhaustive search [105]. Evolutionary tuning is a subfield of genetic programming. It provides a more optimized approach to finding a suitable set of HPs by employing concepts from evolutionary biology [106].

During the biological evolution of a complex organism, when an offspring is born, there is the possibility that the specific combination of genes that occurs can combine in a previously unseen way or unexpected way, this is known as a mutation. These can either be advantageous or not, depending on if the mutation increase the chance of survival for the being. Within computer science terms, a mutation is judged on its effectiveness by use of a chosen metric (known as a fitness function).

To apply this process to our problem, we began by choosing a broad set of possible HPs (details in appendix 2). A set of twenty neural networks were trained, each composed of a random subset of HPs. Each network is evaluated based on our fitness function, the minimization of the *Hamming loss* criteria [102]⁵. The five best performing networks are chosen, along with three random others from the remaining 15. This is to ensure a certain level of variability in the population in hopes of an advantageous mutation.

The fundamental architecture of the model we employ is a multilayer perceptron algorithm, composed of a minimum of one input layer (neurons = size of feature vector), one hidden layer, and a final output layer (neurons = 4). In all cases, the models were trained for 50 epochs. A dropout of 0.2 was applied to all hidden layers that were added. The following hyperparameter categories were then optimized:

⁵The Hamming loss is the fraction of labels that are incorrectly predicted. Given four label, an HL of .25% suggest one label is incorrect.

Figure 4.4: Average sigmoid cross entropy score for each generation across the training

the number of hidden layers, the number of neurons, the activation and optimizer functions.

We train eight generations of networks, generations are trained in a sequential order, and within each generation twenty different neural networks are trained each composed of different HPs. For the next generation in the sequence, we carry over seven existing networks as explained above. To create an additional 13 we select random combinations of hyperparameters from the seven first networks and combine these in 13 unique ways. Our aim is to find a mutation that is advantageous. All networks are trained and evaluated again, and the process repeated. A graph of sigmoid cross entropy value across generations is presented in Figure 4.4

The final optimal HPs, based on the minimized *Hamming loss*, were five hidden dense layers with dimensions of 1024, 768, 256, 128, 64 in that order. Each layer contained a *relu* activation function, except for the final layer, which contained *Sigmoid*. Binary cross-entropy was applied to compute the loss function and *adagrad* function as the optimizer.

The following HPs were employed for the random forest classifier (RFC), number of trees in the forest = 10, split criterion = gini, no max depth of trees, minimum samples to split a tree = 2, minimum leaf sample = 1.

4.2 Dialogue System

The following section provides an overview to our approach for Hypothesis 2.

As explored in Section 2.3, empathy can be broadly viewed "as the ability to recognize emotions in others and react appropriately". Representing emotions in language has long been a topic of interest to NLP researchers. As reviewed in Section 3.2, previous approaches include categorical labelling of emotions (Happy, Sad, Fear), embedding space vectorization of emotional labels, or sentiment embeddings. One limitation seen with the previous attempts to combine emotions with dialogue to

Figure 4.5: Sample annotation from the DeepMoji framework, showing the five highest probability emojis for a specific text input.

model empathy is the limited use of emotions in annotating the dialogue utterances. In most cases, a single one of Elkman major six emotions is used [91]. Firstly, this assumes that all human connections can be modelled in x number of emotions which has been shown to be false [107]. Secondly, this implies that each dialogue utterance can only represent a single emotion.

DeepMoji is an annotation framework that has seen growth in popularity over the last year [108]. The authors of this work use a novel method to extract a text corpus from twitter that contains emojis ⁶. Using a DNN approach, they developed a model that predicts (or annotate) text inputs with the probability that the input represents each of the 64 most popular emojis used on English speaking twitter. A sample annotation is provided in Figure 4.5 displaying the emojis with the five highest probability for a specific text input.

Within the context of our work, DeepMoji offers an interesting perspective on emotional labelling. Emojis are not direct labelling of human emotions [108], their use is considered to be more fluid and may adapt over time. Instead of a top-down labelling of the observed behaviour, bottom-up approaches were developed to match certain behavioural patterns [109]. As a result, the authors of [108] argue that by leaving them undefined, they provide a more realistic annotation of human feelings and emotions. However, certain work which has attempted to label them within Elkman emotions [109].

As per the definition mentioned above, we propose that "the ability to recognize emotions" will be handled by the DeepMoji framework. This means that for each user input, the framework will annotate the input with its predicted emojis (three most likely). To model the "react appropriately" aspect, we propose using a seq2seq data-driven approach. As discussed in Section 2.5.1, a standard seq2seq model can be used to generate dialogue utterances in a conversation. The question therefore concerns how to train this approach to "react appropriately" to emotions.

We propose achieving this by adapting the approach proposed by the authors in [110], originally designed to train multilingual, multiway neural machine translation models. When developing a model to translate a single language, the data and architecture is normally such that a source language is passed into an encoder model, and a target language is passed into a decoder model. Backpropagation through time is used to train both the encoder and decoder to appropriately predict this language. The multiway model is proposed to overcome the limitation of dealing with a smaller dataset that are common for low resourced languages. The approach begins by using a standard parallel aligned translation corpus with multiple languages within the same corpus. Each parallel alignment is predated with a source and target language

⁶Emojis which are a picture or an icon-based version of the text emoticons. They are standardised by the Unicode consortium internationally. Examples can be seen in appendix 1.

token as per Equation 4.3.

$$\underbrace{EN - > FR}_{\text{Source and target language tokens}} \quad \text{Hello world} \rightarrow \text{Bonjour Monde}$$

Where the left side of the arrow is the source dataset and the right side is the target dataset. (4.3)

Compared to a single language translation model, with one encoder and one decoder architecture, the multiway model has N encoders, M decoders and a shared attention mechanism. Both M and N are set by the number of source and target languages. For example, if the parallel corpus has four languages on the source side, four separate encoders are trained. Meaning that a single translation model is used for translating the source language to the multiple target languages.

M and N are set by the number of source and target languages. One encoder and one decoder exist for each source and target language. Meaning that a single encoder or decoder is shared for translating the language to multiple target languages. However, a single attention mechanism is employed across all encoder and decoder language pairs. The experiments completed by [110] demonstrate that this approach performs well for low resource language, since the approach captures both language-specific aspect and combines general language characteristics.

This architecture allows a general seq2seq model to specifically adapt to a given context. In the same way, a multiway seq2seq model would use the format shown in Equation 4.3, our proposal is that by replacing the source and target language tokens with source and target emoji annotations, we can direct the network to incorporate emotional context in the dialogue generation.

