

Towards Knowledge-based Mining of Mental Disorder Patterns from Textual Data

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ABSTRACT

Mental health disorders may cause severe consequences on all the countries' economies and health. For example, the impacts of the COVID-19 pandemic, such as isolation and travel ban, can make us feel depressed. Identifying early signs of mental health disorders is vital. For example, depression may increase an individual's risk of suicide. The state-of-the-art research in identifying mental disorder patterns from textual data, uses hand-labelled training sets, especially when a domain expert's knowledge is required to analyse various symptoms. This task could be time-consuming and expensive. To address this challenge, in this paper, we study and analyse the various clinical and non-clinical approaches to identifying mental health disorders. We leverage the domain knowledge and expertise in cognitive science to build a domain-specific Knowledge Base (KB) for the mental health disorder concepts and patterns. We present a weaker form of supervision by facilitating the generating of training data from a domain-specific Knowledge Base (KB). We adopt a typical scenario for analysing social media to identify major depressive disorder symptoms from the textual content generated by social users. We use this scenario to evaluate how our knowledge-based approach significantly improves the quality of results.

KEYWORDS

Cognitive Science, Knowledge Base, Machine learning; Business Process Analytics

1 INTRODUCTION

We begin this Section with an overview of the research problem and challenges in identifying and understanding mental health disorder patterns from textual data. We present our contributions and discuss how the proposed method may facilitate acquiring insight into the mental status of individuals who may be suffering from mental disorders in general and depression in particular. Finally, we present the structure of this paper.

1.1 Overview and Research Problem

The mental health of individuals and communities is a pressing challenge in the world, nowadays. Since COVID-19¹ pandemic outbreak in 2019, most governments have been preoccupied with handling and combating the epidemic. The prevalence of the Covid-19 has been significantly controlled and lowered as a result of the global success in vaccine development and mass inoculation. But now, for most governments, a key concern is harnessing and dealing with the impacts of years of virus exposure, including the associated psychological and economic problems. COVID-19 has impacted our lifestyles and workplaces. These changes can cause us to feel frustrated, stressed, and anxious, which may seriously affect our mental health. Based on a recent study, after being diagnosed with Covid, roughly one out of every five people develops a mental disorder^{198, 201}. Hence, governments are trying to guide families and business owners to deal with these devastating effects and improve the situation. On the other hand, as businesses reopen, it is important for organisations to provide a mentally healthy workplace².

¹<https://en.wikipedia.org/wiki/COVID-19>

²<https://covid19.swa.gov.au/collection/covid-19-resource-kit>

Prior to any support, mental disorders need to be diagnosed. On the other hand, due to their complexity, identifying mental disorder symptoms (e.g., depression symptoms) and their patterns could be a challenging task. Hence, it is necessary to identify mental health issues accurately and facilitate their treatment. As a critical mental health issue, depression is one of the leading causes of disability worldwide. It plays an essential role in the overall global disease burden^{69, 124} and could turn into a drastic health condition ³. Depression is a leading cause of disability, with 5% of adults and 5.7% of 60-year-old and above people suffering from it. Data from the United States and Australia show elevated rates of depression and anxiety throughout the epidemic. It is estimated that during the outbreak, depression level (i.e., 25%) is seven times higher than pre-pandemic levels worldwide (i.e., less than 4%)⁴. Consequently, due to its importance, we focus on depression identification in this research.

There are various clinical and non-clinical approaches available to identify depression symptoms. Using questionnaires and interviews are two main clinical approaches for depression identification. On the other hand, analysing medical data (e.g., EEG and fMRI images) and vocal, video, and textual data are different approaches to identifying and predicting depression. In addition, there are very few recent studies that proposed knowledge-based approaches to identify behavioural and mental disorders such as depression.

To extend the state-of-the-art in this line of work, in this paper, we propose a domain-specific Knowledge Base (KB) to organise complex structured and unstructured clinical knowledge about symptoms, risk factors and supportive symptoms that are effective in identifying mental disorders. We introduce a pipeline that leverages the KB knowledge to facilitate the identification of mental disorder patterns in textual data. We evaluate our approach with a dataset, generated from social media activities, and highlight how the proposed framework can help analysts in the e-Safety⁵ community to gain insight into the mental status of potential individuals suffering from depression-related symptoms.

1.2 Contributions

The state-of-the-art research in identifying mental disorder patterns from textual data, uses hand-labelled training sets, especially when a domain expert's knowledge is required to analyse various symptoms. This task could be time-consuming and expensive. In this paper, we present a weaker form of supervision by facilitating the generating of training data from a domain-specific Knowledge Base (KB). The knowledge in the KB is gathered from both cognitive and psychological sciences as well as previous best practices in the field. This KB contains a set of concepts organised into a taxonomy, instances for each concept, and relationships among them. The KB then will be used for developing a weakly supervised¹⁶⁶ classifier for mental disorder identification. We propose a method to link the concepts and instances in the KB to the features extracted from textual data.

We discuss a motivating scenario in which leveraging a domain specific KB for depressive patterns could enable e-safety community to monitor the trend for the emergence of depression-related symptoms, during special periods of time such as the Covid-19 period. This paper makes the following contributions:

- We leverage the domain knowledge and expertise in cognitive science to build a domain-specific Knowledge Base (KB) for the mental health disorder concepts and patterns. This KB contains a set of concepts organised into a taxonomy, instances for each concept, and relationships among them.
- We present a weakly supervised learning approach by facilitating the generating of training data from a domain-specific Knowledge Base (KB).

³<https://www.who.int/news-room/fact-sheets/detail/depression>

⁴<https://www.forbes.com/sites/debgordon/2021/05/28/mental-health-got-worse-during-covid-19-especially-for-women-new-survey-shows/>

⁵<https://www.esafety.gov.au/>

- We adopt a typical scenario for analysing social media to identify major depressive disorder symptoms from the textual content generated by social users. We use this scenario to evaluate how our knowledge-based approach significantly improves the quality of results.

2 BACKGROUND AND STATE-OF-THE-ART

The fundamental part of each scientific research is to study previous related works. In this Section, we review the literature with respect to our research problem, namely mental disorder identification, focusing on depression, a mental health condition marked by a consistently depressed mood or a loss of interest in things, resulting in severe impairment in everyday life.

There are numerous studies each address this problem from a different point of views. In this Section, we study and analyse the recent work in mental disorders and cognitive analytics. We discuss Cognitive science and cognitive analytics and the way they are connected to mental disorders. In addition, some cognition-related mental disorders such as depression are explained from a psychological and cognitive analytics perspective. Finally, we study and analyse the related work in clinical and non-clinical approaches for identifying depression symptoms.

2.1 Mental Disorders and Cognitive Analytics

Mental health issues are proved to play a significant role in reaching worldwide developmental objectives. Mental disorders have risen notably during the past decades. They caused severe consequences on the economy and health of all the countries¹⁵⁴. Mental disorders have a significant role in every aspect of people's life. It affects the way people behave, act and work, while having a significant influence on people's physical health and their personal and social relationships. Mental health issues have drastically affected most countries. For example, nearly one-half of Australian adults, including 7.3 million individuals, would experience mental-related matters at some point in life. These issues cause Australia's economy an approximate cost of up to 220 billion dollars yearly.

Mental health issues could negatively impact anyone at any life-stage as well as people around them¹⁵⁰. There are several factors such as genetic, drug and alcohol abuse, early life circumstances, trauma, stress and personality factors contributing to mental disorders⁶. In addition, a recent study found that the recent global pandemic (i.e., Covid-19) has caused nearly one in every five patients to develop a mental disorder, after being diagnosed with Covid. Also, those with previous mental conditions are 65% percent more likely to be diagnosed with Covid-19, even when other risk factors are considered²⁰¹. Despite extremely varied Covid-19 prevalence and fatality levels, research from the United States and Australia demonstrate heightened rates of depression and anxiety throughout the epidemic. The approximated level of depression in the outbreak (i.e., 25%) is seven times greater than the ratio before it worldwide (i.e., less than 4 percent)⁹⁰. Hence, the importance of addressing mental health and facilitating their treatment has become much more prominent.

Mental disorders could be classified into several categories, such as 'Anxiety Disorders', 'Depressive Disorders', 'Neurocognitive Disorders', 'Paraphilic Disorders' and 'Bipolar and Related Disorders'. Each of these categories consists of different instances of that category. For example, some cases of depressive disorders are 'Premenstrual Dysphoric Disorder', 'Disruptive Mood Dysregulation Disorder', 'Premenstrual Dysphoric Disorder' and 'Substance/Medication-Induced Depressive Disorder' and 'Major Depressive Disorder (MDD)'. Throughout this study, mainly, we refer to MDD as depression. Also, the category of 'Anxiety Disorders' contains some instances such as 'panic disorder', 'social anxiety disorder', 'agoraphobia' and 'generalized anxiety disorder'.

Mental disorders are originated from psychological processes impairment. Psychological processes consist of cognitive processes (i.e., the main factor), Individual experiences, behavioural, social and biological factors¹¹⁶. a key element that contributes to mental disorders such as 'Bipolar and Related Disorder', 'Sleep Disorders' and 'Depres-

⁶<https://www.healthdirect.gov.au/mental-illness>

sive disorders' is cognitive processing changes that remarkably affect the individual's capacity to function.^{72, 98}. Cognitive Science, referring to the scientific study of mind and brain^{81, 143}, is mainly related to understanding the nature of cognitive processes such as problem-solving, language, perception, reasoning, attention and motor control²¹⁰.

More acceptable recognition of the relationships between cognitive processing and mental disorders is necessary for treatment interventions¹⁴⁹. On the other hand, one of the main advantages of data science and machine learning (ML) techniques are finding various relationships among variables. Hence, using data analytics and cognitive analytics helps researchers see the relationships between different variables related to cognitive processing and mental disorders. Consequently, developing ML models for identifying mental and behavioural disorders patterns would be enabled²⁰.

Cognitive analytics means data processing aiming at understanding varied, intricate, heterogeneous and qualitative data⁹⁹. It could be considered as doing analytics, originating from a human-like intelligence. Cognitive analytics refers to the advanced approaches integrating the cognitive science knowledge (e.g., the logic behind human decision-making, thought patterns and cognitive processes) with data analytics techniques (e.g., ML and artificial intelligence and other technologies related to data science)⁹⁹.

Cognitive analytics could help with recognising the natural human language and interactions¹⁵⁷, through analysing both structured and unstructured data⁹⁹ such as text, conversations, email, social posts, images and video data. It also allows cognitive applications to improve continuously, while could be used to help companies understand the emerging trends and behavioural patterns of their customers. Hence, they would be able to predict the probable future consequences and plan ahead for their objectives¹⁶⁸.

There are several studies related to applications of data and cognitive analysis in identifying and predicting mental and behavioural disorders^{69, 131, 170}. Cyberbullying¹⁶⁹, radicalisation, and suicidal-related behaviours are examples of such applications. Social media is a valuable source of data for analytical purposes, making preventing and intervening actions in such disorders possible³⁰. In the following sections, these three applications are briefly explained. In addition, depression and anxiety are briefly described as two major mental disorders associated with cognitive impairments^{5, 51}.

2.1.1 Cyberbullying

Cyberbullying is known as an online bullying matter. It is a kind of antisocial behaviour that may include aggression and intentional power abuse in a cyber environment (e.g., social media or internet-based platforms), leading to detrimental social, mental and psychological effects. Sending inappropriate online messages and comments with adverse content could be indicative of cyberbullying actions¹⁷⁰. Cyberbullying gained considerable attention from researchers and governments because of the negative psychological issues and problems that arise from it²²⁴.

The brain could be influenced by cyberbullying in various ways depending on the age, and gender¹⁹⁰. Cyberbullying appeared to be more and more common among adolescents⁷. In adolescence, there are significant changes that may happen in the brain's developmental processes, which consequently cause substantial changes in adolescents' behaviour, cognition and emotion⁴⁰. Hence, they could be more vulnerable in terms of being affected by adverse events and experiences (e.g., cyberbullying behaviours), which in turn cause them various emotional, mental and behavioural problems¹³⁴. Changes in mental health status, and decision-making processes, and self and emotional regulations are all examples of changes that could happen during adolescence. Cyberbullies have poor brain execu-

⁷<https://en.wikipedia.org/wiki/Cyberbullying>

tive functions, low empathy and social cognition. Cyberbully victims are prone to suffering from mental disorders, specially suicide attempts^{134, 190}. Brain executive function refers to the capacity for controlling and coordinating thoughts and behaviour. Also, social cognition capacity encompasses self-awareness and the ability to understand other people's minds⁴⁰.

Kinds of words (e.g., self-focused words, hate speech, positive or negative emotion, death-related, anger), sentence sentiments and natural language that are used in the daily communications are reflections of individuals' real-life manners, thoughts, cognitive processes, behaviours, and mental health status^{6, 69, 87, 184, 186, 203, 208}. As the studies show, Cyberbullies tend to use a high rate of profane and vulgar words, which is demonstrated in their cyberbully activities in an internet-based environment such as social media^{170, 202}. Social media, as a virtual daily communication platform, is proved to be a rich source of different types of data, especially textual data. Social media enables researchers and data scientists analyse cognitive and behavioural processes and patterns related to the social media users⁶⁹. As an example application of data science in finding cognitive and mental-related patterns, Rezvani et al., Proposed a Cyberbullying detection pipeline for social media data (i.e., Twitter and Instagram). It benefits from several data analytics techniques such as 'Natural Language Processing (NLP)', 'Neural Networks (NN)', and 'Long short-term memory (LSTM)'¹⁷⁰. Through their pipeline, different types of textual and contextual features, image-related features and metadata features are extracted with the aim of developing a cyberbullying identification model¹⁹⁷.

Textual features include Parts of speech, named entities and sentiment analysis, etc. In this cyberbullying pipeline, TF-IDF and NLP methods are used to extract textual features. Besides, image-related features (i.e., labels for images of social media posts) and metadata are extracted. Metadata features mainly refer to behavioural information of the corresponding social media user. Metadata features that are related to social media include 'Number of followers', 'Number of followees', 'Number of likes', 'Popular categories', 'Average reactions', 'Average replies', 'Frequent mentions'. They also used Google standard profanity word list aiming at enriching the feature extraction process. Finally, they built an LSTM classifier along with Neural Network for context2vec embeddings that combine features to recognise probable useful features¹. Their proposed model had notable evaluation results for both Twitter and Instagram data. Twitter data analysis illustrated 0.85 accuracy, 0.87 Precision, 0.83 Recall, and 0.85 F-score. Similarly, the results of Instagram data analysis showed 0.86 accuracy, 0.87 Precision, 0.83 Recall, and 0.85 F-score. All these results are indicative of promising results originated from cognitive and data analytics in identifying mental and behavioural disorders.

2.1.2 Radicalization

Radicalization is known to be the mechanism of alteration in individuals' cognitive processing, beliefs, emotions and consequently their behaviours. These changes lead to legitimizing inter-group violence and the need for sacrifice in favour of one's own group⁴¹. Cognitive opening refers to the moment when the ideology of thinking-radicalised as a cognitive process is shaped within a person. It happens when accepted beliefs of a potential individual who is experiencing political and socioeconomic discrimination are shaking, and he/she becomes susceptible to accept those ideology²¹⁸. Some of the cognitive factors that assist the cognitive opening are feeling deprived, perceiving unfairness, injustice, societal disconnectedness, and societal disconnectedness; whether as an individual or as a group member. Besides, feeling symbolic threats along within-group superiority are considered to be other effective cognitive factors. Feeling symbolic threats occur when in-group members believe out-group individuals are acting in a way that is harmful to their in-group members, consequently getting the belief that their group's moral and values are more important. All these factors may help in feeding violent attitudes²⁰⁷.

Influential cognitive and behavioural factors, which are causing individuals to experience mental health issues,

could be analysed by leveraging predictive analysis. As an application of data science analysis along with cognitive science, Beheshti et al.³¹ proposed a pipeline to help analysts with exploring potential extremist activity patterns through social media data. With the aim of analysing those factors, they introduced some new concepts such as a cognitive graph, entity, and relationship. The cognitive graph enables exploration and interpretation of significant cognitive and behavioural patterns existing in social data. They also present a particle swarm optimisation algorithm to discover the leading nodes (i.e., influential people such as extremist and radicalised individuals) in a social network. To resolve the issue of recognising the context and ultimate influence of the extremist or radicalised people in social media, Beheshti et al. proposed a context analysis algorithm in their study. They address the issue of detecting those nodes having a remarkable effect on boosting the influence of extremist ideas in social media³¹.

2.1.3 Suicidal Behaviour

There are several studies leveraging ML and deep learning methods aiming at suicide identification^{7, 59, 111}. Suicide is a global health dilemma, while preventable with timely actions⁸. It is among the most common causes of death worldwide¹⁴², and all the countries experience this issue more or less. The suicide rate in Australian men has grown from 16.2 per 100,000 individuals in 2011 to 18.6 in 2020, while women suicidal rate increased from 5.1 to 5.8 per 100,000 in the same years¹⁵¹.

Suicide is a cognition-related¹⁴⁹ disorder and mostly originated from depression (i.e., two-third of suicides occurred due to depression). It is also related to some other factors such as the family history of mental disorder, comorbid anxiety and gender²³⁰. Several cognition-related factors could be considered as predictive risk factors of suicide, namely problem-solving impairments, memory and thinking deficiency, negative cognitive style, the personality trait of neuroticism, rumination and self-criticism¹⁴⁹, causing more discrepancy words usage in their communications²⁰⁸.

In a recent study by Shini Renjith et al.¹⁶⁷, a combined deep learning classification model is leveraged, aiming at the identification of suicidal ideation through Reddit (i.e., an internet-based social platform) posts analysis. They used a hybrid model, consisting of LSTM and CNN for this text classification task. In order to increase the model accuracy, they used an attention technique to mimic cognitive attention¹⁰⁷.

The reason for using attention mechanisms is that some parts of the textual data, which are conveying essential cognitive meaning could be more relevant and should be utilised. For example, negative emotion words, more relevant to suicidal behaviour, should be considered more important in data analysis. Hence, using an attention-based model enables researchers to fix different weights according to the words cognitive importance. This weighting, leads to extracting a better emotional sense from users' posts, while having more cognitive-related patterns recognised by convolutional neural networks. Their proposed model had 90.3% accuracy and 92.6% F1-score, which is greater than the related baseline models¹⁶⁷.

2.1.4 Depression and Anxiety Disorder

Depression and anxiety are two prevalent mental disorders⁵², being proved to be associated with cognitive impairment⁴⁸. They are known to be risk factors for some somatic disorders such as cardiovascular disorder (CVD). They're linked to lower quality of life, as well as higher healthcare costs¹⁴. They are frequent mental health issues

⁸<https://www.who.int/news-room/fact-sheets/detail/suicide>

that have significant financial and social consequences¹⁸⁷.

- Anxiety As an example instance of mental disorder categories, Anxiety disorders are distinguished by a special way of thinking and behaviours, associated with ongoing and mostly illogical panic, concern and horror. For example, panic disorder (i.e., an instance of anxiety disorders) is accompanied by fear or anxiety attacks that are normally brief but can be so intense that the person believes she/he will collapse or die. People who have panic disorder are mainly worried about recurring attacks, and they avoid settings where they may repeat.

Individuals suffering from social anxiety disorder (i.e., another instance of anxiety disorders) are mostly afraid of situations where the person believes he/she will be in the middle of attention. They are also concerned about saying shameful things, while at the same time worrying that others will notice their anxiety and criticise them. On the other hand, months of excessive worry about day-to-day stuff, eluding or looking for reassurance in places when the result is in question are the main thinking pattern of people with generalised anxiety disorder (GAD). They usually are too anxious about things that could go wrong^{12, 72}.

Several studies found that anxious people have decreased performance on a wide range of cognitive tasks. Anxious individuals exhibit difficulties with inductive reasoning, decision-making process, memory length, attention control, and inhibition. They are mainly engaged with emotionally negative concerns. Anxiety may cause people to have problems with some certain cognitive tasks because they selectively process something irrelevant to what really matters⁶⁵.

- Depression Depression (i.e., a kind of depressive disorder) is considered to be one of the main origins of disability globally^{69, 124}, and expected to be the first by 2030¹⁶⁰. This disorder is a leading cause of disability, with 5% of adults suffering from it⁹.

