Submission date: 16/10/2021
Resubmission date: 26/02/2022
Camera ready submission date: 16/05/2022

1st round notification: 21/02/2022
2nd round notification: 12/04/2022
Available online: 07/07/2022
Publication date: 07/07/2022

Section: Special Issue
Information Systems in Life and Health Sciences

A Study about Gathering Features in Depression Detection' Problem with Health Professionals Community

Silas P. Lima Filho[1], **Mônica Ferreira da Silva**[1], **Jonice Oliveira**[1], **Lívia Ruback**[2]

[1]Programa de Pós-Graduação em Informática – Univ. Federal do Rio de Janeiro (UFRJ)
Cidade Universitária, Rio de Janeiro/RJ – Brasil

[2]Departamento de Computação – Universidade Federal Rural do Rio de Janeiro (UFRRJ)
Seropédica, Rio de Janeiro/RJ – Brasil

{silaslfilho, monica.silva}@ppgi.ufrj.br, jonice@dcc.ufrj.br, liviaruback@gmail.com

Abstract. *Understanding individuals, social dynamics, and data consumption within social media platforms arouse curiosity and attention in the scientific community and society. The scientific community has shown how a user's mental health can be affected by technology and its digital environment. For example, a user exposed to constant explicit hate speech may suffer an impact on its well-being. There are already efforts in this research area that propose automated solutions to identify users who require professional health attention. However, these solutions do not frequently use the experience and background from the health acknowledgment area in their contribution construction. To fill this gap, we propose a qualitative feature validation with two stages to identify which characteristics are relevant to health professionals, aiming at machine learning and deep learning solutions to depression detection. First, we validate this set of features using a semi-structured interview with three psychologists. Afterward, we apply a survey with domain experts to validate the information extracted from the first stage. This feature validation will allow us to have a detailed view of how functional and practical are the features commonly used in machine-learning-based solutions and how they are close to clinical analysis.*

Keywords. *Depression, Social Networks, Mental Health Informatics*

1. Introduction

The last decades have shown the growing use of digital media as a communication tool among different groups in society. New behaviors in society have appeared as long as such tools become more common and disseminated. The use of technology can improve or create new solutions for different problems. Such as society or community level, or in a micro-scope, such as an individual. Although, with creating solutions by an artificial or engineering approach, new problems can also arise. In this work, we focus on health

Cite as: Lima Filho, S.P., Silva, M. F. , Oliveira, J. & Ruback, L. (2022). A Study about Gathering Features in Depression Detection' Problem with Health Professionals Community. iSys: Revista Brasileira de Sistemas de Informação (Brazilian Journal of Information Systems), 15(1), 10:1-10:26. DOI: 10.5753/isys.2022.2285

context mental health. Understanding and comprehending the dimensions of affliction and suffering is not new in a great of research. We can cite psychology, philosophy, and other areas that already lean over these problems. Using artificial solutions such as social networks in their most varied shapes are more common and sowed within proper contexts. Incorporating these technologies as a work tool or essential apparel for daily life also becomes usual. Social media platforms have become a communication channel to express and publish opinions.

Social media has been used as an online platform to publish users' social interests and preferences. [Elkin 2008] presents that 34% of health search use social media, and 59% of adults look for health information on the internet. Therefore the content from social media platforms can be seen as a source of information that could help when dealing with disease detection or connection between a psychologist and a depressive patient. The use of technology directly supports institutions professionals and even aids people to make themselves aware of some diseases [Horvitz and Mulligan 2015]. *Infodemiology* and *digital disease detection* are correlated terms used to describe the use of digital platforms and tools to improve social health. These two concepts are efforts to tackle epidemics, identify individuals at risk, and communicate urgent illness.

As one mental health disturb, major depressive disorder (MDD) is one of the most reported diseases in the world. Sometimes called the century illness due to its frequency[1]. The World Health Organization (WHO) presents that around 300 million people from different ages suffer from some level of depression[2]. The Global Burden of Disease indicates depressive disorders as the third lead cause of disability [James et al. 2018]. From 1990, it was the fourth lead cause. The Institute for Health Metrics and Evaluation depicts the progression of depression over the years as stable disease, as also confirmed by [Brody et al. 2018]. [Lech et al. 2014] highlights the urgency in early identification and prediction of depression and its symptoms due to more positive results if treated soon. Sometimes, it is costly to get professional help due to the location or economic scenario.

The task of identifying potential individuals' diseases can be challenging. Due to the plenty of data, selecting the most effective, precise, and representative data can be challenging due to the plenty of data. However, it is relevant to investigate if it can identify signs symptoms of depressive behavior on social media. Due to the scenario above, identifying and attending to someone who could be a potential depressive patient in a brief and unobtrusive form should be very helpful for both patient and professional. Given the growing number of people afflicted by depression, the number of professionals needed to assist a needy population can not be enough.

A more actual scenario of a worldwide pandemic, where more than 600.000 lives were lost only in Brazil[3]. Since the beginning of pandemics, research has been done about the mental health consequences. [Wang et al. 2020] for example measures this type of impact regarding the level of stress, anxiety, and depression of Chinese population groups during the pandemic period. The use of technology as a monitoring tool has

[1] theguardian.com/news/2018/jun/04/what-is-depression-and-why-is-it-rising
[2] www.who.int/en/news-room/fact-sheets/detail/mental-disorders
[3] www.worldometers.info/coronavirus/country/brazil/

become essential to research groups to create solutions, governments to make decisions, and vehicles of communication to inform the population. As cited by [Wang et al. 2020], the prior identification of the groups most likely to develop some psychological illness can help in the adoption of preventive measures. So, in a world that faces pandemics' consequences and other types of difficulties.