Practically this results in training N number of encoders, one for each emotional context in the source dataset and M decoders for each emotional context in the target dataset. While the shared attention layer is general for the whole dialogue dataset. To prevent a unreasonable number of encoder and decoders being trained, we propose methods to reduce the emotional contexts in Section 4.2.1.2.

We observed that the approach satisfies both the conditions of "*the ability to recognize emotions in others*" and "*react appropriately*". A visual representation of the data format is provided in Figure 4.6.

4.2.1 Data

4.2.1.1 OpenSubtitles

The OpenSubtitles dataset is an online collection of subtitles for major movies worldwide [111, 112]. The data is provided in an XML format, ordered by year and encoded with a timestamp and the tokenized subtitles text. We created an aligned dataset by assuming if a subtitle was spoken within one second of the previous subtitle they could be aligned for dialogue consistency, this approach has been seen before from the authors of [8]. We extracted all English subtitles from the corpus and in total generated 80 million parallel dialogue utterances. For the purpose of this work, we selected the first 10 million of these to continue to work with. OpenSubtitles

Figure 4.6: Visual representation of our empathic training approach. Emojis are represented by a single token of type *integer_integer_integer*

is the largest human-to-human non-domain specific freely available dataset. The advantage of the dataset is the size of the data and the wide domain range of the topics and vocabulary.

4.2.1.2 DeepMoji

For the purpose of this project, we made use of the pre-trained DeepMoji model released publicly by the authors of [108]. We passed the 10 million OpenSubtitle source and target sentences through the annotation model and returned the three most likely emojis as each input. Emojis are represented as a single integer of 0 to 63, for more details see appendix Figure A.1. These three emojis were concatenated to form a single token such that 63 63 63 would become "63_63_63".

Concatenating reduced the variability of the number of possible tokens and data sparsity. This was hoped to improve training by strengthening certain token utterances. Given more training data, we wouldn't have aimed to reduced data sparsity in this manner. Text input format was UTF-16 encoded.

To further reduce variability in the model, we apply a rare word encoding approach. We combine both source and target annotations and plot the distribution of all tokens (Figure 4.7). We selected the first 30,000 most occurring tokens, and relabeled all other tokens as an artificial rare word token "64_64_64". The number of relabeled tokens is less than the accumulative 30,000 tokens.

These tokens were appended to the training data after BPE had been applied to the text data.

4.2.2 Dialogue Language Model

To train our generative language model, we employed the *OpenNMT* framework [113]. Our training dataset was ten million dialogue pairs in the format shown as Figure 4.6. A byte pair encoding algorithm was applied to both the source and target textual data [54]. The resulting sentence source data was then predated with

Figure 4.7: Distribution of emoji tokens across both datasets

source and target emojis.

We applied a seq2seq model, with a bi-directional LSTM training algorithm of two hidden layers, 500 hidden bidirectional LSTM units, input feeding enabled, batch size of 64, 0.3 dropout probability and a dynamic learning rate decay. Our dataset was divided into an 80% training cut, 10% testing and 10% evaluation. The model was trained for 13 epochs, whereby the perplexity scores for each of the epochs are presented in Figure 4.8.

For the purpose of evaluation, a non-empathic dialogue system was designed using the same architecture and dataset, with the exception of the emoji tokens.

4.2.3 Implementation Pipeline

For the purpose of the public evaluation, an implementation pipeline was required which would allow the dialogue language model to be run in real-time. The pipeline begins with a user inputting text, which is annotated for emojis using the DeepMoji system ⁷ This provides us with the source text and source emojis. For the multiway model, we additionally require the target emojis to inform the system of how to direct the dialogue generation.

To achieve this, we trained a naive prediction system. For each source token in the annotated OpenSubtitles dataset (from Section 4.2.1.1) we select the highest probability target token shown in the dataset, such as per Equation 4.4. This provides us with a reference table of 30,000 source token and corresponding most probable target tokens. Unseen source tokens are assigned a unique value token of "64_64_64".

$$Source = \max(P(Target)) \quad (4.4)$$

Within the pipeline, a source token is looked up within the reference table and the most probable target token is selected. The source and target token, along with

⁷For the purpose of the project, the released model was merged with a Keras Rest API to allow inferences in real-time.

Figure 4.8: Perplexity score across training 13 epoch iteration

the source text are then all concatenated and interfered into the dialogue language model. This output is the target text and passed to the user.

To ensure dialogue consistently across the user conversation, each input to the model is a concatenation of the last two inputs plus the current one. Where input is the "Source Emoji token + Target Emoji token + Source text". This follows the work of the authors [8].

4.3 Evaluation system

To evaluate both hypotheses, a public-facing experimental system was required. Given the nature of the project, and current concerns regarding data protection, there was a requirement that the system was designed in house as opposed to using an external platform. The system was completely developed by the student of this thesis. For security reasons, it was launched on an institutional virtual machine server. The front end of the program was written in PHP and JavaScript, with a backend system written in python and PERL.

Participants were recruited by convenient sampling. Invitation to participate were distributed across institutional and international mailing lists. Participants were offered the possibility of entering a raffle for a prize in return for completing the study. The system maintained the anonymity of participants as per rectal 32 of the GDPR framework. Participants could complete the study from any location provided they had constant internet access. Once landing on the web page, they were provided with the study information sheet detailing aspects such as the pur-

Table 4.5: Questions to evaluate the empathetic module. All questions were answered on the same three level Likert scale (*Not at all, Somewhat so, Very much so*)

1. Did the responses from the system show understanding of your feeling /experiences?
2. Where the responses seem appropriate to the conversation? (Were they on topic)
3. Could you understand the responses? (Did the language seem accurate)
4. Did you feel trust toward the system?
5. Did you feel the system understood your emotions?
6. Did you feel the system had emotions?

pose of the experiment, requirements and rights of the participants and ethical and legal information. If participants choose to continue, they were provided with an eight form questionnaire to access eligibility. Inclusion criteria required that the participant were over the age of 18 years and could speak a working level of English. Failure to meet these criteria resulted in exclusion.

If a participant did not consent to anonymous data collection, they were offered the ability to talk to the dialogue system but no data was collected. If a participant met all criteria, they were randomly allocated to one of two trained dialogue systems. They were asked to have a short conversation (at least 20 messages) with these systems on any topic they wished. There was no counter system in place, so it was the requirement of the individual themselves to monitor this. A profanity filter was installed on the system to replace words deemed as inappropriate with asterisks.

On completion of the conversation, participants completed the PHQ-4, and four questions concerning the empathic aspect of the system (shown in Table 4.5). Participants were free to leave the study at any time, and were offered a participant distress protocol page if they did so. A full diagram of the experimental protocol is displayed in Figure 4.9. The system employed anonymous ID codes to ensure that all participants followed the same route, if a participant left and returned to the study it was considered a new participant. Screenshot of all pages displayed to the participants are presented in appendix 6.