There are several studies demonstrated that cognition may have a significant role in the start and duration of depression^{98, 124}. Depression is noticeably associated with cognitive functioning impairments such as adversity in executive functioning, working memory and processing speed^{5, 51}. Depression-related cognitive functioning includes ‘cognitive control problems’, ‘negative cognitive biases’ and ‘maladaptive cognitive emotion regulation strategies’¹²⁴.

Cognitive control problems, being prevalent in depressed people, means the inability to prevent negative information from going into the working memory (i.e., the current memory). Besides, negative cognitive biases refer four types of processing as follows. Negative ‘self-referential’ processing, which is indicative of having a negative self-schema and negative self-descriptions. Negative ‘attentional’ biases, showing difficulty in not paying attention to the negative drivers. Negative ‘interpretation’ which means having tendency to interpret events and information in a negative way. Negative ‘memory bias’, also refers to remembering more negative memories rather than positives.

In addition, there are three maladaptive cognitive emotion regulation strategies. First, the ‘reappraisal’ strategy, referring to reviewing a past event with the aim of rectifying the related negative feelings. A depressed individual rarely benefits from this strategy. Second, ‘rumination’, being a maladaptive strategy and one of the depression symptoms. It means thinking about negative past experiences repetitively. And the third strategy is ‘distraction’, being an adaptive strategy, which means causing a person not to think about something. Depressed people show low levels of distraction from thinking to negative memories¹²⁴. Among all mental disorders, in this study, we mostly focus on depression.

2.2 Depression: A Cognitive-Psychological Mental Disorder

⁹<https://www.who.int/news-room/fact-sheets/detail/depression>

Due to the significant adverse effects it may have over global communities, depression has attracted the attention of many researchers and governments to conduct extensive studies in this field. Depression as a cognitive-related disorder is described previously in section 2.1.4. In this section, based on the best practices in the field and the golden standards in cognitive and psychological studies such as 'Diagnostic and Statistical Manual for Mental Disorder' (DSM) and several other resources^{69, 72, 128, 160}, depression is explored in terms of its symptoms, risk factors, supportive symptoms and the relationships among them.

2.2.1 Depression Symptoms

Depression is a complex mental disorder. It contains a set of heterogeneous symptoms²⁵ such as emotional, cognitive, and behavioural symptoms, with persistent depressed mood and lack of interest in usually enjoyable chores¹¹⁷. In this part, diagnostic symptoms of depression that are mainly used by psychologists are explained.

- Depressed Mood: 'Depressed mood' is one of the main symptoms in identifying depressed individuals⁷². As a symptom of various mood disorders such as depression³⁶, it is determined by some feelings such as feeling sad, empty, hopelessness, and discouraged¹⁰. Having pessimistic ruminations, being tearful and unhappy could also be indicative of depressed mood^{108, 186}.

The presence of 'depressed mood' can sometimes be inferred by facial expression or conduct. Also, depressed mood could be shown by bodily pains and aches, a sensation of extreme frustration about little issues, and a tendency to react with angry outbursts¹⁸². In children and adolescents, this symptom mainly may manifest itself in the form of irritability rather than feeling dejected or sad^{72, 163}.

- Loss of Interest: Significantly decreased pleasure or interest, at least to some degree, in nearly all of daily activities, and also the inability to anticipate happiness, almost everyday, is one of the most prevalent symptoms of depression. Individuals may feel not caring anymore, less interested in hobbies, feel no enjoyment in activities that were considered to be joyful in past^{75, 86}. In addition, Social withdrawal^{69, 72}, neglect of pleasurable avocations and reduced levels of sexual desire are some other probable indicators of loss of interest in depressed people⁷².
- Appetite or Weight Change: Around one-third of depressed people identified with an increase in appetite, while about half of them report appetite decrease⁶⁰. Depression is accompanied by several physical health problems such as cardiovascular disease (CVD) and obesity⁵³. These diseases are mainly associated with depression somatic symptoms such as problems with sleeping and fatigue, so there is a mutually-reinforcing relationship between them. Change in appetite, being a depressive somatic symptom, is also affected by these kinds of relationships.

A potential biological cause that relates depression to those physical health issues is systemic inflammation^{38, 136, 137}. Inflammation is defined as the immune system's reaction to damage or irritation. Stress, infection, or chronic diseases could lead the immune system to create inflammatory responses throughout the body⁷⁸.

Based on some studies, the different underlying neural and inflammatory factors could cause some depressed people to tend to infer foods to be pleasant (i.e., increased appetite). In contrast, others feel reluctant to eat most of the foods (i.e., decreased appetite)⁶⁰.

- Sleep Disturbance: Unusual changes in sleep patterns nearly every day are common somatic symptoms of depression⁷². Hypersomnia is characterised by recurrent episodes of Excessive Daytime Sleepiness (EDS). It's

¹⁰<https://www.nimh.nih.gov/health/publications/depression/>

often considered to be the result of interrupted or poor sleep, and it's linked to a variety of sleep problems, such as insomnia⁶⁶.

Insomnia is defined to be a sleep-related difficulty such as falling asleep or remaining asleep for a considerable period of time⁶⁷, waking up during the night and then having difficulty falling asleep again, and also experiencing increased daily sleep¹¹. Insomnia could have reflections such as experiencing irritability, aggression and anger, lack of energy, concentration and motivation, loss of interest in daily activities. It also could lead to some physical tensions such as headaches¹².

- **Psychomotor Problems:** Two different demonstrations of psychomotor problems are psychomotor agitation and psychomotor retardation. Psychomotor agitation is defined as engaging in purposeless movements, e.g., pacing around the room, rapid talking, and tapping the toes and feeling restlessness⁷². Also irritability and suicidal attempts are also considered as its symptoms. The United States (US) Food and Drug Administration has noted that the inner tension and mental distress are, respectively, the original cause of excessive motor activities and restlessness¹³.

On the other hand, Psychomotor retardation could be recognised through some symptoms such as Speech slowness, decreased mobility and cognitive dysfunction⁴⁵. Cognitive functions are indicative of several significant mental processes that directly affect our everyday personal and social behaviours. Perceptual processes, memory, decision-making, language comprehension and attention processes are part of that cognitive functioning¹⁴⁸. Besides, previous studies demonstrated that individuals with negative processing biases^{89, 173, 178, 227} and negative cognitive styles are more susceptible to be depressed⁴⁴. The negativity bias refers to the situations where negative events such as unpleasant thoughts, emotions, or social interactions influence an individual's psychological state and processes much greater than equally emotional events but positive^{109, 176}.

- **Fatigue:** Sustained loss of energy and tiredness without physical exertion are some of the fatigue symptoms. Even the smallest tasks seem to be hard to be done and efficiency in doing tasks may be decreased. This feeling is indicated in a large number of depressed cases⁷². Fatigue could also increase the likelihood of making mistakes.

Based on medical studies, Insomnia and fatigue are interdependently related to each other while having different essences⁶⁷. Fatigue is not the mere feeling of tiredness or drowsiness and could be caused by lack of sleep, long physical or mental activities. Making errors, decreased productivity reduced alertness are some of the probable adverse effects of being fatigued⁹³.

- **Negative Self-Evaluation:** It is very usual for depressed individuals to have a negative self-image, feelings and thoughts of self-loathing and being valueless during their depressive episodes^{75, 186}. The presence of delusional or near-delusional guilt is less common but is indicative of greater intensity. Depressed people may have unrealistic negative evaluations of their worth and will ruminate on their minor past failings. They mainly misinterpret the trivial events as evidence of personal fault and blame themselves for failing in meeting various occupational and interpersonal responsibilities⁷².

Depressed people often tend to react with self-criticism when facing failure, stress or obstacles in life. Individuals with an increased level of self-criticism use more discrepancy words in their communications. This could be a reflection of different levels of confidence and certainty in achieving life goals or probably the degree to which one person is able to concentrate on specific aspects of favourable targets rather than unclear or general ones²⁰⁸. Having the negative self-evaluation is closely related to depression and is a powerful mediator between stressful life events and depression²³⁰.

¹¹<https://www.ampsych.com.au/psychology-treatment-sydney/insomnia/>

¹²<https://www.healthdirect.gov.au/insomnia>

¹³<https://www.ncbi.nlm.nih.gov>

- Impaired Ability to Think: Indecisiveness, diminished ability to think or concentrate, being easily distracted and having memory difficulties, especially in older people, are some of the complaints that depressed individuals may have⁷². Indecisiveness means having difficulty with decision-making in everyday life situations. Relationships, health, and job-related issues are some examples of those situations. Indecisiveness is considered to be associated with distress in different daily activities⁹⁶. On the other hand, depressed people mainly demonstrate a high level of anxiety which in turn makes it hard to make decisions²⁰⁶.

Lack of motivation is one of the reasons that cause depressed people to be indecisive. Having decision-making difficulties is considered to be a somatic issue. A previous study has demonstrated that depressed people suffer from grey matter loss in their brain. Grey matter is some regions in the human brain that are involved with motivation and decision-making ability, emotions, self-control, memory¹⁴.

- Suicidal Ideation or Thoughts of Death: Suicide is one of the main public health dilemmas worldwide. It was the fourth important cause of death in young people on 2019, globally. There is about 700,000 suicide commitment annually¹⁵. Majority of depressed individuals are shown to have suicidal ideation^{126, 171, 230}. Not only the fear of dying but also recurrent thinking about it and suicidal attempts or plans are all kinds of this symptom that can be presented by a depressed person.

Depressed individuals concentrate on committing suicide because they believe they are unworthy of life or since they feel to be unable to deal with the depressive anguish⁷². Based on a recent study⁸⁷, people who are approaching suicidal attempts tend to use more anger-related terms while the positive emotion in their communications is reduced. Besides, negative self-evaluation, negative cognitive style are known to be probable risk factors for suicidal deaths¹⁴⁹

An individual would be diagnosed to be suffering from depression if she/he exhibits either depressed mood or loss of interest and four (or more) of the other above-mentioned symptoms. In addition, this depressive episode must be followed by distress¹⁹³ or a reduction in social or professional performance. These symptoms must have been present during at least two consecutive weeks, indicating a change in functioning compared to the past. It also must be noted that those symptoms that are obvious attribute of another medical conditions are excluded^{72, 160}.

2.2.2 Risk Factors and Supportive Symptoms

Risk Factors.

Depression risk factors include the type of personality traits that a person have, demographic features, having previous episodes of depression, and having major non-mood disorders. In this part, first, personality traits and the way they could affect potential people to be depressed are described. Then other risk factors such as demographic features would be explained.

- Personality Traits:

Suffering from depression is linked with some of the personality traits⁵⁷. Personality is recognised by the way people tend to behave, react to different daily events, and also their patterns of cognitive and emotional processes^{106, 222}. A wide range of past and recent research is evidence of personality traits' effect on vulnerability to some mental disorders. It is also known that personality is a significant risk factor of depression^{8, 9, 19, 94, 112, 113, 118, 125, 129, 165}, and has been hypothesized to be a depression predictor⁹⁴.

¹⁴https://en.wikipedia.org/wiki/Grey_matter

¹⁵<https://www.who.int/news-room/fact-sheets/detail/suicide>

Based on The most acceptable and universal personality model, the Five Factor Model (FFM), there are five different personality traits, named “Big Five”. These Big Five are ‘Neuroticism’, ‘openness’, ‘Extraversion’, ‘Agreeableness’, and ‘Conscientiousness’^{9, 118}. Extraversion is defined to be genial, chatty, assertive, and energetic, while neuroticism means to have negative affectivity, be uneasy, sad, irate, and unsure. On the other hand, conscientiousness trait the characteristics such as being careful, perfect, accountable, and orderly. Agreeableness also is indicative of traits such as being kind-hearted, compliant, unselfish, and gentle. Lastly, openness is defined as being creative and open-minded¹⁷². The main personality traits that are considered to be depression risk factors are neuroticism, extroversion, and conscientiousness^{9, 94}.

Neuroticism as the most significant trait^{112–114} is positively correlated with depressive symptoms. The other two, i.e., extraversion, and conscientiousness, have a negative correlation with susceptibility to be depressed¹¹⁸. Neuroticism, contains two sub-domains, namely ‘withdrawal’ and ‘volatility’. Extraversion consists of ‘enthusiasm’ and ‘assertiveness’, and conscientiousness also includes ‘industriousness’ and ‘orderliness’. Sadness and anxiety are two examples of Withdrawal referring to internal negative emotions, while volatility refers to external negative emotions such as irritability and anger. On the other hand, enthusiasm and industriousness are negatively correlated with depression^{9, 129}. Hence, neuroticism could be viewed as a risk factor while extraversion and conscientiousness are considered to be protective factors^{8, 129}.

Neuroticism is considered to be the state of having negative affectivity⁷², and it has been shown that depressed individual have higher negative emotions than not-depressed individuals⁶⁹. The word “affect” refers to our experienced emotions or feelings and the way they influence us in making decisions⁴. Negative affectivity relates to a variety of negative emotions and poor self-concept, that consists of symptoms such as distress, sadness, disgust, lethargy, and fear¹¹⁹. Distress is a kind of negative stress in comparison with eustress, which is positive stress. Distress has characteristics such as causing anxiety, experiencing unpleasant feelings, reducing the performance, resulting in physical or mental problems¹³⁵. Lethargy is a condition in which an individual mostly has feelings of being fatigue, mood change, reduced energy, alertness or ability to think¹⁶.

- Demographic Feature and Other Risk Factors:

Based on previous studies, the prevalence of depression differs in different age groups. It is three times higher in 18- to 29-year-olds than in 60-year-olds⁷². Females in their early teens had 1.5 to 3-fold higher levels of depression^{60, 76, 114}. It is also shown that there are no obvious variations in symptoms, duration, therapeutic response, or outcomes between men and women. Besides demographic features such as age and gender, there are other risk factors being effective in suffering from depression.

Having a previous history of depression also could make individual more susceptible to be depressed again in future^{79, 114}. In addition, having the background of other non-mood disorders such as substance-related disorders, prominent anxiety^{104, 108}, borderline personality disorders as the most common ones, as well as Other depression risk factors include disabling medical illnesses such as diabetes, severe obesity, and heart disease⁷².

Supportive Symptoms:

- Absolute Word usage : Depressed individuals mostly talk in the absolute language and use a greater percentage of absolutist words in their natural language and daily communications^{6, 186}. Absolutist thinking is the cause of several cognitive falsifications and illogical thoughts that are said to be the mediators of core emotional disorders. There are 19 absolutist words that have been properly verified, e.g., ‘definitely’, ‘absolutely’ and ‘never’⁶.

¹⁶<https://www.healthline.com/health/lethargy>

- **Abnormal Fear :** As mentioned in section 2.2.2, fear is one of the behavioural symptoms of neurotic individuals. It is also illustrated in American Psychiatric Association Manual⁷² that having abnormal fear and phobia could be a supportive symptoms of being depressed.
- **Tearfulness :** Crying is a powerful sign of organismic distress and acts as distress reduction. Clinical studies have indicated that depressed people are crying excessively²² which may reflect the intensity of distress¹⁷⁵. American psychiatric association also has introduced being tearful as a supportive symptom for identifying depressed individuals⁷².
- **Physical Pains :** Being depressed and having physical pain are strongly connected⁷² and could make a vicious cycle. Back pain or headache is the first and most common unexplained body pain, caused by depression. Pain and its consequent issues could affect individuals' mood. Chronic pains could lead to depression, whether injury-related ailments or pains originated from a physical disorder such as diabetes, cancer or heart disease⁹⁵.
- **Obsessive Ruminations/Concerns :** Obsessive ruminations or thoughts are mainly demonstrated in depressed people⁷². Rumination is defined as thinking frequently over a single or specific thoughts which are inducing negative feelings. Obsessive rumination could be harmful in terms of mental health. It causes difficulties in the ability to think and emotion processing. Also, Choudhury et al. illustrated in their study that depressed people tend to use more relational and medicinal concerns⁶⁹.

Having obsessive ruminations, also could make the depression more intense or prolonged. It may cause feeling alone and isolated, which in turn causes pushing people away¹⁷. There are some reasons for rumination, e.g., experiencing previous physical or emotional trauma, dealing with continuous uncontrollable stressors. Also, Neurotic people often tend to ruminate over their relationships¹²³.

- **Self-focused Attention :** Several previous studies have shown that people with depressive symptoms tend to use special words while talking or writing. It is recognisable from the way individuals express their thought whether they are suffering from depression or not. Depressed people use more first-person pronouns, i.e., 'I', 'Myself', 'Me', showing an increase in self-focused attention^{69, 177, 186, 203}. Based on depression cognitive models, self-referent attention and processing, which is negatively biased, have important roles in suffering from depression²⁵. These findings are in line with the fact that one of the symptoms of depression is negative self-evaluation and feeling of worthlessness⁷². Hence, using self-focused words while they are blaming or criticising themselves seems very natural.
- **Anxiety :** Anxiety is a natural body reaction to stressful events. It is accompanied by the fear of what's to come. For example, the first school day or having a job interview could cause anxiety and nervousness.

Anxiety and depression happen independently, however, they could be considered as comorbid disorders that happen at the same time. Anxiety could be a supportive symptom for depression⁷², which leads other symptoms to be worsened¹⁸. It is also considered to be a probable symptom of negative emotion^{9, 129}. Although it could be a kind of background non-mood disorder^{72, 104, 108}, anxiety is mostly illustrated in depressed people's behaviour²⁰⁶.

- **Irritability :** Irritability is known to be the state of quickly becoming annoyed, angry and frustrated even with minor issues⁷⁰. Irritability is considered to be one of the supportive symptoms in depression identification. Depressed individuals, especially children, might feel irritated frequently. Sadness and depressed mood in Children and adolescents mostly is demonstrated as irritability, so that they would react with anger to slight provocation⁷².

¹⁷<https://www.healthline.com/health/how-to-stop-ruminating>

¹⁸<https://www.healthline.com/health/anxiety>

Theme	Unigrams
<i>Symptoms</i>	anxiety, withdrawal, severe, delusions, adhd, weight, insomnia, drowsiness, suicidal, appetite, dizziness, nausea, episodes, attacks, sleep, seizures, addictive, weaned, swings, dysfunction, blurred, irritability, headache, fatigue, imbalance, nervousness, psychosis, drowsy
<i>Disclosure</i>	fun, play, helped, god, answer, wants, leave, beautiful, suffer, sorry, tolerance, agree, hate, helpful, haha, enjoy, social, talk, save, win, care, love, like, hold, cope, amazing, discuss
<i>Treatment</i>	medication, side-effects, doctor, doses, effective, prescribed, therapy, inhibitor, stimulant, antidepressant, patients, neurotransmitters, prescriptions, psychotherapy, diagnosis, clinical, pills, chemical, counteract, toxicity, hospitalization, sedative, 150mg, 40mg, drugs
<i>Relationships, life</i>	home, woman, she, him, girl, game, men, friends, sexual, boy, someone, movie, favorite, jesus, house, music, religion, her, songs, party, bible, relationship, hell, young, style, church, lord, father, season, heaven, dating

Figure 1. List of depression unigrams that depressed people tend to use in their communications as indicated in Chouldhary et al. study⁶⁹.

Other symptoms of irritability could be feeling restlessness, difficulty concentrating and agitation. On the other hand, there are some causal mental and physical condition such as stress, sleeping problems, chronic pain and thyroid that makes individuals experience irritability¹⁹.

- Special Phrases : Some of the most frequent phrases that can be seen as signals for being depressed are "I should", "I can't...", "It's all my fault", "I'm tired", "I want to be alone", "No one cares". As some may believe it is a stigma to have a mental disorder, depressed people often try to hide it behind their positive phrase that "I am fine". Two signalling phrases of losing interest in normally enjoyable activities are "I don't feel like it" and "It's not fun anymore". Besides, ironically use of "I feel better" and also saying "What's the point?" could be warning since all of those mentioned feelings can become overwhelming and make people want to give up¹⁸⁶.

As mentioned before in section 2.2.2, neurotic people are more likely to be depressed, while showing more negative emotion in their daily life. Also, depressed people are more likely to use negative emotion terms than not-depressed people^{203, 204}. The following words are some examples of negative emotion terms could be used by some of depressed individuals, 'down', 'stressed', 'upset' ¹⁸⁶.

- Depression Unigrams : Based on a study by Chouldhary et al., depressed people tend to use special depression unigrams and terms in their communications. As Figure 1 shows, depression unigrams are categorised into 4 areas. Treatment and relationship, life words refers to medicinal and relationship concerns, respectively. These are concerns assumed to be related to obsessive ruminations, a previously mentioned supportive signs. Also, symptom and disclosure words are considered to be separate supportive symptoms for depression⁶⁹.