For that reason, knowing the urgency and need that comes from both groups. The group of people who confront depression, and authorities, professionals, and institutions bring the health service to the population. We present in this work an interaction effort with health professionals. This interaction aims to understand how information from social media can be helpful to identify the depressed population. With a proper selection of information and characteristics from the literature review, we present at the ending which concepts, in general, are necessary to professionals who deal directly with depression identification.

This work addresses some of the conceptual challenges in the Information Systems (IS) area described by the research community in Brazil [Boscarioli et al. 2017]. One of the items describes the challenge of building systems that use the sociotechnical aspect as a relevant factor, and not just the technical factor in its construction [Cafezeiro et al. 2017]. The authors list the importance of taking into consideration subjective and humanistic scopes. By the authors' explanation, the sociotechnical factor takes as a contributor when constructing the solution the society. We intend to join and use two research areas to enrich each other, computing to psychology, and psychology to computing, strengthening their interdisciplinarity. Moreover, our intention with this work is to validate future steps of research in AI field, more specifically in classification models over depression detection.

We divide this article as follows: Section 2 presents the methodology and motivation in this work. In Section 3 we discuss the concepts of depression and social media according to a selected group of papers. Following, Sections 4.1 and 4.2, we present the collected data by measuring the opinions of different professionals. Finally, at Section 5 we conclude with the contributions of this work.

2. Methodology

This section presents the methodology that structures our effort to identify information and data from social media related to the clinical environment on identifying depression. We can define this work as an empirical effort, such as described by [Wohlin et al. 2012], since it comprehends explorative and explanatory views of depressive disorder. At this time, we focus on understanding and answering the question: *Is it possible to identify symptoms of psychological illness through social media?* With a positive answer, we can extend this question to others such as: How to diagnose a disorder using only social media (SM) information? Would SM's information be helpful to doctors, psychologists, etc.? What kinds of analysis techniques can be used for this? What works in the computing area currently that addresses depression?

The first stage of our method is to identify the state of the art of depression detection problems. We have used the concept of Systematic Literature Mapping (SLM)to understand approaches and how the depression problem is tackled in the community. [Nakagawa et al. 2017] describes that SLM is useful to a researcher to have a wider vision of a topic. Section 3 describes this whole process of revision. It also describes some concepts of depression and what it comprehends in the health area. Since our intention after this work is to create a reliable classification model, we focus on works that focus on depressive user identification.

As an exploratory study, this research uses interviews and survey instruments to comprehend depressive disorder. Thus, our objective is to extract the information from such instruments(interviews and survey) and comprehend if it is possible to apply it as information systems artifacts. Moreover, we want to validate information extracted from the literature review. To accomplish such objectives, we have applied a survey with health professionals. As described by [Wohlin et al. 2012], the survey should describe how the population of professionals faces depression when dealing with patients.

We divide this survey into two stages. Both stages have employed the same questionnaire to collect domain information from health professionals. The difference between them is the application form. The number of participants in both stages is a total of 52 professionals. In the first stage, we interviewed three psychologists, and the second stage had a total of 49 professionals from different areas.

We divide the questionnaire into sections with different types of information, and they are presented as follows:

1. *Participant Profile:*
    - Age;
    - Level of education;
    - Estate of actuation;
    - Years of professional experience;
    - Bachelor Title;
2. *Phenomena Context:*
    - How many sessions are usually necessary to identify depression?
    - What information is relevant in clinical scenario for depression diagnosis?
    - How do you describe your method of depression identification?
    - Can depression be reflected on patient discourse?
    - Can depression be reflected on patient daily habits?
    - Can depression be reflected on patient interactions?
    - How relevant can social media data be in the identification of depressive symptoms identification? - (0 to 3 scale)
3. *Perception on Depression Symptoms:*
    - Depressed mood most of the day;
    - Markedly diminished interest or pleasure in all;
    - Significant weight loss when not dieting or weight gain;
    - Insomnia or hypersomnia;
    - Psychomotor agitation or retardation;
    - Fatigue or loss of energy;
    - Feelings of worthlessness or excessive or inappropriate guilt;
    - Diminished ability to think or concentrate;

    - Recurrent thoughts of death;
4. *Features Validation*
    - Discourse;
    - Content Metadata;
    - User Profile;
    - Interactions;
    - Group Characteristics

Each of the questionnaire sections embraces different types of information that will help construct the awareness of depression, the professional's methods of depression identification, an understanding of specialist population, and valuable information to achieve the features validation. The first section, *Participant Profile*, intends to understand who is answering and participating, his/her experience, level of education, and local of actuation. In the case of the respondent being a psychologist, we also ask for his specialization.

In the second section, *Phenomena Context*, we collect information about the respondent's point of view of the depression phenomena context. Most of the answers are descriptive. Some of the collected information is how many treatment sessions are necessary to identify someone as depressive, what information is essential, the type of information in treatment, and whether a depressive patient demonstrates clues on his discourse, everyday interactions, and daily habits.

As the last question, the respondent gives his/her impressions on how relevant he/she believes data from social media are for detecting the depressive symptoms (on a scale from 0 to 3, where 0 means no relevance and three means powerfully relevant).

The third section, *Perception of Depression Symptoms*, obtains the respondent perception of the relevance for each symptom from the DSM-V documentation. The questions in this section are on the Likert scale and have the option of "No opinion". The respondent classifies each symptom from 0 to 3, where 0 is irrelevant, and 3 represents strong relevance.