4.4 Data Protection

Given the nature of the thesis, ethics and data protection were of central consideration at all stages. As the thesis work was completed while part of the Insight Centre for Data Analytics, whose parent institute is NUI Galway. The project was required to adhere to all ethical and data protection requirements of the university. According to Section 3(2) of the Irish Data Protection Act 2018 (Section 36(2) Health Research) Regulations 2018 ⁸, the work undertaken within this thesis is considered to be health research and therefore must adhere to the requirements of

⁸ This statute is an regional implementation of the European general data protection regulation 2016/679

Figure 4.9: Diagram of experimental protocol employed. Followed from a top down approach.

this statue [114].

The statue requires two formal submissions to be made, firstly a *Data Protection Impact Assessment (DPIA)* to both the research centre and university data protection officers and an ethics application to the university research ethics committee (REC). The DPIA is a formal submission concerning the collecting, storage and processing of data that take places within this project. The legal basis for processing data as part of this project were GDPR article 6 subsection 1(A) and article 9 subsection 2(i). The DPIA was approved by both officers by March 2019 following recommended feedback changes.

The ethics application is with specific regards to the human evaluation aspect of the thesis, the application concerns the process of recruitment, what participants will undergo as part of the experiments and the possible risks involved, as well as long term care and support. All participant recruitment material, information sheet, distress protocol and questionnaires were submitted for review. The ethics board approved the study on the 21/04/2019 and written confirmation can be seen in the appendix within Figure C.1. Participant information sheet can be found in appendix 5 and participant distress protocol in appendix 6.

5

Results

5.1 Multi-label Classifier Training

The following are results from the training of the machine learning classifier to predict PHQ-4 scores as described in Section 4.1. For this subsection, all evaluation comparison is on the DAIC-WOZ dataset. As per Section 4.1, the results presented here are calculated on a 20% held out evaluation dataset, which was distinct from the training and testing datasets.

5.1.1 Multi-label

Our first evaluation was performed on the multi-label aspect of the network. DAIC-WOZ PHQ-4 scores were reduced to a binary class (0 for 0, 1 for 1, 2, 3) and *Sigmoid* outputs were binarized on a cutoff point of 0.5. *Hamming loss* was the chosen metric for evaluation, which computes the distance between predicted and true values. A ten-fold cross-validation resulted in a score of 0.388, with a 95% confidence interval of [0.3870, 0.3905]. To compare this against a random baseline, where a set of prediction scores are computed using a random number generator, a *Hamming loss* of 0.49, 95% [0.481, 0.519], is achieved. Hamming loss is an inverse metric, and minimization of the score is desired.

5.1.2 Multidimensional

Using the cutoffs mentioned above in Section 4.1.4, *Sigmoid* scores were transformed into ordinal values. Since the *Hamming loss* is unsuited for this evaluation, a more suitable metric is the *Example Accuracy*. This metric is the same as a normal accuracy metric, but each vector of predictions is consider a singular value y and is either binary correct or incorrect [100]. The result across ten-fold cross-validation is 0.221, 95% [0.201, 0.243]. In comparison to ten-fold cross-validation of the RFC which resulted in a score of 0.087, 95% [0.086, 0.085].

$$EXAMPLE\ ACCURACY = \frac{1}{N} \sum_{i=1}^N I(\hat{y}^{(i)}, y^{(i)}) \quad (5.1)$$

where $\hat{y}$ = Ground truth
 y = Predicted score

Table 5.1: Clinical Metrics for the Evaluation Data

Threshold	Accuracy	Sensitivity	Specificity	LR+	LR-	PPV	NPV
PHQ-4	0.37	0.71 (595/831)	0.33 (2350/6999)	2.52	5.74	0.71	0.35
PHQ-2	0.47	0.57 (329/572)	0.48 (3480/7258)	1.35	2.25	0.57	0.47
GAD-2	0.40	0.71 (809/1126)	0.34 (2334/6704)	2.55	3.09	0.71	0.34

LR+ = positive likelihood ratio; LR- = negative likelihood ratio; PPV = positive predictive value; NPV = negative predictive value.

PHQ-4 = Sum of all questions. Above threshold of 6 considered a positive result.

PHQ-2 = Sum of first two questions. Above threshold of 3 considered a positive result.

GAD-2 = Sum of last two questions. Above threshold of 3 considered a positive result.

5.1.3 Clinical Metrics

Sensitivity values measure how sensitive the test is correctly predicting positive cases as actually being positive. Specificity values measure how efficient the test is at correctly predicting negative (not suffering the disorder) cases from those who actually don't suffer the disorder. Both tests are good indication of the real-life implications of true negatives and false negatives. Positive and negative likelihood ratios are indications of the value of performing a test. They assess if performing the test will significantly increase the probability of knowing if an actual disorder is present or not [115]. Furthermore, positive and negative predictive values score indicate if an individual with the disorder actually has the disorder given a positive or negative test result.

The above metrics are calculated for three different scores, the PHQ-4 which is the summary of the whole assessment tool. The PHQ-2 which is the specific aspect of the tool that measures depressive symptoms and the GAD-2 which is the aspect of the tool that measures anxiety symptoms. All results are presented in Table 5.1.

5.1.4 Limit of Agreement Tests

To evaluate the effectiveness of our prediction system against an individual completing the PHQ-4 manually, we employ the work of the authors [116] who propose that the limit of agreement test as a reliable method of evaluating a new clinical approach compared with an established existing approach. The author propose that in cases where there is no clinical gold standard evaluation¹, the most reliable method of evaluation for a new measure is an against an existing well established method. A new test would be considered "better" if it had the same prediction capabilities and overcomes some limitation or complication of the previous test. For example, if you were testing for a type of cancer with a invasive biopsy, and a new test that offered the same prediction capacity could be performed with only a smear this would be considered better overall. The limit of agreement test is proposed as a way of evaluating the difference in prediction capacity.

¹An absolute diagnosis of an disorder/disease as opposite to a screening or indication of a disorder that might be proposed after a psychometric test.

Table 5.2: Limit of Agreements Tests for Evaluation Data

Threshold	Bias ($\bar{d}$)	ULoA	LLoA
PHQ-4	-4.69 [-4.78,-4.59]	3.82 [3.66,3.99]	-13.21 [-13.37,-13.04]
PHQ-2	-2.14 [-2.19,-2.10]	1.79 [1.72,1.87]	-6.09 [-6.16,-6.01]
GAD-2	-2.54 [-2.60,-2.48]	2.70 [2.60,2.81]	-7.80 [-7.90,-7.70]

ULoA = upper limit of agreement; LLoA = lower limit of agreement.
 All confidence intervals presented at 95% level.