2.3 Depression Identification/Assessment Approaches

¹⁹<https://www.healthdirect.gov.au/irritability-and-feeling-on-edge>

Likewise, with other chronic disorders, the sooner treatment of depression will help the full remission of it⁷². Therefore, due to the importance of this issue, a valuable collection of studies has been done over depression from various perspectives. In this section, we will review three different approaches (i.e., clinical, non-clinical and knowledge-based), aiming at the identification and assessment of depression.

2.3.1 Clinical Approaches

In contrast to most physical disorders that can be identified through methods such as imaging and laboratory tests, the majority of psychological and cognitive abnormalities are not easily diagnosed. Generally, mental health issues need to be assessed before any Therapeutic prescription⁹². Depression, considered to be the main health problem around the world¹⁵⁸, is no exception and attracts the attention of many researchers in terms of developing reliable assessment gadgets. In order to provide adequate care, validated scales must be used in the screening, diagnosis, and measurement of therapeutic efficacy in depression. Clinicians who learn how to utilise those scales can increase diagnostic accuracy, save time, offer greater constant treatment, and track a patient's complicated emotional and behavioural responses to therapy¹¹.

More than 40 years ago, symptom-based scales were established to give a numeric value to a wide range of patient behaviours, emotions, and feelings. They've subsequently evolved into a confusing array of tools developed for a number of objectives, some of which are fairly broad in scope and others more specific¹¹. Depression assessment tools include screening, diagnosis and monitoring instruments, each designed for a specific aim. To identify potential depressed individuals, short self-reported tools, namely screening measures are used. On the other hand, diagnostic tools are interview-based measures used by clinicians. Also, monitoring tools are rating scales to appraise the intensity of depression and identify any changes in the depressive symptoms⁹².

- Screening Tools (BDI-II, CES-D and PHQ-9) :

The Beck Depression Inventory (BDI) is among the most commonly used screening tools for identifying depression severity^{23, 24, 39, 92, 191, 213}. The assessment includes questions related to depressive symptoms related to depressive symptoms like sadness, as well as impaired cognition such as feeling worthlessness, and also bodily symptoms like weight loss¹³³. It was first developed in 1961, having 21 items to assess depression-related symptoms. Individuals must answer to multiple-choice questions based on their feelings on the same day as they are answering²⁴.

In 1971 BDI-IA, being the amended version of the original BDI, was published. BDI-IA must be responded based on the preceding week's events and feelings, including today²²⁵. The BDI-II is a modified edition of the BDI that's been released in 1996 to comply with the new version of DSM³⁷ depression criteria. It replaced four of the original BDI's items, i.e., 'Weight Loss', 'Body Image Change', 'Somatic Preoccupation' and 'Work Difficulty' with four new ones , namely 'Agitation', 'Worthlessness', 'Concentration Difficulty' and 'Loss of Energy'. BDI-II must be answered based on the preceding two weeks²³. Figure 2 demonstrates part of the BDI-II²⁰. The Center for Epidemiological Studies-Depression (CES-D)^{46, 127, 158, 164, 191} and the Patient Health Questionnaire (PHQ-9)^{61, 64, 92, 120} are 2 of the most important tools for depression screening. As Figure 3 shows¹⁵², CES-D is a 20-question self-report questionnaire. It was developed in 1977 by Laurie Radloff to assess depression symptoms. This questionnaire should be answered based on the feeling and affections referring to a week prior to the completion day¹⁶⁴. Respondents rate each question based on the happening frequency. The rating scale is originated from the Likert scale, varying between 0 (i.e., hardly ever or at all) to 3 (i.e., generally or always)⁴⁶.

²⁰<https://naviauxlab.ucsd.edu/wp-content/uploads/2020/09/BDI21.pdf>

BDI - II

Instructions: This questionnaire consists of 21 groups of statements. Please read each group of statements carefully. And then pick out the one statement in each group that best describes the way you have been feeling during the past two weeks, including today. Circle the number beside the statement you have picked. If several statements in the group seem to apply equally well, circle the highest number for that group. Be sure that you do not choose more than one statement for any group, including Item 16 (Changes in Sleeping Pattern) or Item 18 (Changes in Appetite).

1. Sadness

- 0. I do not feel sad.
- 1. I feel sad much of the time.
- 2. I am sad all the time.
- 3. I am so sad or unhappy that I can't stand it.

2. Pessimism

- 0. I am not discouraged about my future.
- 1. I feel more discouraged about my future than I used to.
- 2. I do not expect things to work out for me.
- 3. I feel my future is hopeless and will only get worse.

3. Past Failure

- 0. I do not feel like a failure.
- 1. I have failed more than I should have.
- 2. As I look back, I see a lot of failures.
- 3. I feel I am a total failure as a person.

4. Loss of Pleasure

- 0. I get as much pleasure as I ever did from the things I enjoy.
- 1. I don't enjoy things as much as I used to.
- 2. I get very little pleasure from the things I used to enjoy.
- 3. I can't get any pleasure from the things I used to enjoy.

5. Guilty Feelings

- 0. I don't feel particularly guilty.
- 1. I feel guilty over many things I have done or should have done.
- 2. I feel quite guilty most of the time.
- 3. I feel guilty all of the time.

6. Punishment Feelings

- 0. I don't feel I am being punished.
- 1. I feel I may be punished.
- 2. I expect to be punished.
- 3. I feel I am being punished.

7. Self-Dislike

- 0. I feel the same about myself as ever.
- 1. I have lost confidence in myself.
- 2. I am disappointed in myself.
- 3. I dislike myself.

Figure 2. Part of the BDI-II: An extensively used screening tool for identifying depression severity. The assessment includes questions related to depressive symptoms like sadness, as well as impaired cognition such as feeling worthlessness²³.

Figure 4 also illustrates the PHQ-9 questionnaire, being the most trustworthy in depression screening tool leading to the more accurate identification^{3, 61, 84}. The PHQ-9 is frequently used in physician's and therapist's workplaces as part of routine screenings or to assess the mental well-being. This simplified version is inspired by the original PHQ form, which includes a wide range of mental health problems such as depression, panic disorder, anxiety, and difficulty sleeping, and more²¹¹. It is a 9-question tool, each question refers to one of the criteria indicated in DSM-5⁷² manual and scores them as '0', '1', '2', or '3'. In which '0' means not at all and '3' means nearly every day²¹.

• Diagnostic Clinical Interviews (SCID and CIDI) :

Screening attempts are mainly followed by diagnostic interviews. Interviews are used by clinicians to identify potential people with mental disorders (e.g., depression). Two reliable mental disorder diagnostic interviews are the 'Structured Clinical Interview for DSM Disorders' (SCID) and The 'Composite International Diagnostic Interview' (CIDI)⁹². The last version of SCID interview is SCID-5, constructed in accordance with DSM-5 diagnostic criteria. To help with evaluating each criterion as existing or absent, interview questions are simply supplied alongside each relevant DSM-5 criterion¹⁸.

In addition, the CIDI is a detailed and thoroughly structured diagnostic interview for assessing mental disorders. CIDI, the first and the second versions (i.e., v1 and V2) were developed by WHO in 1994²²⁰ and 1998 respectively¹³. The latest version is structured in 14 sections, one of them especially related to depressive

²¹<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC1495268/>

Center for Epidemiologic Studies Depression Scale (CES-D), NIMH

Below is a list of the ways you might have felt or behaved. Please tell me how often you have felt this way during the past week.

	During the Past			
	Week	Rarely or none of the time (less than 1 day)	Some or a little of the time (1-2 days)	Occasionally or a moderate amount of time (3-4 days)
1. I was bothered by things that usually don't bother me.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
2. I did not feel like eating; my appetite was poor.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
3. I felt that I could not shake off the blues even with help from my family or friends.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
4. I felt I was just as good as other people.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
5. I had trouble keeping my mind on what I was doing.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
6. I felt depressed.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
7. I felt that everything I did was an effort.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
8. I felt hopeful about the future.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
9. I thought my life had been a failure.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
10. I felt fearful.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
11. My sleep was restless.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
12. I was happy.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
13. I talked less than usual.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
14. I felt lonely.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
15. People were unfriendly.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
16. I enjoyed life.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
17. I had crying spells.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
18. I felt sad.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
19. I felt that people dislike me.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
20. I could not get "going."	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

SCORING: zero for answers in the first column, 1 for answers in the second column, 2 for answers in the third column, 3 for answers in the fourth column. The scoring of positive items is reversed. Possible range of scores is zero to 60, with the higher scores indicating the presence of more symptomatology.

Figure 3. The Center for Epidemiological Studies-Depression: a reliable depression-related questionnaire. It is applied in scientific studies and clinical settings as a depression screening tool. It was developed in 1977 by Laurie Radloff¹⁶⁴.

disorders. Figure 5 is the illustration of a segment in CIDI-V2, being associated with depressive disorders identification interview¹⁵⁵.

- Monitoring Tools (HAM-D, MADRS) :

Monitoring tools are rating scales to appraise the intensity of depression and identify any changes in the depressive symptoms⁹². Two valuable supplementary tools to be used following a proper diagnosis are the 'Hamilton Rating Scale for Depression' (HAM-D)⁸³ and the 'Montgomery-Asberg Depression Rating Scale' (MADRS)⁹². HAM-D is commonly used measure for assessing the level of depression in depressed individuals.

The first unstructured version, HAM-D21 was published by Max Hamilton in 1960 and composed of 21 components. Over the years, different versions of the HAM-D have been developed and used^{47, 97}. Being structured (i.e., containing complementary interview questions) or not is the main difference among those versions. Due to some limitations, such as inefficiency in detecting changes in the course of treatment, criticisms have been levelled at unstructured types. Hence, MADRS, being a structured scale, was developed in 1979 by Montgomery and Asberg to improve the sensitivity of HAM-D¹⁴¹.

Nine-symptom Checklist

Name _____ Date _____				
Over the last 2 weeks, how often have you been bothered by any of the following problems?				
1. Little interest or pleasure in doing things	Not at all	Several days	More than half the days	Nearly every day
2. Feeling down, depressed, or hopeless	0	1	2	3
3. Trouble falling or staying asleep, or sleeping too much	0	1	2	3
4. Feeling tired or having little energy	0	1	2	3
5. Poor appetite or overeating	0	1	2	3
6. Feeling bad about yourself — or that you are a failure or have let yourself or your family down	0	1	2	3
7. Trouble concentrating on things, such as reading the newspaper or watching television	0	1	2	3
8. Moving or speaking so slowly that other people could have noticed? Or the opposite — being so fidgety or restless that you have been moving around a lot more than usual	0	1	2	3
9. Thoughts that you would be better off dead or of hurting yourself in some way	0	1	2	3
(For office coding: Total Score _____ = _____ + _____ + _____)				
If you checked off <i>any</i> problems, how <i>difficult</i> have these problems made it for you to do your work, take care of things at home, or get along with other people?				
Not difficult at all <input type="checkbox"/>	Somewhat difficult <input type="checkbox"/>	Very difficult <input type="checkbox"/>	Extremely difficult <input type="checkbox"/>	
From the Primary Care Evaluation of Mental Disorders Patient Health Questionnaire (PRIME-MD PHQ). The PHQ was developed by Drs. Robert L. Spitzer, Janet BW Williams, Kurt Kroenke, and colleagues. For research information, contact Dr. Spitzer at rts8@columbia.edu . PRIME-MD is a trademark of Pfizer Inc. Copyright 1999 Pfizer Inc. All rights reserved. Reproduced with permission				

Figure 4. PHQ-9: A 9-question depression screening tool leading to the more accurate depression identification. It is originally developed and published by Kroenke et al., on 1999^{120, 121}.

2.3.2 Non-Clinical Approaches

In addition to the clinical approaches explained before, which use assessment tools for screening and identification, computer science society also did a great job in this field by developing various automatic algorithms for identifying or predicting depression. Depression has been investigated through several approaches. Each of those approaches is a special and analysable aspect of depression. For example, facial gestures or language use of depressed people are two aspects that could be analysed. In this way, various data types have been analysed in previous researches. Based on the literature, these types of data include medical data (e.g., fMRI records and EEG), facial, video, vocal, and social media data, In which social media is a rich source of textual data.

There are numerous modern ML techniques and classifiers that have been used for analysing these data¹²². The followings are some of the example techniques leveraged in computer science-based analysis: NLP, convolutional neural networks (CNN), ML classifiers such as Support Vector Machines (SVM), Naive Bayes (NB), Decision trees (DT), Multi-layer Perceptron (MLP), Logistic Regression (LR), etc. Table 1 is demonstrating different approaches in this regard.

- Medical Data

- FMRI Records: As we mentioned before, some depressive symptoms could be derived from zonal anomalies in brain blood flow and activities²¹⁷. Functional Magnetic Resonance Imaging (fMRI) measures these activities and changes¹⁵⁶. Hence, several past studies have used fMRI signatures and leveraged different ML techniques for their studies on depression identification^{82, 226}. These capabilities are arising from ML algorithms' power to contract several variables, e.g., MRI signals in brain voxels²², into a scale that takes the intricate patterns derived from these variables¹⁸¹.

²²Voxel is a 3-dimensional unit that embeds the signals in brain scans

SECTION E

				I EVER IN LIFETIME			
		CODE E1 - E24 IN COLUMN I					
DEP10B1 DP4A1	E1	Now I want to ask you about periods of feeling sad, empty, or depressed. In your lifetime, have you ever had two weeks or longer when nearly every day you felt sad, empty, or depressed for most of the day?		PRB: 1	3 4 5		
		MD: _____ OTHER: _____					
DEP10B2 DP4A2 DEP10S1	E2	In your lifetime, have you ever had 2 weeks or longer when you lost interest in most things like work, hobbies, and other things you usually enjoyed?		PRB: 1	3 4 5		
		MD: _____ OTHER: _____					
		IF E1 AND E2 BOTH CODED 1 SKIP TO E34.					
LACKING ENERGY			I EVER IN LIFETIME		II WHEN MOST SX		
			NO	YES	NO	YES	
DEP10B3 DP4A6	E3	During a period lasting two weeks or longer when you (felt sad, empty or depressed/lost interest in things), [did you lack energy or feel tired all the time nearly every day, even when you had not been working very hard?]	1	5	1	5	

Figure 5. A segment of Composite International Diagnostic Interview (CIDI) related to depression identification interviews. CIDI is a detailed and fully structured diagnostic interview for assessing mental disorders¹³.

Fu et al.⁸² used SVM technique to analyse fMRI data, and Zeng et al.²²⁶ have developed a maximum margin clustering-based unsupervised ML model with 92.5% group- and individual-level clustering consistency. That model was used for identifying depression through analysing resting-state fMRI scans in the absence of clinical information. Based on their study, some brain functional connectivity networks may have a serious role in suffering from depression.

Previous research has revealed that people who previously suffered from depression are more vulnerable to be depressed again in future⁷¹. Similarly, the fMRI data have enabled researchers to do different studies on treated depressed patients aiming at identifying imaging bio-markers of depression susceptibility. For example, Sato et al.¹⁸¹ have developed a ML algorithm, Maximum Entropy Linear Discriminant Analysis (MLDA) with 78.26% accuracy in this regard.

- Electroencephalography Signals: EEG is an electrophysiological measuring technique for recording electrical impulses on the scalp, which has been proven to correspond to the macroscopic activity of the brain's surface layer beneath. EEG measures and record voltage changes arising from an electrical current within the brain's neurones²¹⁶. Several past researches have shown that using ML techniques to analyse EEG recorded data and signals would lead to outstanding results in terms of identifying the predominant mental condition of patients and depression identification.

Betul Ay et al.¹⁶ and Sharma et al.¹⁸⁸, both leveraged CNN and LSTM models in their studies. The first resulted in classifying depressed cases with the accuracy of 99.12% for the right hemisphere signals analysis and 97.66% for the left hemisphere. The second study has been done with 99.10% accuracy and the mean absolute error (MAE) of 0.2040. In addition Aydemir et al.¹⁷ used k nearest neighbor (kNN) classifier with 99.11% and SVM with 99.05% accuracy, and Seal et al.¹⁸⁵ apply a CNN model with the accuracy of 0.914 to classify EGG data into two classes, namely related to the depressed or related to not depressed individuals.

Approach	Explanation	Logic behind the approach	References
Medical Data Analysis	Medical data such as 'functional Magnetic Resonance Imaging (fMRI)' scans and electroencephalography (EEG) recorded data are analysed using different machine learning techniques such as SVM or CNN.	Some brain functional connectivity networks may have a serious role in suffering from depression	[147–149, 152, 153, 155]
Depression Assessment Tools	Psychologists mainly use tools such as 'Center for Epidemiological Studies-Depression' and 'Patient Health Questionnaire', 'Beck Depression Inventory-II (BDI-II)' questionnaire, 'Structured Clinical Interview for DSM Disorders (SCID)' and 'Composite International Diagnostic Interview (CIDI)' for identifying depressed individuals. Besides, they also use scales such as 'Hamilton Rating Scale for Depression (HAM-D)', 'Montgomery-Asberg Depression Rating Scale (MADRS)' as valuable supplementary tools to be used following a proper diagnosis.	These tools help to recognize the existence of depression symptoms in potential patients. These symptoms are golden depression diagnostic criteria used by psychologists worldwide.	[2, 120, 121, 123–126, 131–134, 140]
Video and Vocal Data Analysis	Based on scientific previous studies 'Video', 'facial' and 'speech-based' data contains valuable features which are indicative of depressive disorders. ML techniques such as LSTM and CNN help analysts with depression identification through these data	depressed people could have special gestures, body movements, periodic muscular movements. They mainly talk with special intonation, speaking speed, and articulation.	[156–158, 158, 159, 159–166]
Textual Data Analysis	Textual data demonstrates the linguistic style of its author and the signals based on which we indicate what we mean. Based on previous researches, written data proved to be a reliable and promising kind of data for depression-related studies. There are several machine learning techniques such as BOW, Time series, SVM, CNN, NLP enable the analysis of texts in psychologically meaningful manner.	The words (e.g., pronouns, verb tenses) that are used in the daily communications are connected to individuals' real-life manners, differences, and mental health status.	[1, 11, 40, 167–174]

Table 1. Depression Identification/Assessment Approaches.

• Video and Vocal Data

There is a growing interest in analysing audio and video data to create any probable advances in depression-related areas. Since the facial expression could be used vastly as a depressive disorder indicator²²⁸, there are numerous image- and video-based depression identification studies done previously^{101, 144} to help psychologists with depression diagnosis and therapy¹⁹⁴. Detectable video features such as gestures and movements, and periodic muscular movements make video data analysis a useful approach for depression studies²²³.

Image- and video-based depression identification studies leveraged a wide range of automatic modern tools. Deep regression network with focusing on a single facial image²²⁸, Deep Learning fed with facial images sequence from videos¹⁰² are some examples of those tools¹⁴⁷. In addition, 3-dimensional convolutional neural Networks used over video clips having access to spatiotemporal feature aggregation module (STFAM)¹⁰¹, and also CNN models with attention mechanism using video clips as input data¹⁰⁰ are conducted with acceptable performance.

In addition to video and facial images, there are several vocal- or speech-based studies to developing computerised depression identification models. Generally, depressed people tend to talk slowly and communicate using short sentences in a monotonic way^{63, 219}. Vocal data could enable identifying those depressive patterns by analysing the intonation, loudness, speaking speed, and articulation^{194, 223}.

The work of Srimahhur et al.¹⁹² is an example of Vocal data-based studies. In this work spectrogram-based and also end to end CNN models are used with the aim of identifying potential depressed people. Xingchen Ma et al., also developed DepAudioNet, a deep model made up of CNN and Long ShortTerm Memory (LSTM), enabling the classification of depressed cases through encoding depressive patterns in the vocal channel¹³⁰. Samareh et al.¹⁸⁰, also did an integrative multi-modal study in which, they used the audio, video, and also textual data, in addition to applying gender variety in their research. Their study had promising results in terms of depression symptom identification.

• Textual Data

These data demonstrate the linguistic style of its author and also any other possible metadata. Linguistic style refers to a group of signals based on which we indicate what we mean, and also interpret other peo-

ple's meaning. It includes features like speaking rate and loudness, being straightforward or not, the word choices¹⁹⁹, etc. The linguistic style could be reflected in the spoken and written languages, and the data derived from both could be collected, stored and analysed.