The last section, *Features Validation*, comprehends the interviewee's opinion for the features selected during the literature review process and is divided into five other sections with the categories created. As mentioned before, the categories represent the meaning of the features by their applications. From the initial list of features extracted in the literature review, we represent them as 38 meta-characteristics. After validating these meta-characteristics, we intend to synthesize which types of information are more valuable for the health professionals represented by our respondents. The respondent classifies each symptom from 1 to 4, where 1 is irrelevant, and 4 represents strongly relevant. Each question is on the Likert scale and also has the option of "no opinion".

Therefore, through the interview and the survey, it will be possible to analyze and compare different professionals' opinions. These two instruments might guide a more consistent validation of the literature features and enable the creation of artifacts like better-aligned machine learning models with the psychological area. The Sections 4.1 and 4.2 present the questionnaire results for each validation stage.

The UFRJ Ethics Committee had analyzed and approved this research approach and methodology, the submission register number (CAAE) on *Plataforma Brasil* is 54865821.5.0000.5263. All participants were presented with a free and informed consent term and gave their consent before answering.

3. Literature Review

This section presents the definitions of the phenomena of depressive disorder and also the results for literature research on computer science contributions on depressive disorder detection. The 11^{th} International Disease Classification (ICD 11) classifies depression as a disease relating it to someone's behavior diagnosis. Traumatic events might trigger it, such as when a person loses something important, e.g., a job or a close person, Etc. could start depression symptoms. It is also dangerous because of its extreme consequences: depression, according to ICD 11, can lead to suicide ideation and suicide as a consequence.

Although depression is the common name in society, the Diagnostic and Statistical Manual of Mental Disorders (DSM-V) details different types of depression [Association et al. 2013]. The most common type and more general is *Major Depressive Disorder* (MDD), though the term *Depressive Disorder* covers each variant of depression in [Association et al. 2013]. Other types of the disorder are *Disruptive Mood Dysregulation Disorder*, *Persistent Depressive Disorder (Dysthymia)* and *Premenstrual Dysphoric Disorder*. The DSM-V also lists the characteristics for the diagnosis of each variant. For instance, for MDD, diagnosis criteria are insomnia or oversleep, the depressive mood most of the day, loss of interest in activities, and weight loss. DSM-V also highlights that a group of at least five symptoms must occur in two weeks to confirm a diagnosis.

Identifying if someone may develop a depressive state to prevent the disease can be helpful for both health professionals and potential victims. Over the last years, there has been a growing effort from Computer Science in academic studies to deal with depression identification. We have identified more than 100 features from different works that use social media as a resource to recognize depression symptoms through the literature analysis. A common approach is the use of classification algorithms. They can use different types of data (features) related to the content, relationships, user behavior to train a classification model. Nevertheless, health specialists usually do not validate the features used to identify depression symptoms from social media.

We have reviewed the literature using concepts from the systematic literature mapping (SLM) approach to understanding computer science contributions in depression scenarios better. Some of the concepts used in the SLM protocol are selection criteria, search string, and research questions. Once defined, other researchers can reuse this protocol, ensuring transparency and reproducibility. This approach should give us deeper insights from the most recent research that tackles depression detection in social media and enables improvements if more basis or updates are necessary. Although using some concepts from SLM, we can not consider our literature review as an SLM itself. It occurs mainly because of the lack of protocol items such as quality criteria, protocol evaluation, and a more significant number of bases such as exposed by [Nakagawa et al. 2017].

We included in literature review articles from ACM and IEEE bases. We used

Inclusion	Exclusion
Directly tackles depression	Out of 2013-2018 scope
Have computational approach	Not written in english or portuguese
Introduce process, method, or technique related to computing and mental health problem	It is not a primary study
-	It does not have abstract
-	It does not have computing contribution
-	It has less than 4 pages

Table 1. Selection criteria in literature review.

the search string *("Social Media" OR "Social Network" OR "Complex Network") AND (Depression OR "Major Depressive Disorder").* Since this stage was developed by the year 2019, we included only works from 2013 until 2018. However it is already scheduled a future step to update selected papers. The selection criteria are listed in Table 1. At the final stage, we selected 47 papers, 22 papers from the ACM Library, and 25 papers from IEEE Explore. We list contributions from the literature review that summarizes part of the whole set of papers.

Many articles rely on natural language processing (NLP) to systematically analyze the text in social media publications. Some of the works consider the psychology point of view, which makes them more robust and reliable, as the psychology research area is the main area to address mental disease problems. It is a challenge align quantification made by metrics, e.g., NLP, social network analysis, and other techniques to the cognition of a psychologist on standard clinical treatment.

[De Choudhury et al. 2013c] have developed many articles and researches on identifying depression in the population using social media information. They used psychometrics questionnaires which represent the theory and technique of measuring mental processes, and the Psychology and Education fields usually apply its concepts. In [De Choudhury et al. 2013c], the authors use crowdsourcing to extract data from Twitter by people who were clinically diagnosed with depression. They created a corpus and developed a probabilistic model to detect if a post indicates depression. [Tsugawa et al. 2015] applied the same analysis in a group of users from Japan to replicate the results from previous work.

[Park et al. 2015] present how activities on Facebook are associated with depressive states of users. Their work intended to raise awareness of depression issues at the one university, which previously had seen an increase in the suicide rate of its students. [Andalibi et al. 2017] explore self-disclosure posts on Instagram, tagged with #depression to understand what rather sensitive disclosures do people make on Instagram. The work in [Li et al. 2016] is a qualitative study that tries to understand how is the behavior and comprehension of the Chinese population about depression. It differs from prior ones since it explores the post's disclosures and is not worried about creating a classification model.

[Vedula and Parthasarathy 2017] conducted an observational study to understand the interactions between clinically depressed users and their ego network when contrasted with a group of users without depression. They identify relevant linguistic and emotional signals from social media exchanges to detect symptomatic cues of depression.