PHQ-4 = Sum of all questions. Above threshold of 6 considered a positive result.

PHQ-2 = Sum of first two questions. Above threshold of 3 considered a positive result.

GAD-2 = Sum of last two questions. Above threshold of 3 considered a positive result.

It assumes that if two tests had no difference in prediction capacity, they would predict the same scores for ever patient, regardless of which test was used. To asses this, predicted scores y are subtracted from true scores $\hat{y}$ to create a $\bar{d}$ score. Again, in an ideal situation all $\bar{d}$ scores would be zero. However this is practically rarely the case, therefore the question concerns how to quantify these differences. Equation 5.2 allows the calculation of upper and lower limits of agreements (ULoA & LLoA). These two scores provide an indication of what the upper and lower possible differences could present if using the new test.

Ideally ULoA & LLoA should be tightly bound, indicating using the new test would produce similar results to the old one. In the case of wide bounds, to much variability may be present. Scores for the training and evaluation data are presented in Figure 5.2.

$$\text{Upper and Lower Limits of Agreement} = \bar{d} \pm 2(s) \quad (5.2)$$

where s = Standard deviation of the $\bar{d}$ scores

5.2 Evaluation Participants

A total of 154 individuals participated in the experiment between the 22th of July and the 4th of August. Participants were recruited via a variety of means, including but not limited to the mailing-distribution lists, social media and networking. No demographic details were collected. On average, users assigned to the empathy condition sent 23 messages and had an average of six words per message, while those in the non-empathy condition sent 18 with an average of five words per message.

5.3 H_1 - Hypothesis One

The primary method of evaluation for H_1 consists of a limit of agreement tests as outlined in Section 5.1.4. The results of which are presented in Table 5.3. However, for the purpose of internal evaluation, additional metrics are reported in Table 5.4.

Table 5.3: H_1 Limit of Agreements Tests

Threshold	Bias (d)	ULoA	LLoA
PHQ-4	-4.94 [-5.55,-4.32]	2.65 [1.59,3.71]	-12.53 [-13.59,-11.47]
PHQ-2	-1.29 [-1.63,-0.95]	2.91 [2.32,3.50]	-5.50 [-6.09,-4.91]
GAD-2	-3.65 [-4.04,-3.25]	1.18 [0.50,1.85]	-8.47 [-9.15,-7.80]

ULoA = upper limit of agreement; LLoA = lower limit of agreement.

All confidence intervals presented at 95% level.

PHQ-4 = Sum of all questions. Above threshold of 6 considered a positive result.

PHQ-2 = Sum of first two questions. Above threshold of 3 considered a positive result.

GAD-2 = Sum of last two questions. Above threshold of 3 considered a positive result.

Table 5.4: H_1 Evaluation Metrics

Metric	Score
Hamming Loss	0.4526
Mean Squared Error	4.32
Example Accuracy	0.0718

Furthermore, relevant clinical metrics are presented in Table 5.5. Finally, individual question confusion matrices are included in Figure 5.1.

5.4 H_2 - Hypothesis Two

Hypothesis 2 is composed of six specific questions (see reference Table 4.5), each evaluated on a three-point ordinal scale. One way hypothesis (less then) testing was performed for each question using a *Asymptotic Linear-by-Linear Association Test* (LbL) [117, 118]. This test is derived from the family of Chi-squared X^2 tests. Given a question, it proves if there is a different distribution of responses across the three ordinal options for each of the two conditions users were placed in (empathy aware dialogue system, non-empathy aware dialogue system).

Table 5.5: H_1 Clinical Metrics

Threshold	Accuracy	Sensitivity	Specificity	LR+	LR-	PPV	NPV
PHQ-4	0.32	0.86 (24/28)	0.21 (26/125)	5.99	0.00	0.09	0.20
PHQ-2	0.71	0.09 (3/34)	0.89 (107/119)	0.10	0.01	0.09	0.90
GAD-2	0.26	0.77 (14/18)	0.19 (26/125)	3.50	0.00	0.77	0.19

LR+ = positive likelihood ratio; LR- = negative likelihood ratio; PPV = positive predictive value; NPV = negative predictive value.

PHQ-4 = Sum of all questions. Above threshold of 6 considered a positive result.

PHQ-2 = Sum of first two questions. Above threshold of 3 considered a positive result.

GAD-2 = Sum of last two questions. Above threshold of 3 considered a positive result.

Figure 5.1: Confusion Matrix for predicted and true scores for each of the four PHQ-4 questions

However, in contrast to a Chi-squared test, an LbL incorporates the ranking order of the ordinal variables as a feature in the model. The results of an LbL test for each of the six questions are presented in Table 5.6. z scores, along with p values are reported for each test. Only the results for the first question are statistically significant based on a cutoff value of < 0.05 , while the results of question five are approaching significant level. Question one maintains its significant level with a two-sided hypothesis testing as well. We additionally present effect size and power level, which quantify the size of the difference between the two groups. Furthermore, Figure 5.2 presents the breakdown scores of each question divided by the condition.

Figure 5.2: Responses for each of the six questions, grouped by assigned condition

Table 5.6: H_2 Linear-by-Linear Association Test. * = < 0.05 , Given a sample size = 154, $df = 5$, $\alpha = 0.05$, effect size = 0.3. We generate a power level of 0.83 and critical x^2 of 3.84

Question	z	p
1. Did the responses from the system show understanding of your feeling/experiences?	-2.153	0.015*
2. Where the responses seem appropriate to the conversation? (Were they on topic)	0.572	0.716
3. Could you understand the responses? (Did the language seem accurate)	0.386	0.650
4. Did you feel trust toward the system?	-0.674	0.249
5. Did you feel the system understood your emotions?	-1.627	0.051
6. Did you feel the system had emotions?	1.008	0.843

6

Conclusion

6.1 Overview

The content of this thesis crosses two domains, that of clinical psychology and natural language processing (with the use of applied machine learning). We begin by establishing that depression and anxiety are highly prevalent illnesses worldwide and the current approaches to screening individuals for these disorders suffer from a number of inherent limitations. One such limitation we propose to address is the reliance on individuals completing psychometric screening questionnaires.

Based on an existing body of work, we propose a hypothesis (H_1) that linguistic features in a text could be employed to predict how an individual would complete the PHQ-4 psychometric questionnaire. Going forward from this, we established that research has shown that social desirability can impact the honesty of responses in patient-doctor settings. Dialogue systems have been demonstrated as a potential approach to overcome this issue.

We further propose that the linguistic features mentioned above can be detected from a conversation with a dialogue system. However, to achieve this in a clinical setting. There is a requirement that these system be able to appropriately respond to individuals. In order to do so, a level of empathy is required to be demonstrated by the system.