Based on previous researches, written(i.e., textual) data proved to be a reliable and promising kind of data for depression-related studies, through analysis of different words in sentences and documents⁴⁹. Kinds of words (e.g., pronouns, verb tenses) that are used in the daily communications are connected to individuals' real-life manners, differences, and mental health status. In comparison to mentally healthy people, depressed people frequently utilise the first person pronouns (i.e., self-focused words), negative emotion, and sometimes more death-related words²⁰³.

One of the main and golden standard computerised text analysis tools is the Linguistic Inquiry and Word Count (LIWC) program. It is leveraged as one of the most beneficial ways of extracting various word-based features from textual data such as daily diaries, school assignments, and journal articles^{161, 162, 203}. In analysing textual data, LIWC counts words in psychologically meaningful classes namely function and emotion words. These classes are indicative of emotional and social conditions, motivations, purposes, and thought patterns. Hence, all the LIWC's capabilities make it a suitable source for personality, behavioural, and mental health related studies²⁰³.

The LIWC lexicon was created to analyse a variety of text types, including e-mails, speeches, poetry, or captured daily conversation. LIWC has 90 linguistic, behavioural, and psychological dimensions, consists of 41 word categories (i.e., a list of words) that use psychological notions (e.g., affect, cognition, biological processes, and drives), and six personal concern categories (e.g., job, home, leisure activities), etc¹⁶¹. These lists were made with the help of emotion assessment methods and glossaries, and a judging panel validated them⁸⁸. Various studies leveraged LIWC as a reliable tool for emotion and linguistic analysis^{42, 68, 69, 88, 179}. It is a valuable resource that is widely utilised for measuring positive and negative affect^{68, 88}, while being a well-known lexicon used in content analysis¹¹⁰. There is also another lexicon used aiming at emotion and affect analysis, such as ANEW (Affective Norms for English Words)^{43, 145}, NRC^{139, 140}, Warriner Lexicon²¹², and MPQA²¹⁴.

Recently, considering the popularity of daily communications, social media networks turned out to be a great textual data source for identifying factors associated with depression. This identification, in turn, is a great work in terms of helping psychologists, families and societies to deal with depression side effects. On the other hand, this identification is empowered by different ML techniques' capabilities that make the textual data analysis possible^{69, 209}.

Social media networks are platforms with multifaceted applications. For example, Twitter, Facebook, and Reddit are common spaces in which people can share their beliefs, ideas, thoughts, feelings, experiences, and also many can find answers to their questions. Previous studies show that these networks could help with screening society tendencies and health-related issues such as depression⁵⁴. Several scientific studies have analysed social media data using several ML algorithms with the aim of depression identification and prediction, some of them are as follows.

In a leading study by De Choudhury et al. (2013), a classifier was built to recognise depressed Twitter users based on their social media activities. They introduced social media as a data source for identifying symptoms of depression in a user. They used different features for their analysis namely, user engagement and emotion, depressive language use, linguistic style, ego-network characteristics such as followers and followees number, and mentions of antidepressant medications.

Based on this study, depressed people have notable self-focused attention, lower social activity, higher negative emotion, raised medicinal and relational concerns and increased indication of religious thoughts. In addition, depressed individuals tend to have virtual activities mainly after 8:00 pm or in the early morning, while

non-depressed people prefer to be active on online social media, after work-time and mainly early nights. In this study, several classifiers were tested and SVM, with an average accuracy of 70% and precision of 74% for depression class resulted in the best outcomes⁶⁹.

In 2015, Tsugawa et al. identified a method to show the depression level in Twitter users. They used past activities of users to make different classifiers among which SVM had the best performance with 61% precision and 66% accuracy. The main features used in their model were word frequencies, tweets' topic , ratio of positive-affect and negative affect words, tweets' daily frequency, average number of words per tweet and several metadata such as number of followers²⁰⁹.

Orabi et al.(2018) used CLPsych 2015 shared task, containing Twitter posts tagged with depressed, control and PTSD as their training dataset. They also used Bell Let's Talk²¹⁵ as the test dataset in their study. They used different Word embeddings such as Skip-Gram, CBOW, Optimised and Random and then fed them to various Deep Learning networks, three CNN-based and one RNN-based models for the evaluation phase. The CNNWithMax model, one of those three CNN-baseds, showed the best performance with an accuracy of 87.957% and precision of 87.435%¹⁵³. Also, in 2019, Arora et al.¹⁵, Ziwei et al.²²⁹, Tao et al.²⁰⁰ and some more researchers studied depression on Twitter leveraging sentiment analysis techniques considering the sentences' polarities (positive, negative, or neutral). Besides, a recent study by Martins et al.¹³², the NRC Emotion lexicon and NRC Affect Intensity lexicon were used along with ML and text mining techniques for their analysis. Table 1 is a summary of different studies done with various approaches aiming at contributing to depression identification issues.

2.3.3 Knowledge-Based Approaches

Knowledge base refers to a set of information and concepts, mainly in a specific field, being organised into a taxonomy, instances for each concept, and relationships among them^{29, 50}. Based on the literature, several studies have leveraged knowledge-based systems with this objective to develop various state-of-the-art automated systems. Knowledge-based summarisation systems^{85, 205}, Recommendation Systems^{74, 174, 221} and social streaming analytics⁵⁰ are some examples of these kinds of systems.

On the other hand, a knowledge graph is a kind of knowledge base, empowered by an inference motor⁷³. Knowledge graph is a complex net of various entities and their interrelations¹⁵⁹ that could be related to a specific organisation or area. Knowledge graphs can collect, extract, and integrate information about external resources²⁸. These capabilities lead to constructing an integrated knowledge-based system⁷³.

'Kosmix' is an example of knowledge-based systems, enabling various applications and helping with gaining insight into a variety of issues on social media. Kosmix is a framework for social data streams analytics and identifying the significant incidents that are becoming apparent. It is empowered by a scalable real-time data processing foundation such as RDBMs and Hadoop⁵⁰.

The popularity of using knowledge bases in different areas²³ is illustrative of its power to help with finding new solutions and insights in decision-making processes³⁴. Given the possibility of creating solutions for complex problems, KBs could be considered as beneficial tools for problem solving in a variety of fields, such as mental health issues. In recent years, very few pioneer works conducted studies related to the using knowledge bases and the contextualised data-driven from them, for identifying mental and behavioural disorders.

Few recent studies tried to use knowledge-based approaches to formalise cognitive science knowledge related to

²³<https://www.ibm.com/cloud/learn/knowledge-graph>

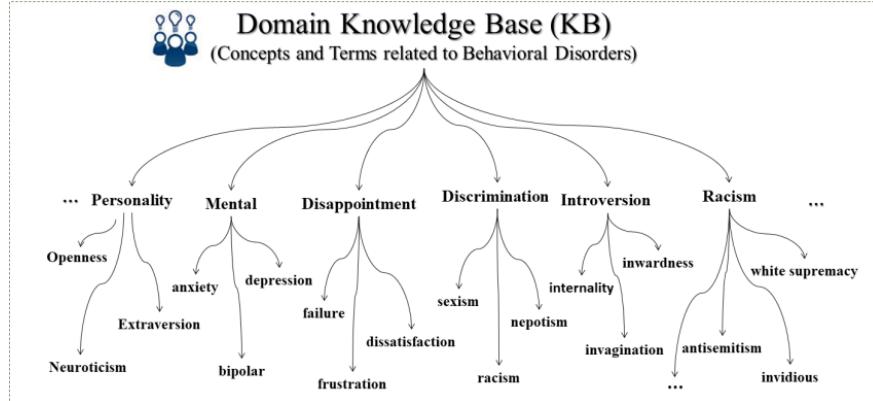


Figure 6. A segment of the domain-specific knowledge base for behaviour disorders³².

behavioural disorders. For example, Beheshti et al.³² provided a new data analytics approach for analysing behavioural disorder patterns in social media platforms. They created a domain-specific KB based on the golden standards in personality and behavioural studies. Figure 6 demonstrate an example snippet of the domain-specific knowledge base for behaviour disorders, introduced by them.

They applied the KB for developing cognitive systems that intelligently contextualise and prepare raw social data for behavioural analytics. For this aim, they proposed a word embedding approach based on patterns to be implemented over each extracted feature to create a social behaviour graph model. As mentioned in their study, the proposed method could be applicable for identifying more specific mental disorders, such as depression and anxiety.

2.3.4 Summary and paper Contribution

Mental disorders were the leading sources of global health-related burden, with anxiety and depression problems accounting for the majority of cases. In recent years, the global COVID-19 pandemic has even worsened the situation. People who are suffering from mental health conditions mostly visit a psychologist to receive supportive advice on their mental situations. In the clinical studies/approaches aiming at screening and identifying potential depressed patients and depressive symptoms, questionnaires (e.g., 3^{127, 189} and 4^{61, 64}) and also interviews are mainly used by psychologists⁵⁵.

Mental health disorders include a wide range of symptoms, risk factors, relationships, and effective interconnections. Most of those disorders (e.g., depression) are not easily identifiable due to their complexity and need lots of time and effort to be identified^{62, 80}. As a result of complexity, mental disorders will not be easily automated or translated into the insights to help clinicians with their identification tasks. It also causes limitations for studies, aiming at using ML and automated analysis in this field. On the other hand, mental disorders such as anxiety and depression are complex subjective issues^{62, 80}. These complexities and subjectivity lead to the fact that having progress in mental disorder issues requires more time, study, and research.

On the other hand, as mentioned in section 2.3, there are lots of evolving studies have been done, and various approaches have been implemented to help with the assessment, screening, identification and prediction of depression. On the other hand, those approaches have evolved to identify better and treat mental disorders. For example, as mentioned before, there are several versions of questionnaires developed during years aiming at progress in depression screening and identification. Although there are valuable progress and improvements in this field, there is still a huge need for further research and contributions to help with identification, prediction and treatment of

mental disorders such as depression.

As our first contribution, we introduce a general-purpose Mental Disorder Knowledge Base (MDKB). Leveraging knowledge-based approaches, the cognitive and psychological knowledge associated with mental health disorders are organised in the form of a knowledge base, providing a rich structure of relevant entities, semantics, and relationships among them. This knowledge base could help with decision-making processes by extracting insights into the mental conditions of potential patients.

3 METHOD

In the previous Section, Section 2, we studied and analysed the various clinical and non-clinical approaches to identifying mental health disorders. We highlighted that state-of-the-art research in identifying Mental Disorder (MD) patterns from textual data, uses hand-labelled training sets, especially when a domain expert's knowledge is required to analyse various symptoms. This task could be time-consuming and expensive. To address this challenge, in this Section, we present a novel approach to facilitate mining of mental disorder patterns from textual data. We leverage the domain knowledge and expertise in cognitive science to build a domain-specific Knowledge Base (KB) for the mental health disorder concepts and patterns. We present a weaker form of supervision by facilitating the generating of training data from a domain-specific KB.

4 CONSTRUCTING A DOMAIN-SPECIFIC KNOWLEDGE BASE

In this section, we explain our methodology to leverage the domain knowledge and expertise in cognitive science to build a domain-specific Knowledge Base (KB) for the mental health disorder concepts and patterns. As illustrated in Figure 7, construction of the proposed mental health disorder Knowledge Base (mKB) consists of five steps: (i) exploring scientific sources; (ii) extracting related concepts, instances and relationships; (iii) constructing the hierarchical taxonomy; (iv) developing instance-to-lexicon connector APIs; and (v) developing instance score calculator APIs from input textual data.

4.1 Step 1: Exploring Scientific Sources

In the first step, a set of golden standards in cognitive computing that are related to mental disorders are explored. There are several best practices, research, online sources, guidelines, and manuals associated with mental disorder identification, helping with constructing the mKB. For example, some of the golden standards and best practices in this field are ‘Diagnostic and Statistical Manual of Mental Disorder’⁷² and ‘Clinical Practice Guidelines and Principles of Care for People with Dementia’, developed by the American psychiatric association and the Australian Government National Health and Medical Research Council (NHMRC)¹⁰³, respectively.

In addition, ‘ICD-11’, a book by World Health Organisation²⁴ and ‘guidance on assessment, diagnosis, and management of dementia’, published together by the British Psychological Society and Royal College of Psychiatrists⁵⁸ are among those sources. Also, ‘panic disorder, social anxiety disorder, and generalised anxiety disorder guide’^{2, 12} contains guidelines for Clinical measures developed by ‘Royal Australian and New Zealand College of Psychiatrists’. These sources could be used for constructing the proposed mKB.

4.2 Step 2: Extracting Concepts, Instances and Relationships

In the second phase of constructing the mKB, after exploring previous studies and golden standards such as those mentioned in Section 2, various mental health related Concepts, instances, and relationships need to be extracted. For example, in designing the mKB, we considered ‘Anxiety Disorders’, ‘Depressive Disorders’, ‘Neurocognitive Disorders’, ‘Paraphilic Disorders’ and ‘Bipolar and Related Disorders’ as instances of the concept ‘Mental Disorders’. Also, anxiety disorders, distinguished by a special way of thinking and behaviours¹², contain instances such

²⁴<https://www.nice.org.uk/guidance/ng54>

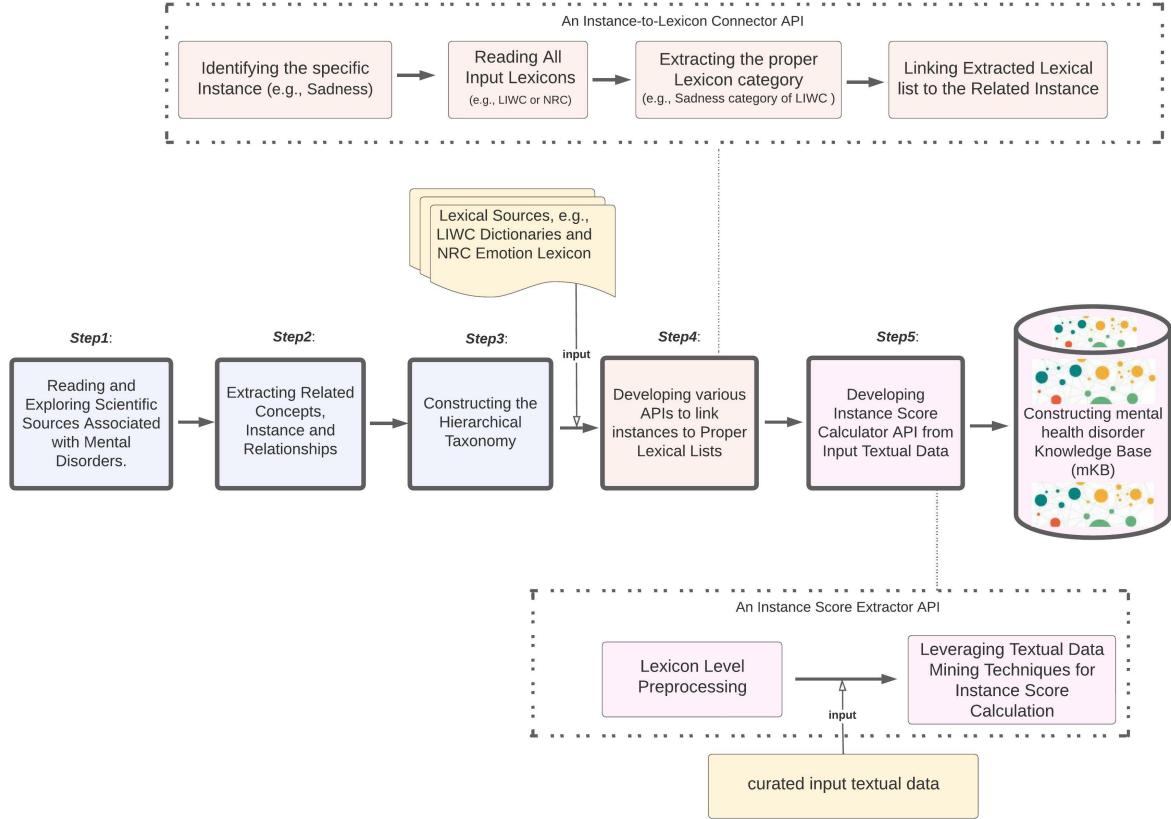


Figure 7. The five-step process of constructing mental disorder knowledge base.

as ‘panic disorder’, ‘social anxiety disorder’, ‘agoraphobia’, and ‘generalised anxiety disorder’.

Each of these instances would probably consist of some concepts, such as ‘Risk Factors’, ‘Symptoms’, and ‘Supportive Symptoms’. As an example, ‘Negative encounters’ could be a risk factor for social anxiety disorder and are very likely to occur in children who are ridiculed, abused, and neglected⁵⁶. Therefore, negative encounters could be considered as instances of the social anxiety disorder risk factors. On the other hand being bullied, rejected, and also ridiculed are considered to be instances of negative encounters. Social anxiety disorder has symptoms such as fear or anxiety attacks, considered to be its instances.^{12, 72}. The rest of the concepts, instances, and relationships in the mKB are extracted in the same way as explained for anxiety disorders.

4.3 Step 3: Constructing the Hierarchical Taxonomy

In this step, all of the extracted mental health disorders related concepts and instances are organised into a taxonomy, being a hierarchical structure for classifying those concepts and instances. The mental health disorder taxonomy contains six main levels. The main concept (i.e., ‘Mental Disorders’) is placed on the top level. The second level contains various instances of mental disorders (e.g., ‘Anxiety Disorders’) each of which represents a specific group of diseases. For example, ‘panic disorder’, ‘social anxiety disorder’, ‘agoraphobia’, and ‘generalised anxiety disorder’ are contained in a group that ‘Anxiety Disorders’ is its representative. All of the instances in this level are connected to the previous level concept (i.e., ‘Mental disorders’) and also to the next level (i.e., third level) instances which are all single disorders contained in a group of related disorders as mentioned before.

Each specific instance in the third level is linked to a set of related concepts in the fourth level. These concepts in the fourth level are ‘Risk Factors’, ‘Symptoms’, and ‘Supportive Symptoms’. Each concept in the fourth level is

connected to its instances in the fifth level and also to the probable sub- and sub-sub- instances in the sixth level and afterwards. All the above-mentioned connections (i.e., from up to down) are shown by solid arrows. However, it is possible that some Concepts and instances would be horizontally connected to each other. Those horizontal connections (i.e., relationships) are shown by dotted arrows. Figure 8 is a snapshot of the mental health disorder Knowledge Base focuses on depression, being one of the main causes of disability globally^{69, 124}. It contains different concepts related to each mental disorder, instances of each concept, and the relationships among them. Vertical solid connections are mainly indicative of relationships between concepts and their instances (e.g., impaired cognitive functioning is an instance of retardation⁴⁵), while horizontal dotted connections are illustrating the different kinds of probable relationships (e.g., impaired cognitive functioning could cause negative emotion)¹²⁴.