[Zhao et al. 2018] have applied text classification using Convolutional Neural Networks to classify depression using text analysis. [Nobles et al. 2018] also have used neural networks to identify patterns on periods when the risk of a suicide attempt increases in SMS texts. [Yazdavar et al. 2017] incorporate temporal analysis of user-generated content on social media for capturing symptoms. They have developed a statistical model that emulates traditional observational cohort studies conducted through online questionnaires and extracts and categorizes different symptoms of depression and modeling user-generated content in social media. [Chen et al. 2018] detected eight primary emotions and calculated the overall intensity (strength score) of the emotions extracted from all past tweets of each user. The authors have generated a time series for each user's emotion and afterward generated a selection of descriptive statistics for this time series.

The papers above do not always take into account how psychologists infer if someone is depressive or not. We also stress that many of the actual contributions rely on textual information generated by one user. Since one of the depression symptoms in DSM-V [Association et al. 2013] is inactivity, a depressive user may not consistently generate online content. The context of psychology regularly deals with information subjectivity, and we believe that combining different methods rather than exclusively text content could bring more relevant information. We believe that the classification of potential depressive users could be more reliable if combined with "subjective information".

Afterward the literature review, we have selected papers with contributions in the artificial intelligence area, specifically in machine learning and deep learning solutions. From these works, we can extract different covered tasks like identifying what symptoms are searchable in social media and will compose a model as features; create a model which classifies an unseen user as potentially depressive or not. The problem of dealing with depression on social media is a translation of the search for people who suffer the symptoms of depression. With the identified contributions in the literature, we have extracted the features used in these works. With a sort of investigation in computing solutions to previous identification of depressive population groups, it is intriguing to know if these contributions are, in fact, practical for domain specialists. Not only practical but whether both, the employed information and data, are relevant in a real scenario of clinical diagnosis of depression.

With the selection above, we can filter and resume the works by their features. These features selected from the literature review are listed in Table 3. Since our main objective is to validate with health professionals, and for a better understanding by the respondents, we called features as *metacharacteristics*, and we have adapted how to present them in the questionnaire since the participants could not be familiar with the standard terminology. As listed in Section 2, these metacharacteristics are *Discourse*, *Content Metadata*, *User Profile*, *Interactions* and *Group Characteristics*.

Within the questionnaire *Features Validation* section, the first subsection is *Discourse* and compares features related to the content created by a user. This group of features is generally used for textual analysis techniques like part-of-speech, sentimental analysis, topics identification, text emotion classification, Etc. *Content Metadata* includes information like the post timestamp, privacy content, post length, and geolocation. *User*

Profile subsection represents user information like age, gender, number of posts for each day of a week, number of posts by a period of the day, Etc. *Interaction* features represent interactions in social media. They can be related when a user interacts with the social media platform or with another user. The last section, *Group Characteristics*, comprehends features about the community where the user is inserted.

4. Experiment

At this section we list the experimental stage where we apply the survey into two groups of professionals. Section 4.1 describes our first contact with psychologists. Section 4.2

4.1. Semi-Structured Interview

This first instrument aims to create a deeper perception of depressive disturbance. As a qualitative study, a semi-structured interview is direct communication with the population that is important to research[Leitão and Prates 2017, p. 56][Weiss 1995]. We present an interview with a questionnaire to collect the opinion of three psychologists about the depressive disorder, identify someone depressive, and collect feedback about the group of features from SLM. Although there are studies with computational advances for identifying depressive groups, nuances are not detectable in a non-direct intervention, such as clinical treatment. This interview captures these nuances to create computational solutions that are more suitable and aligned with the problem domain.

4.1.1. Participant Profile

The three specialists have less than ten years of experience, although two have less than five years of experience. All the professionals are from the same state, Rio de Janeiro, and range from 51 to 60 years old. Two of them are active professionals, and one does not work directly as a psychologist but uses the knowledge to support his work.

4.1.2. Phenomena Context

In this section, the respondents shared their impressions and knowledge of their daily clinical practice. Section 2 already describes these questions.

The first question, about quantification of patient treatment, was not consensual in the answers. There was no unique number of clinical sessions to identify if someone was depressed. Although, for potential depressed ones with more evident symptoms at the first treatment session. For patients who do not demonstrate severe depression, in other words, with a moderate or weak level of depression, more clinical sessions are necessary to confirm the diagnosis because of the subtlety and, as described by the respondents, the patient may not be comfortable in the first clinical session.

We also had different answers in the second question about what information is necessary for the depression identification process, from the description of how the patient expresses himself through words and discourse to physical signs that demonstrate somehow instability. One of the respondents mentioned using draws as a tool for the patient to express himself/herself. So, further the use expression of the patient, which is usual in psychological treatment, it is possible to use other resources to facilitate the patient to express himself. In a more general manner, all the expressions will somehow demonstrate a lack of liveliness or a missing in life goals, as one of the participants explained.

The answer to the second question correlates with the third question. By the time the respondents answered the second question, they had already explained the identification process. It may vary depending on professional specialization. However, it is consensus that the primary way is to use the oral descriptions of the patient's problems and conflicts leading to clinical treatment.

The fourth, fifth, and sixth questions were positive to three participants. These questions expose whether a patient can explicitly demonstrate somehow depression symptoms indications. Either in the discourse, or daily habits, or in how he/she interacts with others. At the end of this section, the participants have given their score for how relevant on a scale from 0 to 3 is social media data helpful in identifying depression symptoms. In this case, all the three participants have answered this question as *powerfully relevant*.