Our work, therefore, begins by reviewing previous approaches that have been employed to achieve this. Given our interpretation of the literature, we propose the second hypothesis (H_2), that encoding emojis into a sequence-to-sequence neural approach will allow a dialogue system to be able to display better emotional understanding as evaluated by users in a randomized trial.

To develop the machine learning classifier, we began by employing the DIAC-WOZ as training data. The dataset contains chatlogs from interviews with volunteers, along with matched PHQ scores taken during the interview. Three types of features we extracted from this data, word embeddings, psycholinguistic scores, and psychometric similarity scores.

We employed a deep neural network architecture to predict PHQ-4 score in a multi-dimensional output form. The hyperparameters of the network were optimized with the use of an evolutionary algorithm. The results of the training stage of the model are presented in Section 5.1. Where we demonstrated that our model performed better than random baseline in all cases. Furthermore, our model outperformed a simpler random forest classifier which validated the use of a deep neural network versus a simpler more interpretable model.

Two dialogue systems were developed using bidirectional LSTMs on sentence aligned datasets (OpenSubtitles). One of these systems has no specific approach to model empathy, however, the other system predates each training sequence with emojis tokens from both the source and target text sequence.

To evaluate both hypotheses, a public-facing experiment was launched. This experiment was approved by the university ethics committee and had an approved data protection impact assessment completed. 154 participants were recruited across a two week period. These participants were asked to have a short conversation with one of the two dialogue systems (random allocation). Following this, participants completed six Likert scale questions on how they felt the system modelled their emotions.

At the same time, participants were asked to complete the PHQ-4 psychometric questionnaire. Chatlogs from the conversation were stored and analysed using our prediction algorithm trained above. The predicted PHQ-4 scores were then compared against manually completed PHQ-4 scores using a limit of agreement tests.

6.2 Ethical Discussion

The fundamental question raised in this thesis concerns if predictive analytics can be achieved for a mental health disorder through extracting linguistic features. This question raises a range of ethical concerns and considerations. Public perception of predictive health analytics varies greatly across stakeholders, within the United Kingdoms survey reports estimate that 63% of adult are uncomfortable with allowing AI systems replacing doctors and nurses in tasks they usually perform [119]. However, up to 83% of medical students agree that AI systems will positively improve their workplace [120]. The final stakeholder group, state decision makers and healthcare organisations report confident that it will improve medicine, but roughly half of them think it will produce fatal errors, will not work properly, and will not meet currently hyped expectations [120].

Noting this disintegration, it is clear that greater consideration from all stakeholder need to be achieved. The authors of [121] propose a number of questions that can be asked to better achieve consensus. Firstly, a clinician must identify an area that has a substantial need for improvement, and which machine learning in medicine (MLm) can reasonably be applied to. This is not always as simple as it would appear, at a minimum, there is generally a requirement that some form of theoretical concept would explain why a given set of data would allow predictive qualities of a disorder [8].

Secondly, the authors of [121, 122] propose that the risk associated with the predictive system is ethical given the underlying risk of not using the system. A number of inherent potential risks should always be considered when using MLm systems. Firstly, it has been repeatedly demonstrated in the literature that ML methods are poor at generalizing outside of trained data [76]. Within this thesis, our training data from the DIAC-WOZ was collected from a sample size within the United States, it is therefore reasonable to assume that the linguistic pattern our model considers important may be heavily influenced by this limited sample size. We have no way of knowing if our system would perform equally well for English speakers who have

learnt outside of the colloquial language pattern of the area.

Furthermore, this could disproportionately bias certain types of predictions for certain groups of people. We do not have demographic variables for the participants who supplied our training data. However, a core facet of medical profession is equal treatment to all groups of people. Simply ignoring demographic variables in our training data does not necessarily create an unbiased model, but rather we should be aware of limitations in our training data and consider manually adjusting this to ensure a fair and accurate system that is neutral to concepts such as gender, age, race, income etc.

Within the context of our this thesis, we consider that bias is a key area to be addressed if this research continue forwards. Effort would need to be made to ensure the training data matches the population it will applied to in terms of linguistic patterns, but also, that reasonable effort has been made to ensure fairness across different personal traits were appropriate.

Secondly, a disadvantage of ML algorithms is often their propensity to a "black box" nature. Where by, a medical professional could reasonably explain to a patient how given their symptoms they have reached a certain conclusion. With deep learning models, it is both technically hard to explain to a patient how certain feature effect the probability of an outcome, but also it is sometimes computationally impossible to explain how these features interact within a algorithm. Although an increasing effort has been made in recent years to better develop computational methods that can allow for understanding of the processing occurring within these algorithms [123].

This has led to an ongoing disintegration between the latest version of the European data protection regulations and current deep learning approaches. The GDPR framework considers *interpretability of decision making* to be a core principle of the framework. This is directly at odds if there is an inability for any of these methods to provide interpretive results. This issue is not limited to MLm, but relevant in any application where deep learning is involved in automated decision making [124]. Finally, the issue of informed consent becomes relevant in these situations. In a medical setting, informed consent of medical treatment has always been a core and required aspect of clinical and research practice [125]. Many medical practices require consent regardless, it would be quite hard to take blood from someone without their knowledge. However, the nature of predictive health from linguistic pattern is considerably more subtle. Individuals may not be aware their written or verbal communication is being processed in this manner, since it's doesn't effect them. Within a professional medical setting, it would be unethical to perform any such process without the informed consent of a patient.

However, private companies do not need to uphold to such ethical standards. Indications have already emerged that certain companies have began to experiment with predictive or inferential analysis of health information from linguistic pattern. Examples include the social media giant Facebook [126]. The GDPR framework prevents private companies performing this type data analysts without consent, but other legal jurisdictions such as the United States and Asia do not have this level of legal framework [126].

The questions proposed above from the authors of [121] are a important starting

ground for any work in this area. Given our interpretation above, it is clear that this work is far from being ethically implemented in practice. Despite this, there is still little legal requirement for these types of system to meet any ethical standards. Although this is likely to change as the public and law maker knowledge of these systems increases.

Within both the context of a student master thesis, and of applied data science. It is clear that work in this field has core ethical considerations. Which may influence how future data scientists are trained, and how research institutes that previously haven't had to consider ethics adapt and support this.

6.3 Research Questions Discussion

Initial results presented in Section 5.1 demonstrate that the approach we employed in training our machine learning classifier outperformed random baseline allocation by 0.11 when measured using the Hamming loss criteria. Furthermore, our model outperformed a trained random forest approach by 0.14 when evaluated using an accuracy score. This demonstrates that although there was a trade-off in the interpretability by employing a multilayered architecture, in this case, our proposed approach was better able to model the interconnectivity of the multidimensional data.