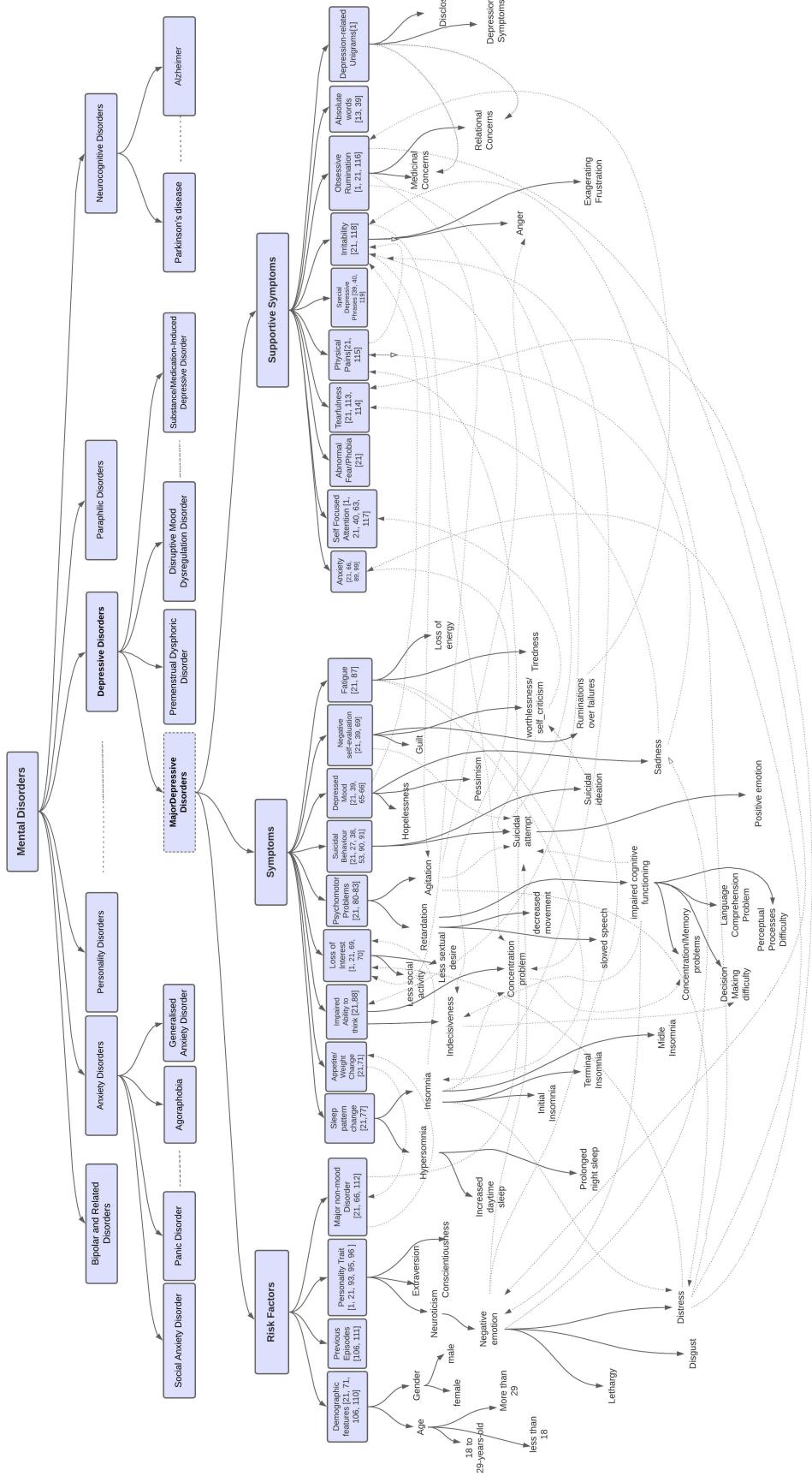


Figure 8. A snapshot of the mental health disorder Knowledge Base focuses on depression, being one of the main causes of disability globally^{69, 124}. It contains different concepts related to each mental disorder, instances of each concept, and the relationships among them. Vertical solid connections are mainly indicative of relationships between concepts and their instances (e.g., impaired cognitive functioning is an instance of retardation⁴⁵), while horizontal dotted connections are illustrating the different kinds of probable relationships (e.g., impaired cognitive functioning could cause negative emotion)¹²⁴.

4.4 Step 4: Developing Instance-to-Lexicon Connector APIs

Kinds of words (e.g., self-focused words, hate speech, positive or negative emotion, death-related, anger), sentence sentiments, and natural language that are used in the daily communications are reflections of individuals' real-life manners, thoughts, cognitive processes, behaviours, and mental health status^{6, 68, 69, 87, 184, 186, 203, 208}. According to numerous studies, there is a clear link between a set of words and the presence of distinctive content (e.g., profane¹⁷⁰, self-criticism²⁰⁸, negative emotion⁶⁸, suicidal attempt/ideation⁷⁷) in textual documents.

As a result, we proposed to use lexical resources for depression identification through text analyses. Hence, prior to this step, various lexical resources are fed into the mKB-related taxonomy, aiming at turning that taxonomy into a lexical-driven knowledge base, which facilitates textual data mining. The goal is to use a collection of related words that can be used for extracting the context-specific features (i.e., linguistic or emotional features) from the text. Some examples of valuable lexicons are LIWC²⁵(i.e., psycholinguistic lexicon), ANEW (Affective Norms for English Words)^{43, 145}, NRC^{139, 140}, Warriner Lexicon²¹², and MPQA²¹⁴. These lexicons contain several categories, related to a specific emotion, behaviour, affect, or linguist style associated with an instance in the MD taxonomy.

For example, LIWC contains the ‘sadness’ category, consisting of a list of around 1,300 words related to sadness. On the other hand, under the ‘Depressed mood’ category of the MD-related taxonomy, there is an instance named ‘sadness’. In this step, these associated items will be linked together by leveraging several APIs. A unique API is developed for each of the instances in the fifth level or their sub-/sub-sub instances in the next levels, and embedded into the mKB. Each of these APIs is a Machine Learning (ML) algorithm that links the corresponding instance (i.e., included in the MD-related taxonomy) to one of the proper input lexicons, as well as the proper category of that lexicon. This step helps with constructing an MD-related taxonomy enriched with thousands of words¹⁰.

4.5 Step 5: Developing Instance Score Calculator APIs from Input Textual Data

In this step, several APIs are developed, each of which is associated with one of the instances in the MD-related taxonomy. APIs are ML algorithms, that calculate the feature scores (e.g., sadness score), corresponding to each instance (e.g., sadness), via analysing input textual data. calculated feature scores act as fundamental parts of our proposed mKB, which enables automated knowledge-based analysis. One of the automated tasks, empowered by using this knowledge-based analysis is the identification of probable individuals with mental disorders. For example, through this research, a classifier is developed (i.e., explained in Section 5), that enables identifying potential depressed individuals, automatically. The main tasks, enabled by the instance score calculator APIs are as follows:

- Lexicon Level Preprocessing: Prior to any score calculations, all the words included in each instance-related lexicons need to be preprocessed. The preprocessing consists of removing unwanted and useless symbols, and punctuation and also stemming all the words included in each lexicon. Stemming is the technique of reducing words to their word stem, base, or root form²⁶. Since the lexicon words will be used for calculating similarity scores between each lexicon category and the input text, stemming could be the most significant and effective technique in this stage.
- Linking the Curated Input Textual Data: As mentioned before, each instance in the taxonomy is connected to the proper lexicon. The instance score calculator API enables linking the curated input textual data to the related instance and lexicon. Data curation is an automated process that prepares the raw input data prior to further data analysis²⁹. In Section 5.1, the data curation process is described in more detail.

²⁵<http://www.liwc.net/>

²⁶<https://en.wikipedia.org/wiki/Stemming>

- Leveraging Textual Data Mining Techniques for Instance Score Calculation: After cleaning and preparing the raw data, different features are extracted from the cleaned data. There are two types of features that could be extracted from the input cleaned/prepared data, namely text-related features and user-related features. Sentiment polarity (i.e., positive, negative, or neutral feeling conveyed through a text) and personality trait (e.g., being neurotic or extravert) analysis are examples of text-related and user-related features, respectively. Afterwards, our data is enriched by different techniques such as stemming. Finally, after data cleaning, preparation, feature extraction, and feature enrichment phases, the output (i.e., featured data) is ready for further analysis and score calculation process³⁵.

In our proposed method, different scores such as cosine similarity scores, suicidal behaviour scores, and personality trait scores are calculated. Cosine similarity scores help us to identify the rate of similarity between the input textual data (i.e., written by a potential depressed person) and the instance-related lexicons. Those scores are expressive of how frequently an MD instance-related words (e.g., sadness-related words) are used by a specific individual. Consequently, they could be indicative of a specific MD-related instance (e.g., sadness feelings) that the writer conveys and shows through his written text.

Cosine similarity scores are calculated by the instance calculator APIs. They are computed using different textual data mining techniques, such as NLP techniques, consisting of ‘Term Frequency–Inverse Document Frequency’ (TF-IDF) and ‘Cosine Similarity’. TF-IDF is a text mining technique for determining the importance of a word in a collection or corpus of documents²⁷. Each word in text mining is given a unique coordinate, and a document is represented by a vector representing the number of times each word appears in the document. Also, cosine similarity is a useful metric for determining how similar two texts are likely to be in terms of content, regardless of their length²⁸.

On the other hand, motivated by a recent study¹³¹, the probability of a special kind of personality trait (e.g., neuroticism) could be extracted. This probability is calculated by a specific API, connected to the personality trait instance on the mKB. This API consists of a sophisticated algorithm, using a 7-layer convolutional neural network and several NLP techniques such as word2vec embedding. In addition, Suicidal behaviour (e.g., suicidal attempts or ideation) scores are calculated using a special score calculator API.

In addition, there could be other APIs that don’t need text mining techniques for score calculation. For example, the ‘Gender’ or ‘Age’ instance-related APIs would create simple numerical scores. For example, ‘Gender’ API’s scores could be ‘0’ or ‘1’, indicative of the male or female users. Also, ‘Age’ API could give some scores based on different pre-defined age ranges. Algorithm 1 demonstrate the process of instance score calculation for those APIs that apply textual data mining techniques for this aim.

Data: Curated Input Textual Data

Result: calculated Instance-related Scores

The mKB Instances;

Linked Instance-related lexicons;

for Each Instance in the mKB do

 Reading the Curated Input Textual Data;

 Reading the linked lexicon;

 Applying proper text mining techniques (e.g., Cosine Similarity Calculation);

end

Algorithm 1: The process of instance score calculation in API’s that work based on textual data mining techniques.

²⁷<https://en.wikipedia.org/wiki/Tf%E2%80%93idf>

²⁸https://en.wikipedia.org/wiki/Cosine_similarity

Finally, developed APIs are linked to corresponding instances, and embedded in the taxonomy. After embedding the APIs into the taxonomy, it technically turns into a knowledge base. Through this KB several mental disorder scores would be calculated. These scores could be shown as an extracted knowledge from mKB aiming to give some insight and alarms to the analysts or psychologists. This knowledge besides analysts' experiences could probably be informative, helping them make more accurate identifications.

5 DEVELOPING A WEAKLY SUPERVISED CLASSIFIER FOR TARGET MENTAL DISORDERS USING DOMAIN-SPECIFIC KB

ML algorithms have notable real-world applications. Most of these applications are enabled by leveraging deep learning models and existence of various open-source ML platforms such as TensorFlow and PyTorch, as well as a large number of modern models. However, large hand-labelled training datasets are required for these models to perform well¹⁶⁶.

In recent studies, hand-labelled training data sets have been employed to find mental disease patterns from textual data. Benefiting from experts and psychologists knowledge to label a dataset with presence or absence of a disorder could be an expensive and time consuming task. Besides, evolving nature of knowledge, makes it necessary to access re-labelling mechanisms for more accurate data analysis tasks¹⁶⁶. In cognitive science area, which includes high levels of subjective knowledge, having access to labelled data for analytical tasks is even more crucial³³. Weak supervision is a learning approach in which a higher level source of supervision can be used to generate a larger training sets¹⁶⁶. In this section, we leverage the mental health domain-specific Knowledge Base (mKB), discussed in previous section, to propose a weakly supervised mental disorder classifier. Using the cognitive and psychological knowledge that is embedded in the mKB acts as a kind of domain experts knowledge to be used as a labelling asset, contributing to the creation of more labelled training data sets for cognitive analytics.

Our approach will enable the mKB to be the main source of supervision. The mKB, is a general KB, consists of several instances of mental disorders and their related concepts and instances. Our proposed approach is applicable at a time to one of the mKB's disorders (e.g., depression), which is called Target Mental Disorder (TMD). The mKB, is empowered with several APIs, which are calculating TMD-related instance scores. These scores are valuable features, associated with specific cognitive, behavioural, and mental conditions, which enable the process of labelling training data sets for any other studies related to mental disorders.

Figure 9 illustrates the proposed pipeline for developing a target mental disorder classifier. There are several stages included in developing the proposed pipeline, as follows: (i) ‘Data Curation’; (ii) ‘Linking Extracted Features to TMD-related Instances in mKB’; (iii) ‘calculating Scores for TMD-related Instances leveraging mKB APIs’; and (iv) ‘Developing a Target Mental Disorder Classifier’. Our proposed approach offers an extensible framework by adopting a service oriented architecture²⁶ to enable new analytical features to be plugged into the system in an easy way. For example, if we find it effective to add other features (e.g., ‘swear words’, ‘hate speech’ or ‘profane words’ scores) to our model, then the extensible architecture will facilitate this for the analyst.

5.1 Data Curation

Data curation defines as a process that turns the raw data into contextualised data and knowledge²⁹. This process helps the ML algorithms run more efficiently. Motivated by two recent studies^{27, 29}, as Figure 10 demonstrates, the raw textual data needs to be prepared and curated before any further analysis. The curation process contains 3 phases, namely (i) Data Cleaning; (ii) Feature Extraction; and (iii) Feature Enrichment, which are explained as follows.

- Data Cleaning: There are different techniques and tools that could be used for cleaning textual data. For ex-

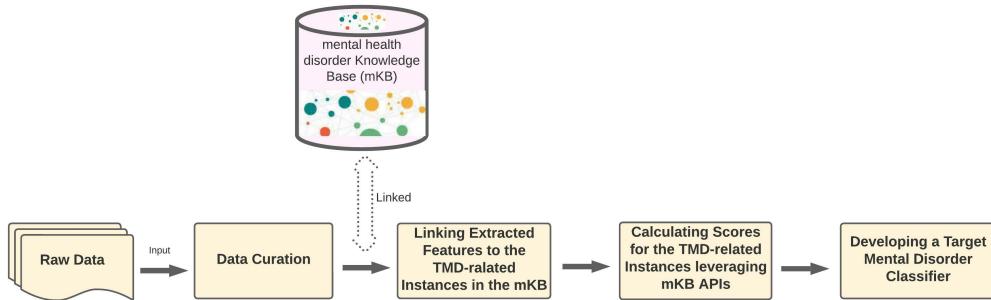


Figure 9. The proposed pipeline for developing a weakly supervised mental health disorder classifier, leveraging calculated scores for Instances related to a Target Mental Disorder (TMD), generated by mKB.

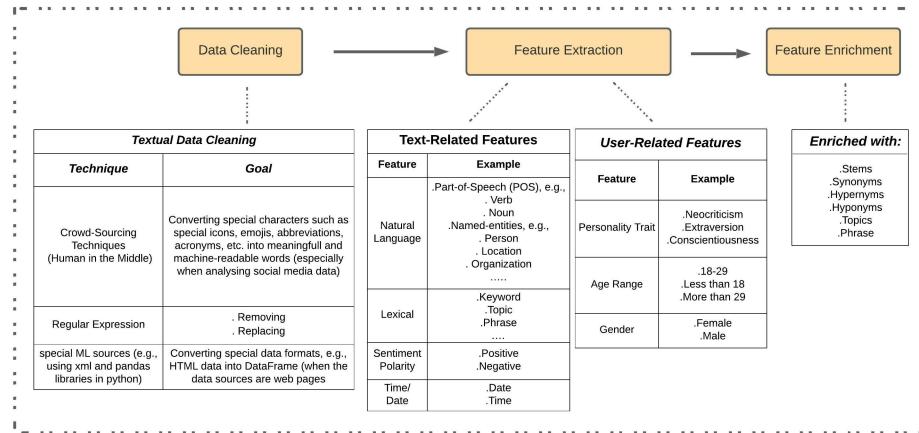


Figure 10. Data curation process motivated by Beheshti et al. study²⁹.

ample, with the help of some ML packages and their corresponding methods(e.g., XML, Pandas, and RegEx (i.e., regular expressions)) useless data (e.g., punctuation, numbers, symbols, etc) could be removed or some special parts of raw data (e.g., acronyms such as PSTD) could be replace with the proper real words (e.g, Post Traumatic Stress Disorder). Also, special noisy data formats (e.g., HTML and web-related data) could be turned into much easy-to-work formats (e.g., DataFrame). Besides, crowd-sourcing is a modern approach for cleaning social data. In this approach, the knowledge of the crowd (e.g., Amazon Mechanical Turks) is used for some correction tasks (e.g., spell- or abbreviation-checking).

- Feature Extraction: There are two types of features that could be extracted from the clean data, namely ‘Text-Related Features’ and ‘User-Related Features’. The text-related type consists of ‘Natural Language’, ‘Lexical’, and ‘Time/Date’ features . The user-related type consists of the user’s ‘Personality Trait’, ‘Age Range’, and ‘Gender’. Some of these features are explained as follows.
 - Natural Language Feature refers to entities that could be retrieved from Natural Language and speech through ML analysis. It includes Part-of-Speech, named entities, etc. Verbs (e.g., developed, caused, felt, experienced), Nouns (e.g., psychiatrist, depression, anxiety, acid Reflux, Acticlate, Zoloft), and adjectives (e.g., nauseous, busy, terrible, bothering) are some examples of the Part-of-Speech. Person names (e.g., Jean Piaget and Albert Bandura), Organisations’ names (e.g., Royal Prince Alfred), locations (e.g., Sydney) are also some instances of named entities¹⁰⁵.
 - Lexical Feature includes examples such as Keyword (e.g., hypochondria, depressive episode, depression), Topic (e.g., Daily Acid Reflux²⁹), Phrase (e.g., ’with my psychiatrist’s help’), Abbreviation (GAD and

²⁹A digestive disease in which stomach acid or bile irritates the food pipe lining.

IBS), and Spelling Errors.

- Time/Date Feature refers to the time (14:14:54) or date(2017/02/21), when a text is created. This feature could help with getting insight into the probable sleep time or when a user is mainly active in social media. It could be a valuable feature in the time series analysis.
 - Personality Trait Feature consists of different personality traits (e.g., neuroticism, extraversion, openness, etc). It is one of the user-related features, extractable via different modern textual analysis techniques¹³¹. A personality trait could contribute to suffering from several mental conditions^{112–114}, and could be an important feature to be considered in the cognitive analysis.
- Feature Enrichment relates to utilising relevant sources and services (e.g., WordNet³⁰ and STANDS4³¹) to identify synonyms and stems for a keyword that has been extracted. For example, 'traumatic' as a keyword could be enriched with its synonyms such as 'disturbing', 'shocking', 'distressing' and 'upsetting'. IBS and GAD are two keywords which are extracted from the text. IBS and GAD are two acronyms, that are equivalent to two types of disorders, namely 'Inflammatory Bowel Disease' and 'Generalized Anxiety Disorder'. Identifying these equivalents relationships leads to creating more enriched data to help with accurate data analysis tasks.

5.2 Linking Extracted Features to the TMD-related Instances in the mKB

Each mental disorder included in the mKB (e.g., depression) contains several instances (e.g., 'Sadness', 'Suicidal Behaviours', 'Gender'). To link these instances to the curated data and extracted features, each instance is provided with an empty list. Then, extracted features (e.g., stemmed keywords or phrases) are added to the corresponding instance list. The kind of added features to the list is dependent on the type of the related instance. For example, extracted gender(i.e., male or female) related to the writer of a text is added to the empty list provided for the instance of 'Gender' in the mKB.

Besides, for 'Sadness' instance, for example, we need extracted features to be added to the list. On the other hand, there are some instances such as 'Suicidal behaviour' that need the whole raw text (i.e., written by each user), instead of extracted features, to be added to the corresponding list, aiming at counting the number of suicidal phrases via corresponding API. Algorithm 2 illustrates the process of linking extracted features to the corresponding instances in the mKB.

Data: Curated input textual data

Result: List of features that are linked to the instances of the mKB

Specify the TMD;

Extract Features from textual data;

TMD_ralated_Instances = Set up and Array for TMD-ralated Instances in the mKB; %(e.g., 'Negative Feeling', 'Anxiety', 'Sadness', etc.)

for Each TMD_ralated_Instances do

 Generate an empty list;

 for Each feature in Extracted-Feature do

 Add the feature to the corresponding instance-related list;

 Link Extracted Features to the instances in mKB;

 end

end

Algorithm 2: Linking Extracted Features from input textual data to the TMD-ralated Instances in the mKB.

³⁰wordnet.princeton.edu/

³¹abbreviations.com/abbr_api.php

5.3 Calculating Scores for the TMD-related Instances Leveraging mKB APIs

The mKB is empowered by several APIs for calculating the instance scores. Each of those APIs has a separate functionality. Some of them (e.g., the ‘Suicidal Behaviour’ or ‘Special depressive phrases’ API) create scores that are indicative of the counted numbers of special phrases that are used in a cleaned text. On the other hand, some of them (e.g., ‘personality Trait’ API) create a score that is the probability of having a special personality trait (e.g., neuroticism) by analysing a cleaned text.

The linked extracted features (i.e., from Section 5.2) are the input for corresponding instance-related APIs. This input enables the score calculation processes for each of the TMD-related Instances. For example, a list of extracted stemmed tokens is linked to the ‘Sadness’ API. This API calculates the cosine similarities between the linked list and the related lexical source, being attached to the instance. The calculated scores act as input features for developing a learning algorithm (i.e., a classifier), and are fed into the next step. Algorithm 3 demonstrates the process of calculating scores for the TMD-related instances, leveraging mKB APIs.