4.1.3. Perception of Depression Symptoms

We have chosen a relevance scale from 0 to 3, where 0 is *not relevant* and 3 is *strongly relevant*. The respondent also had the option *no opinion*, in the case where the respondent does not have an opinion on the question. The symptoms were obtained from DSM-V from the Major Depressive Disorder description. We describe them below:

All the symptoms above were considered by all respondents *relevant* or *strongly relevant*, except the fifth and eighth items. As explained in DSM-V, psychomotor agitation itself can not be an essential factor to classify someone as depressed or not. However, when present, it can be a signal that the depression is at a dangerous level.

4.1.4. Discourse Features

The questions from this section comprehend the features extracted from user publications. Usually, the data from these features are textual. This section contains 14 questions, and they as follow:

1. *Changing in the frequency of terms related to leisure, hobbies or pleasant activities*;
2. *Reference to terms and words related to negation*;
3. *Excessive reference to the past*;
4. *Negative discourse*;
5. *Discourse that refers to negative emotions like anger, anxiety, frustration, Etc*;
6. *Variation of discourse polarity*;
7. *Variation between positive and negative emotions*;
8. *Changing in the frequency of the use of references related to interest subjects*;
9. *Inclusion of new interests*;

10. *Change in frequency and length of discourse (publications)*;
11. *Impersonal discourse, with no reference to friends or friendship relationships*;
12. *Self-reference to physical or mental state, such as lack of concentration and focus, Etc.*;
13. *Explicit reference to some disease or correlate subject*;
14. *Self-reference words and use of pronouns*

We consider it helpful to analyze the features with the highest scores for relevant and powerfully relevant. On the other hand, we discarded features that were not relevant or capable of opine were the most common answers. So, features where more than 50% of the answers were *not relevant*, *relevant* or *no opinion* have been discarded. For the group of discourse features, we have removed only items *3* and *14*. This type of feature could reinforce what [Vedula and Parthasarathy 2017] have presented, that group depressives likely use more this kind of information, such as self-reference as a manner to talk about personal problems.

4.1.5. User Profile Features

This section comprehends ten features that are related to user profile characteristics, listed as follow:

1. *Frequency of posts by their polarity*;
2. *Publications' period within a day*;
3. *Localization*;
4. *Age*;
5. *Civil status*;
6. *Changing in privacy preferences*;
7. *Number of profile changes*;
8. *Publication frequency*;
9. *Number of interactions for each day of the week*;
10. *Gender*

The features with the highest frequency for relevance 2 and 3 are *Frequency of posts by their polarity* and *Number of profile changes*. The other features had variations in their responses. Thus, we have removed the *Publication frequency* and *Number of interactions for each day of the week* items.

4.1.6. Interaction Features

The interaction features embrace information about how the user behaves inside the social media platform. It means that the user can interact with the platform itself, or s/he can interact with another user. We collected ten interaction features from the literature review process, listed below:

1. *Modification in the frequency of direct interactions, such as replies or comments, direct messages, citations, marked pictures*;

2. *Modification in the number of indirect interactions, such as likes, dislikes, or another interaction over some publication*;
3. *Changes of frequency on using emoticons or figures*;
4. *Frequency of news sharing*;
5. *Frequency of news sharing by their polarity*;
6. *Changes of frequency on using emoticons or figures in the place of text as publications*;
7. *Number of friends*;
8. *Variation in the number of friends*;
9. *Variation of frequency in friends interactions*;
10. *Number of associated communities*;

From the list above, we have removed the following features: *Growing use emoticons or figures in the place of text as publications*, *Number of friends*, *Variation in friends number*, *Variation of frequency in friends interactions* and *Number of associated communities*.

4.1.7. Group Features

Four features in this section are related to the characteristics of the groups and communities the user is within.

1. *Participation in communities related to emotions or sentiments related to depression*;
2. *Level of reputation, or importance within the community, or related to friends*;
3. *Participation inside groups with low cohesion*;
4. *Level of repercussion inside the group*;

From the mentioned list above, we kept only item *4*. The other items have a low relevance score, or the respondent has considered himself unable to answer.

4.2. Survey

This section depicts the information collected with 49 Brazilian professionals from the health domain and different regions. This survey was applied not only to psychologists but also to physicians and other health professionals. We have collected answers during seven days in January of 2021, and the survey is divided into four sections, each embracing different types of information. The main goal of this stage is to validate which features and each type of feature are more relevant to the eyes of different specialists. So, with the information from interviews made in Section 4.1, it is possible to check differences and similarities among the two groups of psychologists. Section 2 presents the questions used in this survey. Table 2 presents the ranking of features using the mean of answers. In participants' opinion, the most relevant information on social media is the user's discourse. Understandably, the majority considers most important what the user has to express. In his publications, users can express their feelings, worries, and concerns. This could be tracked by user's posts. The second type of feature with more relevance to participants is group type. This inform that understand the context of the user can help to understand how the user behave in contact with others users.