In addition to simply interpreting the predictive ability of the model, additional metrics from the clinical domain can be employed to examine the implications of these results in practical settings. Within the literature, PHQ-4 scores are generally interpreted in three ways. Firstly, the combination of all four questions can be combined and the resulting value can be divided on a threshold level of <6 or ≥ 6 . Secondly, the first two questions on the PHQ-4 are designed to assess the primary symptoms of anxiety, and represent the GAD-2 questionnaire. Therefore, we can consider the sum of these questions to be able to be cut on a threshold of <3 or ≥ 3 . Finally, the same applies to the last two questions on the PHQ-4, which represent the PHQ-2 questionnaire. We use these three scales, either in a binary or ordinal form to evaluate the model.

When we evaluate the model on the evaluation data from the DAIC-WOZ, we see reasonable sensitivity scores, but poor specificity indicating over prediction of the disorder. For the evaluation of the experimental data (Table 5.4), the same results are seen with the expectation of the PHQ-2. Which has a very low sensitivity and very high specificity score. Based on the confusion matrix plots seen in Figure 5.1 this is likely due to the model almost exclusively predicting a score of 3 for all participants.

For the evaluation data, in all cases, our positive likelihood ratio (LR+) scores indicate that there is a slight to medium effectiveness in performing the test in order to detect a positive result. However, these scores are quite poor for LR- when the outcome of the test is negative. This is linked to the poor specificity scores we mentioned early. LR+ are notably higher for the experimental data, which is a positive sign, however, it is counteracted by extremely low LR-. Indicating the test is likely of no use in predicting a negative outcome.

For the evaluation data, PPV and NPV scores are as reasonable as to be expected

given the previously mentioned scores. However, for the experimental data, PPV scores are very low for the PHQ-4 and PHQ-2 indicating a low likelihood of predicting a positive scores, however, given higher sensitivity scores for the PHQ-4 this is not an issue, and we have already mentioned the noted issue with the PHQ-2. Results for the GAD-2 and NPV scores are as to be expected given the previously reported results.

Our main method of evaluation of H_1 was employed using a limit of agreement tests. The results are presented in Table 5.3 and compared with the evaluation data in Table 5.2. In this case, our focus is mostly on the bias ($\bar{d}$) score, which indicates the difference between the predicted score and the actual score. For all cases, our target is the minimization of this score.

For the evaluation data, all $\bar{d}$ scores are high, indicating a high difference between what the model predicts and ground truth. With the expectation of the PHQ-2, all these scores are similar for the experimental data. This indicates that the model is consistent in its performance on evaluation and unseen data. The PHQ-2 would appear to perform better, with a tighter limit bound and smaller bias term. As mentioned previously, it is subjective as to what is an acceptable bias term and limit bound. However, scores for the PHQ-4 and GAD-2 are high, indicating on that on average a predicted value is 5 points different for the PHQ-4 and 4 points different for the GAD-2.

Figure 5.1 shows the confusion matrices for each of the four questions on the PHQ-4. We see here that in most cases the model predicts scores of either 0 or 3 for each question, indicating quite poor performance. For the purpose of a screening test, we consider both of these scores as being too high. Therefore, for predicting PHQ-4 and GAD-2 scores, we accept the first Null Hypothesis. However, the bias term for the PHQ-2 is only 1. We consider this a reasonable score for the prediction model. Hence, we reject the null Hypothesis for this question.

To evaluate the effectiveness of our empathy approach, we employed six Likert style questions. The difference between how users answered these questions was assessed using a linear-by-linear association test. Only in the case of the first question did the two conditions (empathy, non-empathy) significantly differ in their answering. Question five approaches a significant level. The results seen from question one indicate that our empathic approach displayed a better understanding of feelings and experiences compared with the non-empathic condition.

Given that the five other questions did not differ, we can establish that although the approach made some significant improvement compared to the baseline, there is still a considerable space for improvement. Its important to note however that question five (if you felt the system understood your emotions) was approaching significant with a one-way test. This is an important consideration, given that a key feature of empathy is to be able to give an individual the idea that you are recognizing their emotions. Given the above results, we can reject one of six sub Null Hypothesis for H_2 .

6.4 Considerations and Future Work

In reflection on this work, we note two limitations and a challenge. The first of which; is that it has been repeatedly demonstrated in the NLP literature that different domain or styles of text can affect the generalizability of a model. We propose that the relatively poor performance of our classification model on the experimental data was due to the limited amount of information that could be extracted from the chatlogs. Our training data from the DIAC-WOZ had an average of 168 messages per user, while our experimental data had 18 messages per user.

While considering the importance of volunteers time, a higher threshold for the number of messages that we required participants to talk to our system should have been set. Furthermore, although we do not rule out using dialogue systems for this approach, we propose that the amount of information that needs to be conveyed within these conversations is higher than initially thought.

The second limitation is with regards to the experimental design. A limited period of internal user testing before the experiment was launched resulted in an issue occurring while it was open to the public. Participants who completed the experiment on a mobile device could not move forward through the whole experiment. The program would not allow them to pass the dialogue system stage. This resulted in roughly an additional 80 volunteers attempting to take part in the study but not being able to. If this issue had been fixed, a higher sample size could have been achieved. This limitation shows the importance of user testing.

As the fields of applied data science and medicine converge more, new questions and considerations need to come to the forefront. The work presented here has both practical and theoretical ethical considerations. A considerable amount of time within the project was spent on submitting an ethical application to the university board. This is one of the first times the board would have received a study of this nature, and considerations need to be made for how these types of study differ to classical medical work, and how best to assess them. On a theoretical level, considerations need to be made for the long term implication of this work. Although this work was done in a good faith, and with an aim to improve the lives of people, there is a knowledge that it could be potentially used to screen and harm people in the future.

Given the above limitations and challenges, we examine our overall contribution to the literature. To begin with, our work demonstrates an ability to develop deep learning models to predict PHQ-4 scores given textual data using psycholinguistics features. Compared with previous work in the area [10, 75] machine learning can be used to model outputs that are easily interpretable by both machine learning and medicine domain experts. Our work is the first to propose that psychometric similarity scores might be a useful feature within this domain going forward. Additional work going forward needs to examine how to improve the generalizability of this work to allow it be applied across different domains.

Regarding our second Hypothesis, our contribution to the literature is firstly, that emoji tokens are better representations of emotions compared to annotations of Ekman emotional categories. Secondly, we demonstrate that predefining each dialogue utterance with both source and target emotions is efficient in improving empathy

appearance. We propose that future work in this area would investigate how the diversity of emojis is related to performance. Not ignoring that considerable work is still required on developing neural generative models that can hold a reasonable conversation.