Data: Linked Features (i.e., the Algorithm 2 output)

Result: Scores Related to Instances

Specify the TMD;

for Each TMD-related Instance in mKB do

 Instance-related Score = Embedded-score-calculator-APIs(linked features);

 %Embedded-score-calculator-APIs() is a function for calculating scores

 %functions mainly use techniques related to TFIDF or Cosine Similarity calculation

end

Algorithm 3: Calculating Scores for TMD-related Instances Leveraging mKB APIs.

5.4 Developing a Target Mental Disorder Classifier

In this step, the calculated scores for each TMD-related instance act as input features of the TMD-related classifier. Several ML algorithms such as Random Forest, Logistic Regression, SVM and XGbooster could be deployed to develop this classifier. After feeding related scores, a binary learning algorithm is developed to classify whether an input text is associated with a target mental health disorder or not.

For example, considering depression as a TMD, the corresponding classifier would take a textual document and give it the labels of ‘0’ or ‘1’ for ‘not depressed’ or ‘depressed’ tags, respectively. In the next Section, we will discuss how we create a depression-related classifier with a high accuracy, using ensemble techniques. Algorithm 4 illustrates the process of developing a TMD-related classifier.

Data: Calculated Instance-related Scores

Result: Developed TMD-related Classifier

Specify the TMD;

for Each TMD-related Instance do

 Generate Instance score using related API;

 Integrate all the scores as a feature array;

 Deploy a Proper ML classifier using the feature array;

end

Algorithm 4: Process of Developing a TMD-related Classifier.

6 EVALUATION AND EXPERIMENT

In this Section, the outcomes derived from the proposed method in Section 3 are explained and evaluated. We will demonstrate how this model can help analysts and domain experts to get insight into the mental health status of their target population. First, a depression-related motivating scenario is described, clarifying the importance of this research. Afterwards, we present the experimental setup, the dataset, experimental results, and evaluation of our method.

6.1 Motivating Scenario

The mental health of individuals and communities is a pressing challenge in the world, nowadays. Since COVID-19³² pandemic outbreak in 2019, most governments have been preoccupied with handling and combating the epidemic. After the global success in vaccine development, a key concern for most governments is to harness the impacts of years of virus exposure, including the associated psychological problems in the community. Based on a recent study, after being diagnosed with Covid, roughly one out of every five people develops a mental disorder²⁰¹. Data from the United States and Australia show elevated rates of depression throughout the epidemic; It is estimated that during the outbreak, depression level (i.e., 25%) is seven times higher than pre-pandemic levels worldwide (i.e., less than 4%)⁹¹. Hence, it could be a critical issue for governments to monitor, identify and take proper actions in this regard.

Due to the importance of the issue, as a motivating scenario, we focus on depression. We use the framework proposed in Section 3 to highlight how our method significantly assists e-safety³³ community to monitor and identify the trend for the emergence of depression-related symptoms, during special periods of time such as the Covid-19 period. We leverage the domain specific KB (that discussed in Section 3) and expertise in cognitive science to build a domain-specific Knowledge Base (KB) for depressive patterns. This KB contains a set of depression-related concepts organised into a taxonomy, instances for each concept, and relationships among them. Then, we use the proposed weakly supervised learning approach (Section 3) by facilitating the generating of labelled training data from depression-related KB. To evaluate our approach, we adopt a typical scenario for analysing social media to identify major depressive disorder symptoms from the textual content generated by social users.

6.2 Experimental Setup

6.2.1 Experiment Environment

We use Jupyter notebook from Anaconda 3 environment, Python version '3.9.0', Pandas ('1.3.4'), NLTK ('3.5'), Sklearn ('1.0.1'), XGBoost ('1.5.0') for performing our NLP, textual data analysis, and developing depression-related classifier.

6.2.2 Dataset

People's ideas and feelings can be viewed through social media platforms such as Twitter. New studies have centred on the investigation and mining of such data in a range of fields, including financial systems, politics, and healthcare⁶⁸. On the other hand, social media is a rich source of textual data, enabling researchers and data scientists analyse cognitive processes and behavioural patterns of the social media users^{69, 183}. Hence, as we are interested in identifying potential depressed individuals (i.e., part of our motivating scenario) through textual data mining, we use a real-world dataset³⁴ from Reddit³⁵, i.e., a social news aggregation, web content rating, and dis-

³²<https://en.wikipedia.org/wiki/COVID-19>

³³<https://www.esafety.gov.au/>

³⁴<https://github.com/BigMiners/eRisk2018>

³⁵<https://en.wikipedia.org/wiki/Reddit>

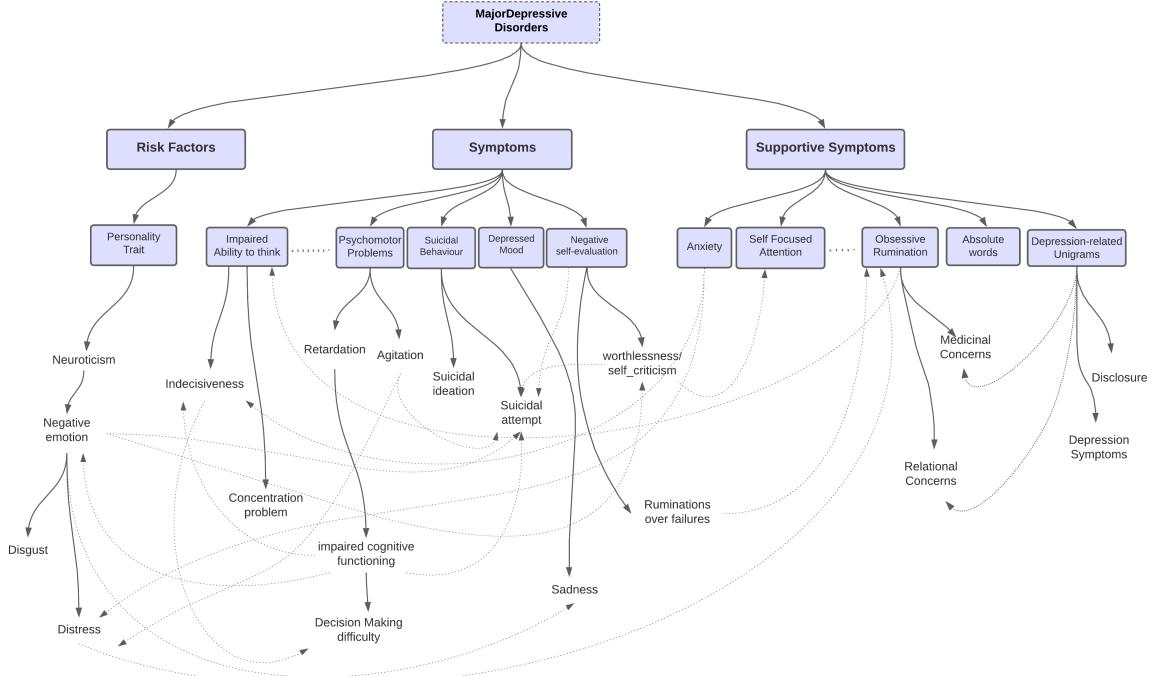


Figure 11. A Snapshot of depression KB, containing some of concepts and instances used in evaluation part.

cussion Website. The dataset contains 820 users, each tagged with ‘1’ (i.e., ‘depressed’) or ‘0’ (i.e.,) ‘not depressed’ labels. From a total of 820 users, 79 were tagged as depressed and the rest (i.e., 741 users) were tagged as not depressed. The raw data is in the form of XML files and it is organised into ten chunk’s. Each chunk contains 820 folders (each folder for one user), and each folder consists of parts of the posts related to one of the 820 users. Considering all of the posts related to each user (contained in all 10 chunks), the average number of posts for each user is 664 numbers.

6.3 Experimental Results

In this part, we describe the experimental results derived from our method. First, we explain the construction of depression-related KB. Then, we explain the process of developing a weakly supervised classifier for depression, using the results derived from the constructed depression-related KB.

6.3.1 Constructing a Depression-related Knowledge Base

As mentioned before, a knowledge base consists of a taxonomy, several concepts, sub-concepts, instances, and the relationships between them. Figure 11 illustrates a snapshot of the depression KB, containing some of the concepts and instances used in the evaluation part. A more detailed Image of depression concepts and instances could be found in the Figure 8. In this section, different steps for constructing depression-related KB are described.

- Concepts and Instances of Depression-related KB In this section, different components of depression-related KB, namely concepts (i.e., ‘Symptoms’, ‘Risk Factors’ and ‘Supportive Symptoms’) and their instances are explained. We also describe how different components are linked to each other. We also represent some examples in each part for more clarifications and ease of interpretation.

- ‘Symptoms’

There are nine main depression symptoms, namely ‘Sleep pattern change’, ‘Appetite/Weight change’, ‘Diminished ability to think’, ‘Loss of Interest’, ‘Psychomotor Problems’, ‘Suicidal behaviour’, ‘Depressed Mood’, ‘Negative self-evaluation’, ‘Fatigue’. We consider them as nine instances linked to the ‘Symptoms’ concept.

Impaired cognitive functioning, being the sub-instance of psychomotor problems, has several instances such as ‘decision-making difficulty’. On the other hand, ‘Indecisiveness’ is an instance of the concept of ‘diminished ability to think’. Since indecisiveness and decision-making difficulty both are the same impaired cognitive functioning, they are connected in the KB by a dotted arrow indicative of the ‘same as’ relationship.

- ‘Risk Factors’

There are four instances of the ‘Risk Factors’ concept. They are ‘Demographic features’, ‘Previous Episodes’, ‘Personality Trait’, ‘Major non-mood Disorder’. These instances are placed under the ‘Risk Factors’ concept, in the KB. Some of these instances such as Personality Trait consists of some more sub-instances.

A personality trait is one of the depression risk factors. ‘Neuroticism’ is the most significant instance of the personality trait concept, consisting of the ‘negative emotion’ and ‘distress’ as its instance and sub-instance, respectively. In the KB an instance (e.g., negative emotion) is linked to its upper concept (i.e., the personality trait of neuroticism) or its following instance (e.g., distress) by a solid arrow. Besides, the relationships between instances of a concept to the other concepts or their instances are shown as dotted lines.

- ‘Supportive Symptoms’

There are 10 instances of the ‘Supportive Symptoms’ concept. They are ‘Anxiety’, ‘Self-focused attention’, ‘Abnormal Fear/Phobia’, ‘Tearfulness’, ‘Physical pains’, ‘Special depressive Phrases’, ‘Irritability’, ‘Obsessive Rumination’, ‘Absolute words’, ‘Depression-related unigrams’. Some of these instances such as Depression-related unigrams include some sub-instances such as ‘Depression-Treatment’ and ‘Depression-Symptoms’. These sub instances are indicative of special terms related to depression treatment or symptoms, for example.

In addition, ‘Anxiety’ and ‘self-focused attention’ are two instances of depression supportive symptoms concept. Anxiety is caused by excessive distress. Hence, they are connected to each other by a dotted arrow, indicating a ‘cause in’ relationship. In addition, the feeling of worthlessness/self-criticism could lead to increased self-focused attention. Therefore they are also connected by the dotted arrow.

- Lexical Sources Linked to the Depression-related KB In this research, we use several lexical sources to be linked to the depression-related KB. As Figure 12 illustrates, our final lexical database is in the form of an excel file. It is constructed by merging four lexicons, namely LIWC2015 lexicon (i.e., categories related to depression instances)¹⁶¹, NRC emotional lexicon¹⁴⁰, absolute word lexicon⁶, depression Uni-gram lexicon⁶⁹. Different lexical sources, used in the construction of this research lexical database, are described as follows.

- LIWC2015: As explained in Section 2.3.2, LIWC2015 is one of the main and golden standard computerised text analysis tools. It is a valuable resource that is widely utilised for measuring positive and negative affects^{68, 88}, as well as extracting various word-based features from textual data^{161, 162, 203}. LIWC2015 consists of an English dictionary with 90 linguistic, behavioural, and psychological categories. Each category includes a list of related words. In order to construct the depression-related KB, we used all of the categories, related to the depression instances.
- NRC Emotion lexicon: It is a broad, high-quality English term-emotion association lexicon focusing on ‘joy’, ‘sadness’, ‘anger’, ‘fear’, ‘trust’, ‘disgust’, ‘surprise’, ‘anticipation’¹⁴⁰. To enrich the categories

word list, we merge them with proper categories of NRC Emotion lexicon¹³⁸, including For example, we merge all the words in the ‘negative emotion’ categories of both LIWC and NRC, together. On the other hand, some NRC categories such as ‘disgust’, being an instance of negative emotion in depression-related KB, was separately used to form the list of related words of ‘disgust’ instance.

- Absolute word lexicon: Depressed individuals mostly talk in absolute language and use greater percentage of absolutist words in their natural language and daily communications^{6, 186}. In this study we use the absolute word list, developed by Al-Mosaiwi et al.⁶.

LiWC	negative_nrc - added	sadness_nrc - added	discrepancy- liwc	tentative-liwc	certainty-liwc	fear_nrc	disgust_nrc	symptoms_- unigram	treatment_- unigram	Absolute Words_abs
i);	abandon*	abnormal*	alot	absolute	abandon	aberration	anxiety	medication	absolutely
i'd	:{	agoniz*	besides	almost	absolutely	abandoned	abhor	withdrawal	side-effects	all
i'd've	abandon*	agony	could	alot	acura*	abandonment	abhorrent	severe	doctor	always
i'll	abuse*	alone	could've	ambigu*	all	abduction	abject	delusions	doses	complete
i'm	abus*	bereave*	couldn't	any	altogether	abhor	abnormal	adhd	effective	completely
i've	ache*	broke	couldnt	anybod*	always	abhorrent	abominable	weight	prescribed	constant
id	aching*	cried	coulde	anyhow	apparent	abomination	abomination	insomnia	therapy	constantly
idc	advers*	cries	desir*	anyone*	assur*	abomination	abortion	drowsiness	inhibitor	definitely
idgaf	afraid	crushed	expect*	anything	blatant*	abortion	abundance	suicidal	estimulant	entire
idk	aggravat*	cry	hope	anytime	certain*	absence	abuse	appetite	antidepressant	ever
idontknow	agress	criing	hoped	anywhere	clear	abuse	accusation	dizziness	patients	every
idve	agressed	depress*	hopeful	apparently	clearly	abyss	actionable	nausea	neurotransmitter	everyone
ikr	agresses	depriv*	hopefully	appear	commit	accident	adder	episodes	prescriptions	everything
ily*	agressing	despair*	hopes	appeared	commitment*	accidental	adultery	attacks	psychotherapy	full
im	aggression*	devastat*	hoping	appearing	commits	accursed	adverse	sleep	diagnosis	must
ima	aggressive	disappoint*	ideal*	appears	committed	accused	affliction	seizures	clinical	never
imean	aggressively	discourag*	if	apprehens*	committing	accuser	afront	addictive	pills	nothing
imma	aggressor*	disheaten*	impossible	approximat*	complete	accusing	aftermath	weaned	chemical	totally
ive	agitat*	disillusion*	inadequa*	arbitrar*	completed	acrobat	aggravation	swings	counteract	whole
me	agoniz*	doom*	lack	assum*	completely	adder	agirst	disfunction	toxicity	
methinks	agony	dull	lacked	barely	completes	adjudicate	airs	blurred	hospitalization	
mine	alarm*	emptier	lacking	bet	confidence	admonition	alcoholism	irritability	sedative	
my	alone	emptiest	lacks	betts	confident	adrift	alien	headache	150mg	
myself	anger*	emptiness	liabilit*	betting	confidently	advance	alienate	fatigue	40mg	
	angrier	empty	mistak*	blu*	correct*	adverse	alienation	imbalance	drugs	

Figure 12. A snapshot from a part of lexical database used in this research. It is constructed by merging four lexicons, namely LiWC2015 lexicon (ie., categories related to depression instances)¹⁶¹, NRC emotional lexicon¹⁴⁰, absolute word lexicon⁶, depression Uni-gram lexicon⁶⁹.

- Depression Uni-gram Lexicon: Based on a study by Choudhary et al.⁶⁹, depressed people tend to use special depression unigrams and terms in their communications. Through their study they developed a lexicon of some depression-related categories. In this study, we use those lexicon to make a more comprehensive lexical database.
- Suicidal phrases source: Based on Fernandes et al., there is a list of terms and phrases, used to detect and extract documents that may include references to attempted suicide⁷⁷. This list may aid in the identification of suicidal thoughts and attempts in textual data³⁶. Hence, in this research, we leveraged this list of words and phrases, aiming to calculate a score for this symptom. Table 2 illustrates different phrases related to suicidal behaviours.

suicid* ideat* after a suicide attempt another attempt to end life another suicid[e/al] attempt attempt at self-harm attempt on [his/her] life attempt to commit suicide attempt to suicide attempt[ed] suicide attempt[ed] to commit suicide attempt[ed] to end [his/her] life attempt[s][number] suicide attempted to kill myself attempted to take [his/her] life depression with suicide attempt failed suicid[e/al] attempt first attempt at [his/her] life following [his/her] suicid[e/al] attempt	after a suicide attempt following a suicide attempt jumped off a bridge his suicide attempt was not successful history of suicide attempt[s] in an attempt to kill myself leapt in front of motor leapt in front of moving leapt in front of traffic leapt in front of vehicles next time [he/she] attempts suicide suicid[e/al] attempt[s] previous [number] attempt by previous [number] attempt to shot myself suicid[e/al] [number] attempt[s] suicid[e/al] attempt due to depression	suicid[e/al] attempt was not successful suicid[e/al] attempt[s] suicid[e/al] behaviour suicid[e/al] gesture suicide attempt age [Number] suicide attempt failed took firearm to myself took gun to myself took handgun to myself took knife to myself took rifle to myself tried to drown myself tried to end my life tried to hang myself tried to kill myself tried to shoot myself tried to take my life
--	---	---

Table 2. List of terms and phrases used to detect and extract documents that may include references to attempted suicide or ideation in this regard⁷⁷.

- Depression-related KB’s APIs: In depression-related KB, we deployed several APIs, aiming at calculating instance-related scores. There are three kinds of APIs used in our KB construction. The task and the structure of each API are explained as follows.
 - Instance to Lexicon Connector API: In this step, each depression-related instance is empowered by an APIs, which is linking the instance to the proper lexical source. For example, there is a special API that connects the ‘Absolute word’ instance to the ‘Absolute word lexicon’, also another API links the suicidal behaviour instance to the suicidal phrase’s source, etc.
 - Cosine Similarity Calculator API: In addition to the Instance to Lexicon Connector API, most of the instances are linked to another API, which provides different instances with the cosine similarity scores. This API, which is linked to the instance-related lexical source, uses different NLP techniques (e.g., TFIDF and Cosine Similarity) to calculate those scores.
- In those APIs that are created for cosine similarity calculation, TFIDF technique is applied, first. For this aim, concatenated texts in each of the 10 chunks for each user (i.e., mentioned in Section 6.2.2), are considered as different documents. These documents, used in the TFIDF technique, make it possible that important and meaningful words, that are used by each user, to be considered in the analysis. Consequently, we could come up with reliable results.
- Suicidal Behaviour API: We use a list of phrases, related to suicidal behaviours for identifying the scores of suicidal attempts or ideation from texts. Suicidal behaviour API consists of the regular expressions to count the number of suicidal phrases in texts. the calculated number is used as the calculated score to be used in further stages.

³⁶https://github.com/andreafernandes/NLP_Tools_Development

6.3.2 Leveraging the Proposed Pipeline to Classify the Textual Data as ‘Depressed’ or ‘Not depressed’

After constructing the depression-related KB, several calculated instance scores enable us to develop an automated machine learning (ML) algorithm (i.e., depression classifier). This algorithm is equipped with the knowledge derived from the mKB and could be used in labelling different texts into ‘depressed’ or ‘not depressed’. For example, if a text is labelled as ‘depressed’, it shows that the writer of the corresponding text was probably depressed. In this approach, we use a data analytics tool for identifying the depression status of a person who wrote a text, instead of receiving direct consultancy or supervision from experts or psychologists. Hence, this classifier is considered to be a kind of weakly supervised learning algorithm. This classifier could facilitate many future depression-related studies in terms of creating a large amount of labelled data (i.e., training data set) for their deep learning analysis. In this section, as shown in Figure13, we apply the proposed pipeline explained in Section 5 to develop a learning algorithm for depression identification by textual data analysis.