Feature Name	Mean	Type
Negative discourse	3.489	Discourse
Explicit reference to some disease or correlate subject	3.428	Discourse
Discourse that refers to negative emotions like anger, anxiety, frustration, etc	3.408	Discourse
Self-reference to physical or mental state, such as lack of concentration and focus, etc	3.346	Discourse
Participation in communities related to emotions or sentiments related to depression	3.326	Group
Variation between positive and negative emotions	3.270	Discourse
Reference to terms and words related to negation	3.208	Discourse
Variation of discourse polarity	3.208	Discourse
Changing in the frequency of terms related to leisure, hobbies or pleasant activities	3.163	Discourse
Excessive reference to the past	3.061	Discourse
Variation of frequency in friends interactions	3.042	Interaction
Self-reference words and use of pronouns	2.955	Discourse
Changing in the frequency of the use of references related to interest subjects	2.916	Discourse
Impersonal discourse, with no reference to friends or friendship relationships	2.872	Discourse
Level of reputation, or importance within the community, or related to friends	2.869	Group
Publications' period within a day	2.863	Profile
Number of profile changes	2.851	Profile
Frequency of posts by their polarity	2.844	Profile
Frequency of news sharing by their polarity	2.804	Interaction
Modification in the frequency of direct interactions, such as replies or comments, direct messages, citations, marked pictures	2.782	Interaction
Variation in the number of friends	2.739	Interaction
Change in frequency and length of discourse (publications)	2.673	Discourse
Inclusion of new interests	2.673	Discourse
Publication frequency	2.659	Profile
Number of friends	2.659	Interaction
Level of repercussion inside the group	2.590	Group
Modification in the number of indirect interactions, such as likes, dislikes, or another interaction over some publication	2.577	Interaction
Number of interactions for each day of the week	2.574	Profile
Participation inside groups with low cohesion	2.547	Group
Changing in publications' privacy preferences	2.543	Profile
Age	2.5	Profile
Number of associated communities	2.425	Interaction
Changes of frequency on using emoticons or figures in the place of text as publications	2.409	Interaction
Frequency of news sharing	2.361	Interaction
Localization	2.279	Profile
Civil status	2.25	Profile
Changes of frequency on using emoticons or figures	2.232	Interaction
Gender	1.893	Profile

Table 2. Ranking of features by the mean of answers' score.

4.2.1. Participant Profile

As presented before, the first stage of the survey contains data about participants' profiles. From the population, around 32% of the participants' age is between 51 to 60 years old, and nearly 28% of participants are from 41 to 50 years old. 68%, have at least a bachelor's degree and have some specialization course. Most of the participants, 59.2%, are from the same state, Rio de Janeiro. Despite that fact, the remaining respondents are from 8 different estates. The majority of this group is composed of psychologists, 86%. The professional experience measured is very sparse, and the average of experience covers a period slightly grander than five years. However, nearly 38% of participants have more than 20 years of experience, reflecting a good representativity in the group answers.

4.2.2. Phenomena Context

The questions used to understand contexts phenomena are the same from Section 4.1.2. Similar to the interviews, the answers are very sparse, and this reflects in the first question, which refers to how many sessions are necessary to identify someone as depressive. Some opinions quantify how many clinical sessions are needed, and in this case, the value varies from 1 session to even 12 clinical sessions. It is possible to group answers among *does not quantify* and *quantify*. So, from the 49 valid answers, a total of 12 answers does not make any reference to a specific number of sessions. On the other hand, 37 participants cite different numbers of sessions needed to identify a potential depressive.

A consistent point in answers is how the easiness to identify the symptoms is related to how comfortable the patient feels when received in the clinical environment. This information confirms the answers in the semi-structured interviews.

The answers for the second item are also very sparse due to its high-level abstraction. This question asks what information is necessary for a clinical scenario for a depression diagnosis. Answers like the emotional history of the patient or the anamnesis (which is medical history related sometimes related by the patient) are the more frequent. The answers indicate in a general manner a direction of context understanding. So the professional would search this kind of information in anamnesis or through the patient discourse and explanation about his habits, daily routine, interaction with family and friends from usual environments. Some of the answers relate to the patient's posture and looking, or in resume to physical signals at the moment of clinical treatment. A good amount of answers describe symptoms listed in DSM-V, such as suicide ideation, sleep disturbance, sadness mood, there is no leisure in activities.

The third question is also a free answer question, where the respondent describes his/her method to identify depression. Here the answers indicate how the professionals proceed to find the related information on the last question. The opinions are still sparse and demonstrate the base of psychology, which is the patient's reception. This concern allows the patient to feel comfortable describing a specific problem and the secure environment allows a more depth investigation and details about the context of living of the patient.

The fourth and sixth questions are almost unanimous on positive answers. These questions ask whether the patient's discourse, daily habits, and interactions are affected by depressive disorder. Only one respondent has indicated that depression can not reflect on patient discourse or interactions.

The answers in the last question about how the respondents see social media data about habits and interactions are not consensual. Although 49% of the answers consider *relevant* and 24.5% consider this kind of information *strongly relevant*. From 49 valid answers, 5 of them were *no opinion*. So the answers indicate that there is potential in using social media data since the majority have given some significance.

4.2.3. Perception of Depression Symptoms

The third section embraces questions about the perception of the participant about the level of relevance on depression symptoms, as described in Section 4.1.3. Their level of relevance has classified the symptoms. Almost the whole group of symptoms were considered strongly relevant. The only exceptions were: *Psychomotor agitation or retardation*, *weight loss or weight gain*. The participants have considered them the most relevant answers. These responses can reflect the personal answers about how many sessions are necessary to diagnose someone as clinically depressed. Even with the symptoms that are not considered the most important information to seek, the whole set of symptoms is necessary and can guide the professional to determine if someone is depressed. At the end of this section, we also questioned suggestions of other symptoms that were not listed.

The following section will present the results of the selected features from the literature review. We present to the participant four different groups of features. Inside each group, we present the features used in machine learning and deep learning model constructions more adaptable. The primary justification for this adaptation relies on the might unawareness of the respondent. So, adaptation is needed to reach a significant number of respondents inside the health community.

The fourth section comprehends discourse features, and the following section comprehends features related to the user profile. The sixth section depicts features that represent interactions in social media. Interactions can be related when users interact with the social media platform or another user. The last section comprehends features about the community where the user is.