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A

Appendix 1 - DeepMoji

The following is an conversion from integer to emoji form for the DeepMoji framework.

Figure A.1: Emoji representation in integer form

B

Appendix 2 - Pool of Hyperparameters

Pool of hyperparameters which were employed in the training our PHQ-4 prediction system.

- **Neurons:** 64, 128, 256, 512, 768, 1024
- **Layers:** 1,2,3,4
- **Activation functions:** relu, elu, tanh, sigmoid
- **Optimizer** rmsprop, adam, sgd, adagrad, adadelata, adamax, nadam

C

Appendix 3 - Institutional Ethics Committee Approval

NUIG Research Ethics Committee Decision Report

REC Application Reference Number: 19-Mar-03

Title: Passive prediction of mental health disorders

Principle Investigator: Mihael Arcan

Application Type: NEW

Meeting Date: 12 March 2019

28 March 2019

Dear Mihael,

I write to you regarding the above proposal which was submitted for Ethical review. Having reviewed your response to my letter, I am pleased to inform you that your proposal has been granted **APPROVAL**.

All NUI Galway Research Ethic Committee approval is given subject to the Principal Investigator submitting annual and final statements of compliance. The first statement is due on or before 27 March 2020.

See annual and final statement of compliance forms below. Section 7 of the REC's Standard Operating Procedures gives further details, and also outlines other instances where you are required to report to the REC.

Yours sincerely

Kevin Davison

Chair, Research Ethics Committee

Figure C.1: Approved ethics application from the NUI Galway institutional ethics committee.

D

Appendix 4 - Participant Information Sheet

1. Introduction

Passive prediction is a new method of diagnosing mental health disorders. It is based on the concept that the way in which people talk and write can be analysed to extract certain information. In this study, we have designed a chatbot that has a normal conversation with a person. During the conversation we monitor certain aspect of the written text and use machine learning methods to predict the possible presence of depression and anxiety. The first aim of the study is to test if our machine learning methods are effective. The second aim of the study is to test if the chatbot is an effective way to interact with people.

2. Invitation to take part in the study

You are being invited to take part in the study to help us test our aims mentioned above. Before you decide, it is important for you to understand why the research is being done and what it will involve. This Participant Information Sheet will tell you about the purpose, risks and benefits of this research study. If you agree to take part, we will ask you to complete a consent form which is on the next page. If there is anything that you are not clear about, we will be happy to explain it to you. Please take as much time as you need to read it. You should only consent to participate in this research study when you feel that you understand what is being asked of you, and you have had enough time to think about your decision.

3. Purpose of the study

This study is firstly looking to test if our machine learning method is as effective in diagnosing depression and anxiety symptoms as standard questionnaires. Secondly, to test if chatbots are a suitable means to apply these machine learning modules. Anyone over 18 years of age, who can speak English can take part in this study.

4. Taking part - What it involves Do I have to take part?

It is up to you to decide whether to take part. If you do decide to take part, you will be asked to sign a consent form. If you decide to take part you are still free to withdraw at any time and without giving a reason. A decision to withdraw at any time, or a decision not to take part, will not affect your rights in any way.

What will happen to me if I take part?

Step 1) You will be asked to complete a consent form and data protection form.

Step 2) You will be asked to complete a short conversation with our chatbot about any topic you wish. We would like you to hold the conversation for at least 20

messages, but you can leave at any time.

Step 3) You'll be asked to fill out 8 short questions. Your conversation with the chatbot, and your answers to the questionnaire is completely anonymous.

How long will this take?

We estimate no more than 10 minutes of your time, but you are free to leave at any point.

What are the benefits of taking part?

Depression and anxiety have two of the highest illness prevalence in the world, diagnosing people with these illnesses is very hard for a range of reasons. Our system aims to solve some of reasons, and hopefully help people suffering these illnesses. By taking part in this study, you in turn will help us help people. You will also have a chance to talk to a state-of-the-art artificial intelligence system.

What are the possible disadvantages and risks of taking part? While talking to our chatbot, it there is a very small chance it might say something you are not happy with. Our chatbot learns from the behaviour and language of people who talk to it, it may on occasion use language and produce apparent meaning that some consider unsuitable or inappropriate. We have done our best to train the chatbot to be nice, however during the experiment we have no control over it. If you feel uncomfortable for any reason at any point, you are free to leave. We will also recommend support services for you if you feel the need to talk to someone further. In the second half of the study we ask questions about your feelings. You might find, while you are answering it, that you would like to talk to someone about some of the issues it raises. We will be happy to recommend someone to talk to you further. You are free to skip any questions you'd rather not answer.

What happens at the end of the study?

On completion of the study you will be thanked for your participation.

Voluntary participation

Your participation in this study is voluntary, you can stop and leave at any time without any penalty. Please click the "Exit study" button to do this.

Will I receive any information after my participation?

Due to the nature of this study, you will not receive any results on the outcome of your participation in this study.

4. Confidentially and your data rights

By taking part in this study on passive prediction of mental health disorders, we request permission to process certain aspects of your data. As part of NUI Galway data protection policy, this study has completed an approved data protection impact statement.

In the consent form that follows this information sheet, we will ask your permission to collect and store the following data as part of our study. This data is anonymous (As per recital 26 of the GDPR), meaning we will not be able to identify any individual based on the data submitted. If you consent, we will store and process

the following data;

- Your answer to the consent statements.
- The text inputs you provide to the chatbot.
- The answers you provide on the final questionnaire.

No additional data is recorded or stored in any way. This data will be stored for six months on NUI Galway servers. We request you do not provide the chatbot with any personal information that might be used to identify you (Name, address etc). Any indication of this will be deleted after the experiment. If you choose not to allow us collect and store this data, you will still be free to participate in the experiment, but your data will be deleted once you exit the study.

If you consent to us storing your data, you will be further asked to consent for us to process your data as follows;

- The text inputs you provided will be analysed using machine learning models. These models will predict patient health questionnaires scores based on linguistic features provided in the text.
- We will use several statistical agreement tests to compare the answers you provided on the questionnaire with the predictions from the machine learning models. This allows us to evaluate the effectiveness of these models.
-

Below are additional details on the data protection aspects of this study;

6. Your data protection rights under Irish law

The Insight Centre for Data Analytics (a Research Preforming Organisation) is a research centre within NUI Galway. You are receiving this document because Insight may hold personal information about you and as such there are rights attached to this information of which you should be aware. Depending upon the activities that Insight is performing (e.g. research, pre-trial, clinical trial, participation or attendance at events and conferences etc.) the information which Insight holds and / or process may contain personal data about you. You have rights which ensure that the information that Insight processes relating to you is factually correct, available to those authorised to access it and used for the purpose(s) stated. The list below sets out your rights as a Data Subject and they relate to the personal and/or sensitive data which Insight may process in the following formats: manual forms or documents, electronic data, photographs, video and recordings of your image or voice.