- Pre-Processing and Data Curation: As mentioned before,in Section 6.2.2, our input dataset (i.e., Reddit posts) contains 820 users’ posts (i.e., posts of each user is divided in to 10 chunks). They are in the form of ‘XML’ files, containing the textual posts during different time ranges. In the first step, through preprocessing and data curation process, the raw input data should be organised into a proper format. Hence, we use the ‘XML’ and ‘pandas’ packages to turn the XML files into data frame, making the ML analysis feasible. The first data frame consists of 820 rows (i.e., the number of users) and three columns, namely ‘user-names’, ‘depression status’ and ‘concatenated-texts’. All the single posts of each user were concatenated together, forming a single long text. This document forms the content in the ‘concatenated-texts’ column of the data frame. The values in the ‘depression status’ column are ‘0’ or ‘1’, indicative of not-depressed and depressed tags, respectively.

We also create another data frame (i.e., the second data frame) containing 8200 rows, each 10 rows related to one of the users. It has the same columns as the previous one. We used the content of this data frame for the ‘TFIDF’ and ‘Cosine Similarity’ scores, mentioned in Section 6.3.1. Afterwards, we use regular expressions to remove stop words, symbols, numbers, and other useless data from the texts. We apply NLP techniques such as the word tokenisation method to the cleaned texts. In addition, all of the words were stemmed using ‘nltk.stem package’. The output would be lists (i.e., in the first data frame) or strings (i.e., in the second data frame) of words, within a specific column in the data frames, which are considered to be our extracted features. A part of Figure 13 is indicative of an example curation process over a text, which is extracted from an XML input file. The final result of curation part, is a list of stemmed forms of extracted and tokenised features.

- Linking Extracted Features to the Depression-related Instances in the mKB: For the evaluation part, we use 17 instances of depression KB (i.e., named in the next part) that could be provided with a proper lexical source. In this part, we assumed every single word that is used in the user’s texts is a valuable asset to be considered in the analysis. Hence, we link stemmed and extracted words from input text to the 16 (exclude one out of 17) instances in the mKB. The linked data is provided in the form of a list of stemmed words, related to each user to be used by the corresponding instance-related API for score calculation. The excluded instance is the ‘Suicidal behaviours’ instance. This instance is not linked to the stemmed forms of extracted words, but to the original cleaned text. The aim is to use this original text for calculating a score for the ‘Suicidal behaviours’ instance, which is simply the count of special phrases used in the texts.
- Calculating Scores for Depressive Instances: There are 17 depression-related instances in mKB that are provided with score calculator APIs. These instances are related to one of the three depression-related concepts, namely ‘Symptoms’, ‘Risk factors’, and ‘Supportive Symptoms’. Some instance scores, such as those related

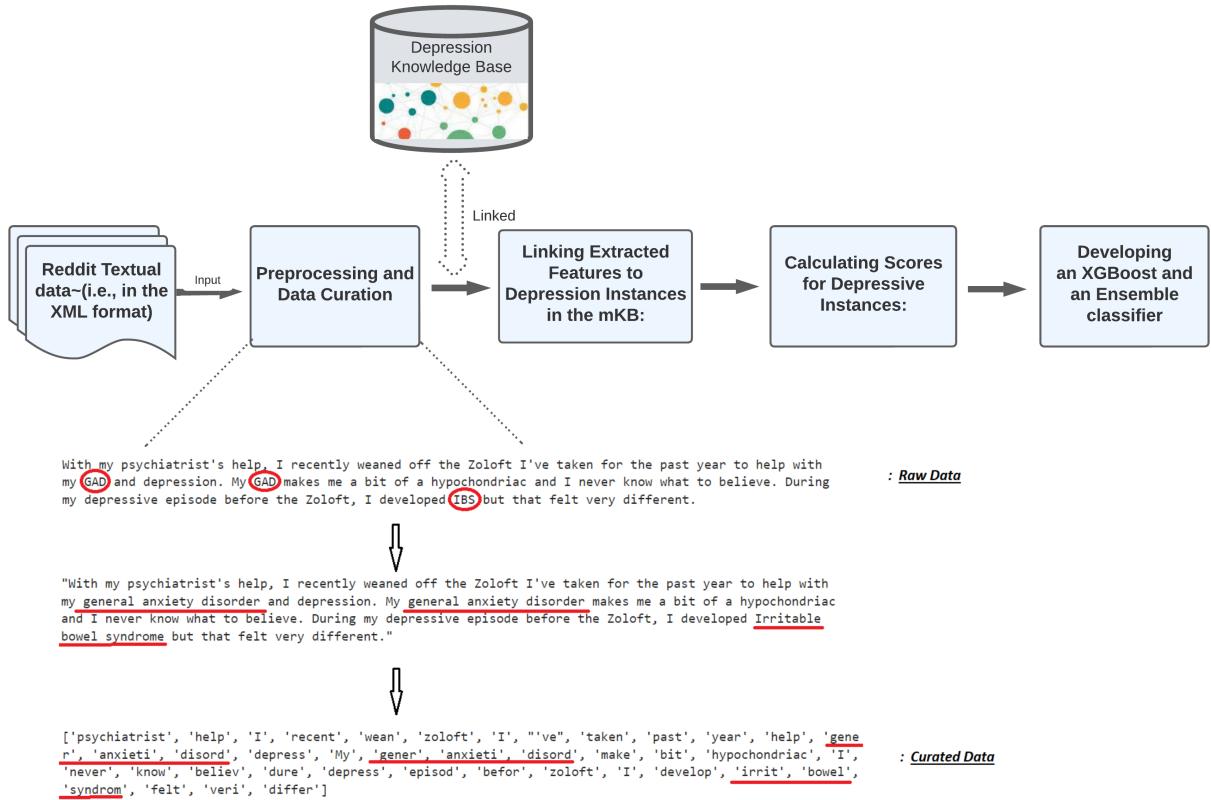


Figure 13. A snapshot of applying proposed pipeline in the Method Section, containing an example curation process result.

to ‘having physical pain’ and ‘change in appetite’ are not extractable by the KB APIs, because the current APIs are enabled by being linked to the lexical sources. Lexical sources are great sources for calculating linguistic- and emotion-related instances, not those related to the individual’s physical status.

On the other hand, scores related to instances like ‘change in the sleep pattern’ and ‘social activities’ could be calculated by analysing the related metadata. For example, the time and the date of having an activity on social media, the number of followers, or the people who are followed by a user, are useful metadata for calculating some more instance scores. In this research, we are just focusing on calculating the lexical-enabled instance scores, regardless of other metadata-based scores. Consequently, 17 depressive instances are considered to be used in our evaluation. Their related scores (i.e. for 16 instances) would be calculated and used for developing the depression classifier. Those features, as shown in Figure 14, being in the form of calculated cosine similarity scores are fed into the classifier, as its input features) in the next step.

In addition, the suicidal behaviour scores, calculated by the corresponding API in the KB, are not in the form of cosine similarities. They are integers, ranging between ‘0’ to ‘31’. On the other hand, calculated cosine similarity scores ranged from ‘0’ to ‘1’. Hence, we normalised these instance scores, prior to being fed to the classifier as its features. The normalisation process is conducted by applying ‘StandardScaler’ technique from ‘sklearn.preprocessing’ package, in Python. The depressive instances and their corresponding concepts, which are considered in our evaluation, are as follows:

- Concept 1: Risk factor-related features are ‘Negative Feeling’, ‘Disgust’
- Concept 2: Symptoms-related features are ‘Sadness’, ‘Discrepancy’, ‘Tentativeness’, ‘Certainty’, ‘Leisure’, ‘Suicidal behaviours’

sadness	discrepancy	tentative	certainty	leisure_nrc_joy	fear_nrc	disgust_nrc	symptoms	treatment	disclosure
0.006983	0.015471	0.016817	0.014043	0.014505	0.004836	0.003971	0.007539	0.000823	0.027747
0.006352	0.014462	0.020103	0.011822	0.018937	0.003966	0.003494	0.000437	0.001113	0.035014
0.008314	0.005167	0.004817	0.008356	0.012140	0.010178	0.005453	0.007619	0.001108	0.010388
0.009271	0.014084	0.012214	0.005647	0.016891	0.006861	0.003884	0.003880	0.001318	0.020330
0.005957	0.013093	0.022684	0.008859	0.014967	0.004992	0.003699	0.007329	0.001088	0.024066
...
0.007377	0.021924	0.027412	0.015397	0.015608	0.004967	0.004019	0.000861	0.005259	0.026308
0.009934	0.020935	0.020886	0.007537	0.014709	0.006605	0.006575	0.008360	0.002760	0.028033
0.010213	0.026084	0.020955	0.012652	0.014603	0.007279	0.005105	0.005290	0.006474	0.027836
0.006655	0.018907	0.012428	0.012675	0.015356	0.005243	0.003650	0.002416	0.001464	0.023736
0.009338	0.014119	0.013868	0.010602	0.013000	0.007561	0.004883	0.009777	0.007749	0.026894

Figure 14. A snapshot of calculated lexical-enabled depressive instance scores.

	precision	recall	f1-score	support
0	0.91	1.00	0.95	149
1	0.00	0.00	0.00	15
accuracy			0.91	164

Figure 15. The classification report of the SVM classifier.

- Concept 3: Supportive symptoms-related features ‘Self-focused attention’, ‘Anxiety’, ‘Anger’, ‘Fear’, ‘Symptom unigrams’, ‘Treatment unigrams’, ‘Disclosure unigrams’, ‘Relationship unigrams’, ‘Absolute words’
- Classifier: To identify the best algorithm for our classifier, we tried several simple and complex models. The implementation results for several simple models such as KNN (k nearest neighbour), SVM (Support Vector Machines), Linear Regression, and Naive Bayes were unpromising. The classification reports for all of them were indicative of ‘0’ scores as the outputs for precision, recall and f1-score regarding the depressed class (i.e., labelled as ‘1’ in the report). Figure 15 shows an example classification report for the SVM algorithm. This result derives from the incapability of these models to deal with our imbalanced data. Therefore, we decided to implement two ensemble techniques, namely an XGBoost and a stacking model, being more complex and robust models compared to the previous ones. XGBoost is an ensemble model that enables applying several hyper-parameters to control the learning process¹⁴⁶. This model teaches each of its predictors sequentially based on its predecessor’s error. It also makes it possible to give weights to the majority and minority classes, consequently eliminating the issue of having imbalanced data. Figure 16 illustrates the classification report of developed XGBoost classifier with 0.82 accuracy. Applying 10-fold-cross validation, also, leads to an increase in accuracy to 0.87. We also developed a stacking model. It contains five stacked classifiers, namely a Random Forest (RF), a KNN, an SVM, a Naive Bayes, and an XGboost. We removed the imbalanced data issue by down-sampling. To do so, Each of the five stacked classifiers are trained and tested on a separate sample, which are created using 78 depressed users’ data and randomly selected one-fifth of not depressed individuals. So we could implement SVM, and other simple models by using the balanced data. We aimed at building a model to anal-

	precision	recall	f1-score	support
0	0.97	0.82	0.89	148
1	0.32	0.75	0.44	16
accuracy			0.82	164

Figure 16. The Classification report of the developed XGBoost model for depression identification by textual data analysis.

	Sample1	Sample2	Sample3	Sample4	Sample5	Mean
Accuracy	0.75	0.78	0.75	0.73	0.65	0.732
F1-score	0.74	0.78	0.76	0.76	0.7	0.748
Recall	0.7	0.8	0.8	0.85	0.8	0.79
Precision	0.78	0.76	0.73	0.68	0.62	0.714
Prediction on user 79 text	0.97	0.9707	0.9715	0.9704	0.6621	0.90894

Figure 17. The classification report of the developed ensemble model for depression identification by textual data analysis.

use our data considering both linear (e.g., SVM) and non-linear (e.g., RF and XGboost) approaches in decision making process. Figure 17 is illustrative of the developed ensemble model and the classification report for the test data tagged with '1', showing depressed L.

To compare the prediction results of the developed algorithms on a single unseen text, one of the samples in the data set (i.e., related to a depressed user) were extracted and removed from the data set. Then, it was fed to both of the models. the prediction results for XGBoost and stacking models showed a probability of 0.90 and 0.77 for being depressed, respectively. Taking into account the classification reports, the stacking method could be considered a better method in this regard. Consequently, developed stacked algorithm could be used as a reliable weakly supervised learning model to be used in labelling large data sets (i.e., 'depressed' or 'not depressed' tags).

6.4 Evaluation

Through this research, we had two contributions: constructing the depression-related KB, and developing a depression-related classifier. To evaluate our proposed approach, we conducted a survey and requested domain experts to provide their feedback. We design three hypopaper to validate the knowledge in the mKB as well as validating the proposed methodology. To achieve this goal, we invited participants with knowledge and background in psychology and cognitiev science, as well as participants with AI and ML skills.

- Hypopaper 1 (H1):The construction and components of the depression knowledge base, namely "Symptoms", "Risk Factors", and "Supportive Symptoms" are relevant to depression Identification.
- Hypopaper 2 (H2):Depression-related instances that are used for developing the Machine Learning algorithm are relevant to the identification of depression patterns.
- Hypopaper 3 (H3): The structure of the developed depression classifier leads to a reliable results from analysing textual data.

6.4.1 Experiment Setup

We carried out the experiment in a controlled setting. In our survey, there were two groups of participants, namely psychology-related (first group) and computer science-related (second group) participants. The first group consisted of seven participants with psychological expertise, consisting of psychology university professors, Master's

and last year bachelor's students. The second group consisted of eight participants that were mainly chosen from Ph.D. students with computer science and AI-ML expertise at Data Analytics Research Lab³⁷. Through the questionnaire, the participants were provided with some explanations, examples, and instructions to figure out how the questionnaire was organised as well as understanding the aim and the approach of our research. We also arranged a meeting with the participants of the computer science group to present the cognitive and psychological aspects of our research in more depth. The content of the descriptive parts of the questionnaire include the following information:

- Brief description of our motivating scenario and the structure of the questionnaire.
- Brief description of the depression-related KB construction and its components to make the participants ready for answering the questions related to each section.
- Brief description of the process of developing the automated depression classifier as well as demonstrating some snapshots from the developed methodology and sample results.

6.4.2 Questionnaire

To test the hypotheses, we created a questionnaire and shared it with the participants. The questionnaire was divided into four sections with multiple-choice questions. The participants were instructed to select one alternative depending on their assessment. We asked each participant to rank the hypotheses' relevancy based on the 'Likert scale system', which utilises a five-point scale to allow the participant to give their opinion (5: Strongly relevant, 4: Relevant, 3: Neutral, 2: Weakly relevant, 1: irrelevant). After asking the main questions, in the last part, we ask participants to give us their suggestions for improving our approach and method.

The initial part of the questionnaire consists of four questions. It was used to gather demographic and background information of the participants, and the next three parts were used to test the H1, H2, and H3 hypotheses. In the second and third parts (i.e., related to H1 and H2), there are several questions asked to evaluate the components and the knowledge included in the depression KB. Hence, for validating the H1 and H2, we focus on the responses of the psychology group.

On the other hand, the fourth section (i.e., related to H3) has four questions. These questions target the participants with AI/ML backgrounds. The aim is to evaluate the technical aspects, which is developing an ML classifier that could act as a weakly supervised tool for identifying depression patterns from textual data. However, to consider the assessment of the psychology group participants for the technical aspect of our method, the first question of this section, is also shared with the psychology group participants. Finally, participants from both groups, were requested to share feedback, suggestions, and/or ideas to improve our approach and method.

The questionnaire was created using Google Forms, and a few screenshots from its different sections are shown in Figure 18, 19, and 20. Figure 18.(A) relates to the first part of the questionnaire, aiming to briefly describe the motivating scenario and the structure of the questionnaire as well as asking for demographic information. In Figure 18.(B), we briefly presented the definition of 'Knowledge base' and also showed the overall view of our depression KB. There are also some snapshots provided in Figure 18.(C) and Figure 19.(A), related to example questions that are asked from participants for evaluating H1 and H2, respectively. As mentioned before, H3 is designed to

³⁷<https://data-science-group.github.io/>

Questionnaire

Through our research, we've proposed a general mental disorder knowledge base(MDKB) to help analysts gain insight into the mental status of target individuals. This questionnaire is designed to evaluate our research method, concentrating on the construction of a depression knowledge base. There are 3 sections in this questionnaire as follows:

- Section1: Your demographic information.
- Section2: Survey questions, organised into 3 parts. Each part is related to a hypothesis in our research. Your answers will help us evaluate our approach.
- Section3: Your suggestions to improve our approach.

Section 1: Demographic Information

Please state your highest academic qualification.*

- Bachelors
- Masters
- Doctorate

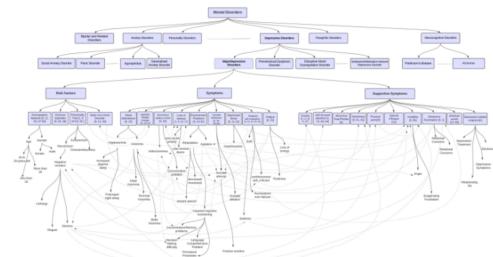
(A)

Section 2: Evaluation of the Hypotheses

Knowledge Base (KB) is a hierarchical taxonomy that consists of a set of concepts, instances of those concepts, and the relationships between them. For example, "Symptoms", "Risk Factors" and "Supportive Symptoms" are concepts of the depression knowledge base, which is developed in our research. Each of these concepts (e.g., "Symptoms") includes some instances (e.g., "Fatigue", "appetite change" or "Depressed mood").

The following picture demonstrates the overall view of the depression KB. This KB makes it possible to extract some depression-related features (i.e. in the form of scores) from textual data. We used these features to develop an automated algorithm to analyse an input text and identify the depression status of the writer.

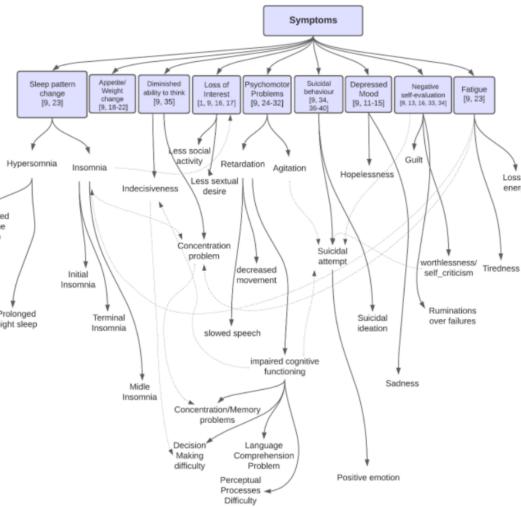
Overall view of depression knowledge base



(B)

H1: The construction and components of the depression knowledge base, namely "Symptoms", "Risk Factors", and "Supportive Symptoms" are relevant to depression identification.

Depression symptoms, their instances, and relationships



Based on the above image, how do you find "Symptoms" concept and its instances relevant to depression?

- Irrelevant
- Weakly relevant
- Neutral
- Relevant
- Strongly relevant

(C)

Figure 18. Segments of the questionnaire. (A) Demographic questions. (B) An overall view of depression KB. (C) Evaluation of the first hypothesis associated with 'Symptoms' concept and its instances as some components of depression-related KB.

evaluate the technical aspects and machine learning approach of our research. Hence, as illustrated in Figure 19.(B) we showed some snapshots of the ML algorithms that we developed to help with depression identification. To give the participants a better view of the content of the analysed text and the results of these analyses, as Figure 20.(A) shows, a short part of the corresponding text is included in the questionnaire. We also showed some of the primary results as well as the final result, derived from analysing textual data by those ML Algorithms in Figure 20.(B&C).

6.4.3 Survey Results

In this section, using the data gathered throughout the experiment, we intend to evaluate the hypotheses.

- Evaluation of H1: Hypopaper 1 presumes that the construction and components of the depression knowledge base are relevant to depression Identification. To validate this hypopaper, the Psychology-group answers are considered. Figure 21.(A) demonstrates that totally, all of the participants recognised that concepts and

H2: Depression-related instances that are used for developing the Machine Learning algorithm are relevant to the identification of depression patterns.

There are 17 depression-related instances that are extracted from textual data, using the depression knowledge base. They are used to develop a depression identification algorithm. Those instances are divided into 3 categories as follows.

Category1 (Risk factors): "Negative Feeling", "Disgust"

Category2 (Symptoms): "Sadness", "Discrepancy", "Tentativeness", "Certainty", "Leisure", "Suicidal phrases"

Category3 (Supportive symptoms): "Self-focused attention", "Anxiety", "Anger", "Fear", "Symptom unigrams", "Treatment unigrams", "Disclosure unigrams", "Relationship unigrams", "Absolute words".