4.2.4. Discourse Features

As described in Section 4.1.4, here we present the level of relevance for each feature following the opinion of respondents. The features are the same as the prior section, and the list number indexes them. As mentioned before, there are four levels of relevance, from 1 to 4. Where 1 means *no relevance*, 2 means *weak relevance*, *relevant* is represented by number 3, and *strong relevance* is represented by number 4. The respondent can also choose *no opinion* which is not considered as score. We consider

Figure 1 represents the quantity for each feature in the discourse features group. The caption for each subplot represents the index in the list of features presented in Section 4.1.4. The x-axis for each subplot represents the level of relevance for the feature in question. So, for example, at subplot *1*, there were only answers which classified feature 1, *Changing in the quantity of terms related to leisure, hobbies or pleasant activities*, as *weakly relevant*, *relevant* and *strongly relevant*. Responses depict that most participants considered this feature relevant in the depression identification process. The next feature depicts a feature where one respondent chooses the option *no opinion*.

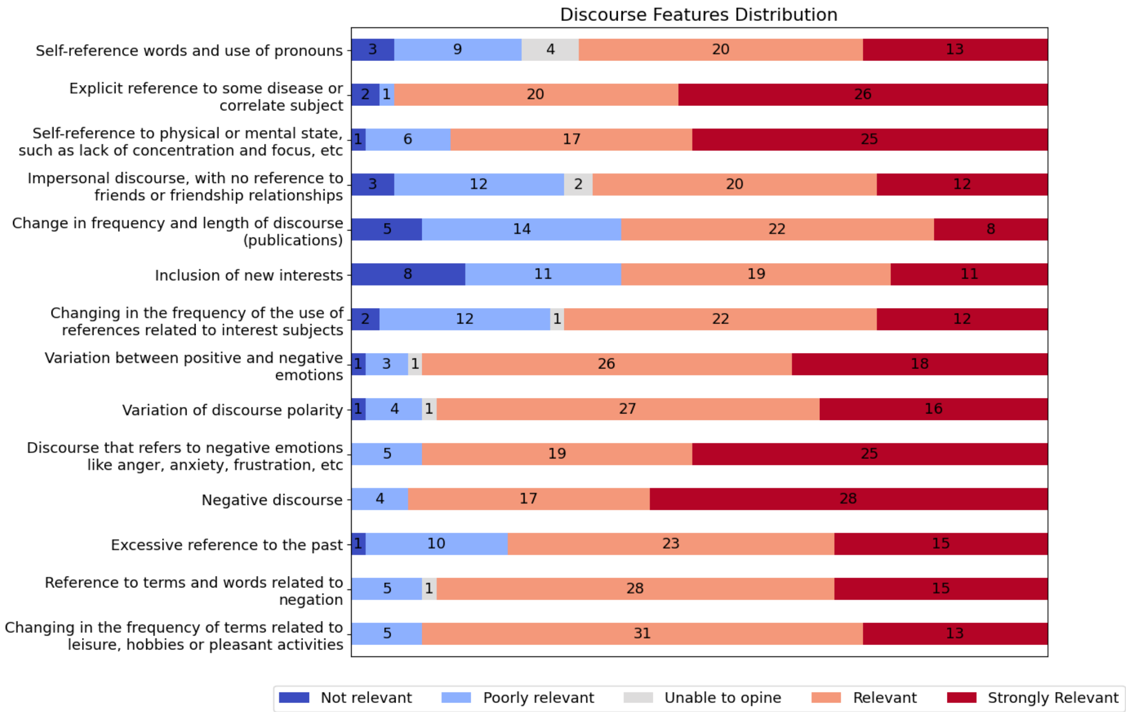

Figure 1. Frequency of level of relevance for each feature inside Discourse Features Group.

This group of features is the only group where all features are still somehow with some level of relevance. We highlight features 12 and 13, which are respectively *Self-reference to physical or mental state* and *Explicit reference to some disease or correlate subject*. Most answers consider these features relevant in the interviews, which is score 2.

4.2.5. Profile Features

The considered features in this section have been listed above at Section 4.1.5. Figure 2 depicts the quantity of relevance scale for each feature. For this group of features, we have removed some of them due to the majority quantity of answers that considered it as *not relevant* or *weakly relevant*.

The difference compared to interview results begin at feature *Publication frequency*. In the interviews, this feature was considered *weakly relevant*, meanwhile, at