- Right to have your details used in line with data protection regulations.
- Right to information about your personal details.
- Right to access your personal details.
- Right to know if your personal details are being held.
- Right to change or remove your details.
- Right to prevent use of your personal details.
- Right to remove your details from direct marketing list.
- Right to object to the processing of your own personal data.
- Right to freedom from automated decision making.
- Right to refuse direct marketing calls or mail.

To request a copy of your own personal data please fill out the university form at the link below: <https://www.nuigalway.ie/data-protection/accessandrectificationrequests/>

In order to enable the university to process your request efficiently, please provide any details which will help us to identify you and locate your data. Please be clear about the details you are looking for if you are looking for very specific information. If you make a data access request, the university will respond within 30 days from receipt of the request. If you only want to enquire if the university holds personal data, we will respond to your request within 21 days from receipt of the request. In order to avoid unnecessary delays or confusion please be clear in your instruction that it is an enquiry and not an access request. It should be noted that under the Freedom of Information Act 1997 and 2003 records containing personal information may be released to a third party, where the public interest so requires. If you have a complaint regarding the way in which your personal data has been handled by Insight, please contact the University's data protection officer on the details below. You also have the right to make a complaint to Irish Data Protection Commissioner who can be contacted at the address below:

7. Funding for this study

This study has been funded by Science Foundation Ireland under grant number Insight (SFI/12/RC/2289). The funding body has no role in this study.

8. Summary

Thank you for reading and considering taking part in this study.

If you have any questions or concerns, or would like to know more about the study you are welcome to contact the principal investigator Email: Mihael.arcan@insight-centre.org

Relation to the data controller: Employee

Postal Address; UNLP unit, Insight Centre for Data Analytics, NUI Galway, IDA Business Park, Galway, Ireland If you have any concerns about this study and wish to contact someone independent and in confidence, you may contact 'the Chairperson of the NUI Galway Research Ethics Committee, Email: ethics@nuigalway.ie

you have any concerns about the data processing aspects of this study and wish to contact someone independent and in confidence, you may contact NUI Galway data protection officer, Email: Dataprotection@nuigalway.ie

E

Appendix 5 - Participant Distress Protocol

You have successfully left the NUI Galway study on “Passive prediction of mental health disorders”. We apologize for any distress this study may have caused you. We thank you for trying the study and supporting the scientific community. If you feel the need to talk to someone about the issues that were raised in the study, or you feel the need for any level of emotional support, we encourage you to make contact with one of the following national support services:

Service	Phone (From within ROI)	Email
Samaritans (24 hours support)	116 123	Jo@Samaritans.ie
Aware (10am to 10pm)	1800 80 48 48	Supportmail@aware.ie
Pieta House 24/7 Suicide Helpline	1800 247 247	

F

Appendix 6 - Experimental System

The following are screenshots from the whole experimental system.

F. Appendix 6 - Experimental System

Figure F.1: Landing page

Figure F.2: Participant information page

Participant Consent Declaration
For the study in passive prediction of mental health disorders

Please reference the patient information sheet [here](#)

You can click the "consequences of my choice" button to see how each statement will impact your participation

I understand I will be talking to a chatbot that is not controlled or monitored by a human being, and that responses may be incoherent and unfriendly at times.	☐ Yes	☐ No
Consequences of my choice		
I confirm I am over 18 years of age.	☐ Yes	☐ No
Consequences of my choice		
I confirm I can speak English to a working professional standard.	☐ Yes	☐ No
Consequences of my choice		
I confirm that I have read the information sheet for this study and have had the opportunity to ask questions.	☐ Yes	☐ No
Consequences of my choice		
I am satisfied that I understand the information provided and have had enough time to consider the information.	☐ Yes	☐ No
Consequences of my choice		
I understand that my participation is voluntary and that I am free to withdraw at any time, without giving any reason, without my legal rights being affected.	☐ Yes	☐ No
Consequences of my choice		
I agree to take part in the above study.	☐ Yes	☐ No
Consequences of my choice		
I agree that my conversation with the chatbot and answers to the questionnaires may be collected and stored by NUI Galway as was outlined in the study information sheet.	☐ Yes	☐ No
Consequences of my choice		
I agree that my conversation with the chatbot and answers to the questionnaires may be processed by NUI Galway as was outlined in the participants information sheet.	☐ Yes	☐ No
Consequences of my choice		

To begin the study, talk to the dialog system click below.

[Next](#)

Figure F.3: Consent declaration page

Instructions

The following are instructions to complete the task:

1. On the next page you will have a short conversation with our chatbot, you are welcome to talk about any topic you wish.
2. Please try and hold the conversation for at least 20 messages, you will need to count this yourself
3. On the following page you will be asked to fill out some short questions about your mental health and your experience talking to the chatbot

[Next page](#)

Figure F.4: Instructions reminder page

Figure F.5: Dialogue system

Questions

Not secure | vmunip19.data-scienceinstitute.ie/8025/study/Questionnaire.php?id=av396oamC5Dof5Sapmut3dq3b

Apps | Order | MyE Editor | The Python Graph... | The Insight Centre f... | Departmental proje... | Your Repositories | NiceR Plots | Use Jupyter noteb... | bash - Conda env a... | How do I use scree... | Data Visualization... | Other bookmarks

Insight

Questionnaires

Exit Study

Please complete the following two questionnaires as honestly and openly as possible.

Questionnaire 1

Over the last 2 weeks how often have you been bothered by the following problems?

	Not at all	Several days	More than half the days	Nearly every day
Feeling nervous, anxious or on edge	☐	☐	☐	☐
Not being able to stop or control worrying	☐	☐	☐	☐
Little interest or pleasure in doing things	☐	☐	☐	☐
Feeling down, depressed, or hopeless	☐	☐	☐	☐

Questionnaire 2

During the conversation you just had with the chatbot system.

	Not at all	Somewhat so	Very much
Did the responses from the system show understanding of your feelings/experiences?	☐	☐	☐
Did the responses seem appropriate to the conversation? (Were they on topic)	☐	☐	☐
Could you understand the responses? (Did the language seem accurate)	☐	☐	☐
Did you feel trust toward the system?	☐	☐	☐
Did you feel the system understood your emotions?	☐	☐	☐
Did you feel the system had emotions itself?	☐	☐	☐

Next

Figure F.6: PHQ and empathy questionnaire

Figure F.7: Finish page