Based on the literature, "self-criticism" (i.e., a depression symptom) is resulting in using more "discrepancy" words (e.g., 'could not', 'could have', 'hope', 'if', 'impossible', 'inadequate', 'lack'), which is reflecting different levels of confidence in achieving life goals. How do you find it relevant to identifying depression patterns?

- Irrelevant
- Weakly relevant
- Neutral
- Relevant
- Strongly relevant

(A)

H3: The structure of developed depression classifier leads to a reasonable results from analysing textual data.

Besides the psychological aspects, to evaluate our research from more technical points of view, we provide some snapshots from lexical sources as well as the ensemble algorithm that was used in our research. We also, illustrate some of the NLP-related algorithms.

A snapshot from the lexical sources

I-LWC	negative_mrc_added	sadness_mrc_added	discrepancy_lwc	tentative-lwc	certainty-lwc	fear_mrc	disgust_mrc	symptoms_unigram	treatment_unigram	Absolute_Words_abs
1	abandon*	abnormal*	alot	absolute	abandon	abortion	anxiety	medication	absolutely	
2d	{ agony*	besides	almost	absolutely	abandoned	aborer	withdrawal	side-effects	all	
2we	abandon*	agony	could	alot	acura*	abandonment	abhorrent	severe	doctor	always
3l	abuse*	alone	could've	ambigu*	all	abduction	abject	delusions	done	completely
3m	berate*	alone	couldn't	ambigu*	also	aberrant	abominable	abnormal	affection	constantly
3n	ache*	broke	couldn't	anyvoid*	already	abhorrent	abominable	weight	prescribed	constant
3d	aching*	cried	coul've	anyhow	apparent	abominable	abomination	insomnia	therapy	constantly
3dc	advers*	cries	desir*	anyone*	assur*	abomination	abortion	drowsiness	inhibitor	definitely
3gef	afraid	crushed	expect*	anything	deaten*	abortion	abundance	suicidal	estimant	entire

Part of the Algorithm developed for 'Cosine Similarity' calculation. This algorithm calculates the similarity between 'words used in a written text' and 'words contained in lexical dictionaries'.

```
def create_dataframe(matrix, tokens):
    doc_names = [f'doc_{i+1}' for i, _ in enumerate(matrix)]
    df = pd.DataFrame(data=matrix, index=doc_names, columns=tokens)
    return(df)

import re
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity

Tfidf_vect = TfidfVectorizer()

doc_1 = liwc_docs['sadness'][0]
doc_2 = joint_posts # input texts in the form of string
doc_2 = re.sub("[^A-Za-z0-9.\\"\\"]", " ", doc_2)
data = [doc_1, doc_2]
vector_matrix = Tfidf_vect.fit_transform(data)
cosine_similarity_matrix = cosine_similarity(vector_matrix)
df = create_dataframe(cosine_similarity_matrix,['doc_1','doc_2'])
score = df.loc['doc_1']['doc_2']
```

(B)

Figure 19. Segments of the questionnaire. (A) Evaluation of the second hypothesis associated with the depression-related instances that are used for developing the depression identification ML classifier. (B) Evaluation of the third hypothesis associated with the structure of the developed ML algorithms and depression classifier.

instances of developed KB are relevant to the identification of depression as a mental disorder. Participants were asked questions related to different concepts of depression KB, namely "Symptoms", "Risk Factors", and "Supportive Symptoms". All of the participants but one found the components of the developed KB relevant to depression. Figure 22 demonstrates the evaluation results for each of the concepts.

- Evaluation of H2: Hypopaper 2 presumes that the Depression-related instances used for developing the classifier are relevant to the depression identification. To validate this hypopaper, the answers from Psychology-group are considered. Figure 21.(B) demonstrates that totally, all of the participants recognised that the instances that are used for implementing the developed classifier are relevant to the identification of depression patterns. Participants were asked several questions related to 17 instances. All participants found that the instances are relevant to depression identification. Figure 23 demonstrates the evaluation results for each of the instances.
- Evaluation of H3: Hypopaper 3 presumes that the structure of the developed depression classifier leads to reliable results from analysing textual data. To validate this hypopaper, the AL/ML group answers are considered. Figure 21.(C) demonstrates that totally, all of the participants recognised that the approach for developed ML algorithm is relevant to the identification of depression through textual data analytics. Participants were asked for their assessment regarding the final results of the depression classifier after analysing

In the following parts, we demonstrate four snapshots from four texts, which are related to four different users. Another snapshot is also provided after each text, which is indicative of the frequency of the words used in the corresponding text. Then, we illustrate the results of our developed classifier, after feeding the whole texts related to each of the corresponding users and ask you a question considering the result of the classifier.

A snapshot from different sentences (separated by //), written by user_1.

My doctor has prescribed antidepressants so I'll be starting those, but thanks for the other suggestions. I'll also be attending group therapy - crossing my fingers!// I definitely am, thank you. Group therapy starts tomorrow. The therapist who diagnosed me figured out right away that I had anxiety. I've been an anxious person for as long as I can remember, but it's just gotten worse through the years. It was one of the reasons I was diagnosed with Major Depression instead of it just being a result of life adjustments. Honestly, I'm excited to start therapy because I'm tired of being anxious all the time (even though when I get there I will probably refuse to participate or say anything). // The saddest thing is that I don't know if I'll be happy to go back to my 5th graders, and I don't know if they'll be happy to see me. Part of the stress has been moving from Kindergarten to 5th grade within the course of a year.

(A)

The frequency of words used in the texts written by user_1.

```
[i:i;259,'me:47,'my:86,'myself:7]
negative_nrc_neg:[anxieti:4,'depress:5,'long:4,'problem:3,'stress:3]
anxiety:[anxieti:4,'stress:3]
anger_nrc_added:[action:3,'anxieti:4,'box:4,'depress:5,'die:4,'feel:21,'fit:8,'play:3,'will:26]
sadness:[depress:5,'long:4,'anxieti:4,'concern:3,'die:4,'feel:21,'imposs:3,'love:8,'problem:3,'still:12,'subject:4,'want:8,'will:26]
discrepancy:[could:5,'hope:9,'if:23,'imposs:3,'need:7,'problem:3,'should:16,'want:8,'would:2]
tentative:[an:13,'ap:th:5,'hope:9,'if:23,'lot:9,'luck:3,'may:6,'most:10,'often:3,'or:20,'pretti:5,'seem:3,'some:6,'someone:4,'someth:9,'someth:3,'suppos:5,'tri:16,'wonder:8]
certainty:[all:19,'always:3,'definit:13,'everi:7,'everyon:6,'fact:4,'never:7,'positi:6,'sure:9,'true:3]
leisure_nrc_joy:[play:3,'come:5,'fit:8,'game:3,'child:4,'creat:4,'feel:21,'found:7,'good:8,'great:9,'happi:3,'help:16,'hope:9,'improv:5,'kind:3,'like:33,'love:8,'luck:3,'major:3,'pretti:5,'provid:3,'readi:3,'receiv:3,'rescu:3,'share:3,'support:3,'teach:6,'thank:18,'true:3,'wonder:8]
fear_nrc:[anxieti:4,'chang:8,'concern:3,'depress:5,'die:4,'feel:21,'problem:3,'social:5,'still:12,'watch:3]
disgust_nrc:[action:3,'air:3,'depress:5,'die:4,'feel:21,'secret:3,'social:5]
symptoms:[anxieti:4]
treatment:[doctor:4,'antidepress:3]
disclosure:[play:3,'help:16,'want:8,'social:5,'talk:3,'care:3,'love:8,'like:33]
relationships_life:[she:18,'him:17,'girl:3,'game:3,'someon:4,'her:13,'style:5]
Absolute Words:[alway:3,'definit:13,'everi:7,'everyon:6,'everyth:6,'full:5,'never:7]
```

(B)

After analysing the posts related to the above mentioned user, all of the 17 scores, calculated for that text, were fed into the developed ensemble algorithm. The output of this classifier shows the 0.90 probability of depression for the user_1.

How do you find the final result for user_1 reasonable/reliable? *

- Not reasonable/reliable
- Weakly reasonable/reliable
- Neutral
- Reasonable/reliable
- Strongly reasonable/reliable

(C)

Figure 20. Segments of the questionnaire, related to the evaluation of the third hypothesis.

four different texts written by potential depressed individuals. All of the participants but one found that the construction of depression classifier leads to reliable results from analysing textual data. Figure 24 demonstrates the evaluation results for each of the four questions.

6.4.4 Discussion

Since there are some validity issues, the results of our study should not be taken as conclusive. Although the overall results of the survey support the H1, H2, and H3, there is still room for improving the proposed approach. As Figure 23 illustrates, some of the instances used for developing the depression classifier (i.e., referring to H2) were rated as ‘neutral’ by some of the participants, e.g., instances related to the question three (i.e., shown as H2-Q3), nine and eleven.

There are seven instances that were rated by one or two participants as ‘neutral’, namely, ‘disgust’, ‘self-focused attention’, ‘disclosure’, ‘relationship, life’, and ‘absolute words’. There could be several reasons for such issues. e.g., insufficient clarification and explanation prior to completing the questionnaire. These issues will be further

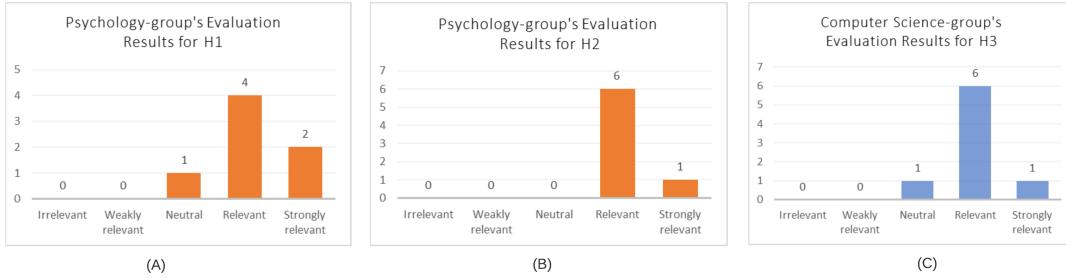


Figure 21. Evaluation of the hypotheses based on data collected during the survey. (A) Evaluation of depression KB construction. (B) Evaluation of instances that are used for developing depression classifier. (C) Evaluation of depression classifier structure.

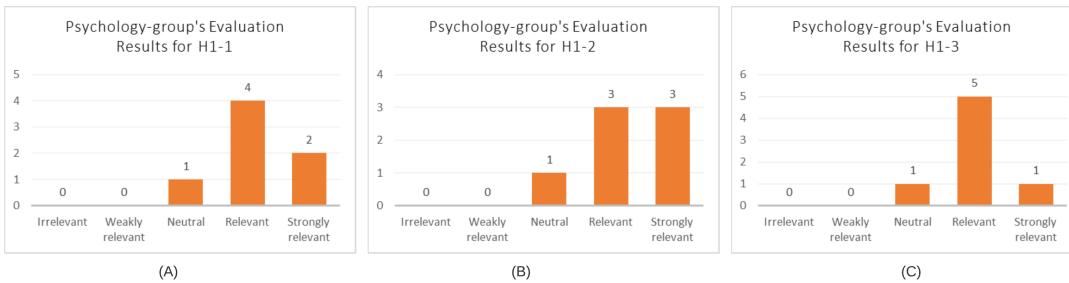


Figure 22. A demonstration of the evaluation results for each of the three questions related to concepts of depression KB, aiming at validating H1.

explored, in our future works. In addition, based on the comments received from participants and the lessons learned during this study, some future improvements are considered in Section 7.

7 CONCLUSION AND FUTURE WORK

This Section highlights the paper’s contributions and discusses possible future research areas.

7.1 Conclusion

Mental health is a key issue around the globe today. Most governments have been engaged in handling the COVID-19 pandemic since it broke out in 2019. As a result of global success in vaccination, the prevalence of the Covid-19 has been considerably reduced. However, for most countries, a major concern now is coping with the consequences of years of viral infection, particularly the psychological and economic consequences. COVID-19 has changed the way we live and work. These shifts can make us feel disappointed and resentful, all of which can have a negative impact on our mental health.

As a result, governments attempt to assist families and business owners in dealing with the negative results and improving the situation³⁴. Mental problems must be diagnosed before any assistance may be provided. But, Identifying mental disorder symptoms and their patterns, might be difficult due to their intricacy. As a result, it is critical to accurately diagnose mental health concerns and enable their treatment. As a serious mental health problem, depression is one of the top causes of disability around the world. It is a significant contributor to the global illness burden and has the potential to become a serious health problem.

Through this research, we proposed a domain-specific Knowledge Base (KB) to integrate the clinical knowledge regarding symptoms, risk factors, and supportive symptoms that are useful in recognising mental disorders. The KB’s knowledge comes from cognitive and psychological studies, and also prior practices in the field. Additionally, in current studies, hand-labelled training sets are used to identify mental disorder patterns from textual data, es-

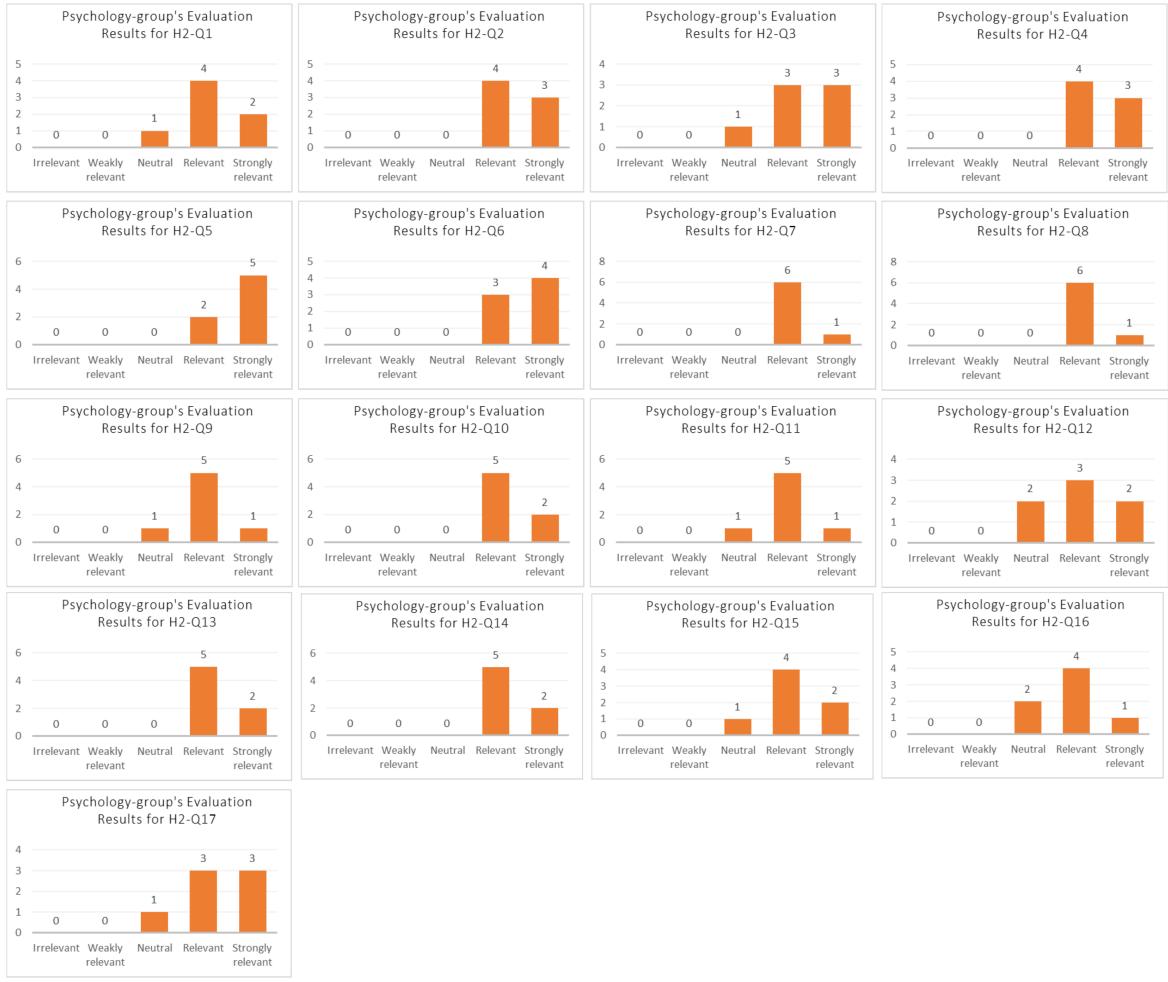


Figure 23. A demonstration of the evaluation results for each of the 17 questions for depression-related instances, leveraged in developing depression classifier, aiming at validating H2.

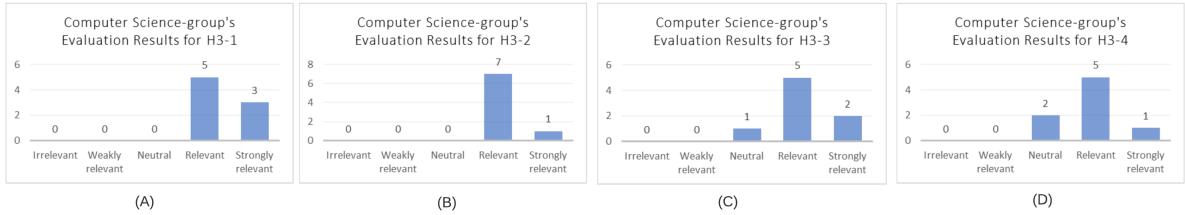


Figure 24. A demonstration of the evaluation results for each of the four questions related to the depression classifier results, that are asked for validating H3.

especially when a domain expert’s knowledge is needed. This task could take a long time and be costly. We provide a weaker form of supervision by enabling the generation of training data from developed KB.

7.2 Future Works

Considering the comments from participants in the preceding Section, as well as the lessons learned from this study, this research’s approach could be improved from two different points of view. The first is improving the construction of the developed mental disorder Knowledge base (mKB), and the second is bettering the technical aspects of

the developed mental disorder classifiers. In the following sections, these two viewpoints are described more.

7.2.1 Components of Mental Disorder Knowledge Base

Based on the results derived from the survey, conducted in Section 6, we found that there are some instances in the KB that got rated as ‘neutral’ by some of the participants, e.g., ‘disgust’, ‘self-focused attention’, ‘disclosure’, ‘relationship, life’, and ‘absolute words’. To improve the validity and relevancy of components of developed KB to depression identification patterns, in our future work, we will consult and interview some experts who have a high academic background (i.e., at least with PhD degree) or more than five years of experience as a therapist to see their opinion and get their comments in this regard.

Hence, we would improve the construction of the KB to a user-friendly and interactive mode, aiming at enabling the ‘add item’ or ‘remove item’ capabilities to the KB. For example, if after consulting with therapists, it becomes clear that the ‘disgust’ instance is not relevant enough to the depression identification patterns, we could easily remove it from our KB and consequently from the corresponding classifiers. On the other hand, if during our interview sessions it turns out that other instances could be added to the KB, It will quickly be done by using the ‘add item’ capability of the KB.

In addition, the instance-related APIs of the KB, were mainly constructed based on the textual analysis over single words (i.e., unigrams), that are included in a text. As future work, we would consider analysing the bi-grams (i.e., a pair of consecutive words) and tri-grams (i.e., a group of three consecutive words) to have a more effective text analysis. Therefore, The APIs could recognise the sequential meaning of the words. For example, the difference between ‘am not happy’ and ‘am happy’ could be detected using these APIs.

7.2.2 Technical and Classifier development Processes

As one of our future works, we would leverage more sophisticated learning algorithms such as deep neural networks and rule-based approaches, to consider more complex mental disorder patterns in our analysis^{115, 195}. For example, ‘Convolutional Neural Networks’ could enable the classifier to mine the hidden and complex patterns of mental issues that lay behind the input data. Also, using rule-based approaches could help us in developing a mental health-related knowledge graph, including an inference engine, aiming at gaining more accurate insights^{21, 196}. These approaches could help us improve the reliability of the results derived by our weakly-supervised classifier for labelling training data sets.

Mental disorders (e.g., depression) are mainly developed over time. On the other hand, learning algorithms such as time series are learning models to forecast future outcomes based on prior observed values. Hence, it could be an ideal approach for predicting the mental status of potential individuals suffering from mental disorders. Therefore, we would consider this approach in our future studies.

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