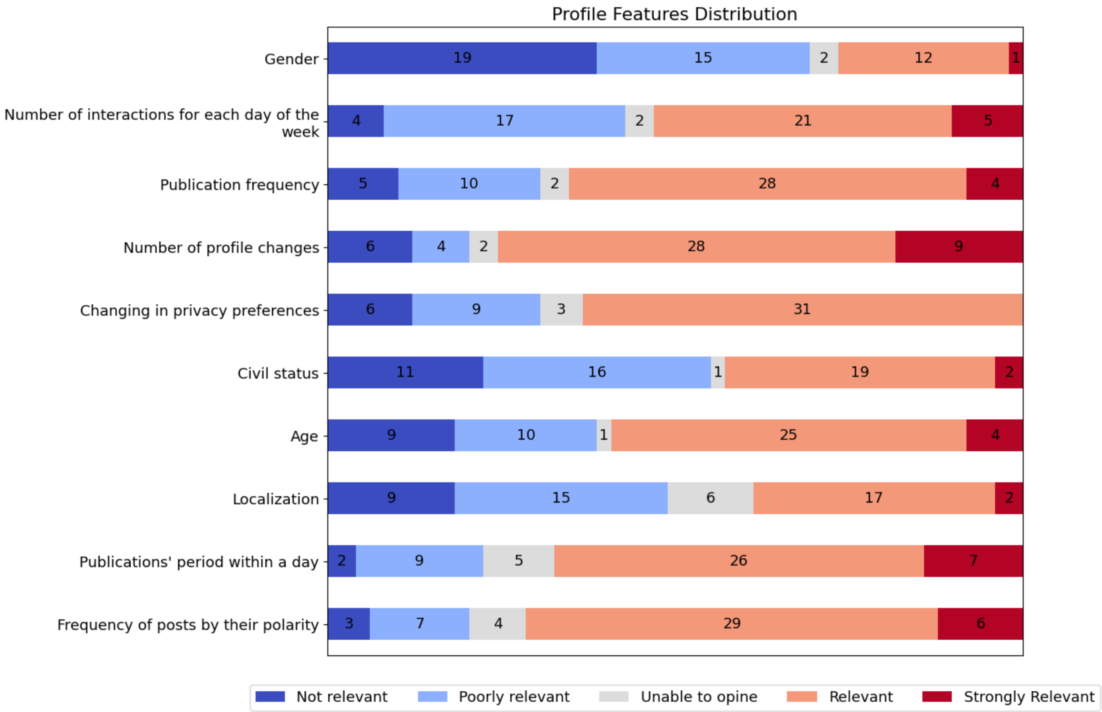

Figure 2. Level of relevance for Profile Features.

the survey, 57.1% considered this information relevant, and 8.2% think it is *strongly relevant*.

Another difference is for feature *Number of interactions for each day of the week*. The interviewees did not consider these features as relevant at all. The survey indicates 42.9% as *relevant* and 10.2% as *strongly relevant*. Even though the sum of other levels makes it more balanced.

Gender variable also has differences between the two instruments. Where is more relevant in the interviews and less relevant in the survey environment. For the interviews, it is for 2 of respondents *relevant*, and for the majority of answers in the interviews, 69.4%, indicate it as nonrelevant or weakly relevant. This behavior repeats for *Civil estate*.

4.2.6. Interactions Features

From the features presented above, not all were selected at least as *relevant*. Two features from this group have been marked for more than 50% as *not relevant*, *weak relevance* or tagged as *no opinion*. The figure below presents the distribution of the answers for selected features. From the list above, the following features have been removed: *Growing use of emoticons or figures* and *Growing use emoticons or figures in the place of text as publications*. Figure 3 depicts relevant features after this trial and their answers frequencies.

There is no difference in opinion about feature *Growing use emoticons or figures*

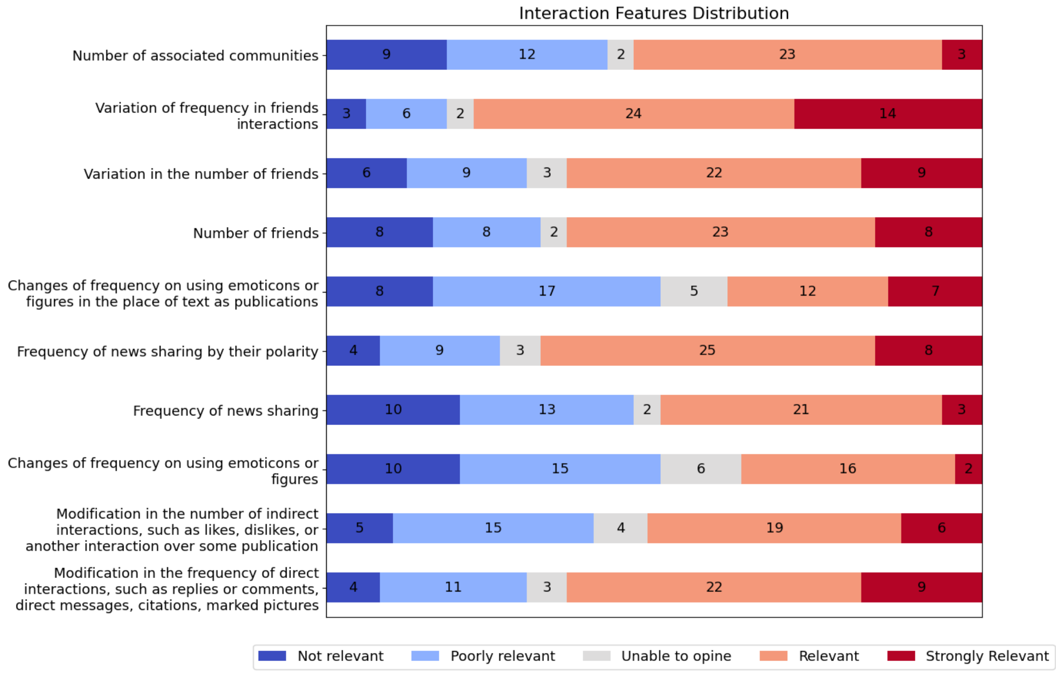

Figure 3. Level of relevance for Interactions Features.

in the place of text as publications. Both the interviews and survey consider this feature not relevant at all. Features *Number of friends*, *Variation in friends number*, *Variation of frequency in friends interactions* and *Number of associated communities*, are considered not relevant in the interviews and relevant for the majority in survey.

4.2.7. Group Features

This group of features is an adaptation of analysis provided by social network analysis. The second item, for example, is related to centrality measures like betweenness. Meanwhile, the third item is an abstraction of community connectivity. The fourth item is related to propagation level inside some communities. This group of questions, likewise the questions from the second and third sections, does not have a majority in *strongly related* answers. The only exception is the first question. Where 42% of answers consider this information at the highest level of relevance. Although only one feature have been considered *strongly relevant*, the sum for levels *not relevant*, *weakly relevant* and *no opinion* does not reach 50% percent. This information demonstrates that a good part of the answers sees this type of information with some level of relevance. We believe that a better explanation of the features, combined with some user context, could be more helpful in a clinical scenario.

Figure 4 depicts the distribution for each question the number of answers by their level of relevance. Each number of the subgroup is related to the number in the list above in Section 4.1.7.

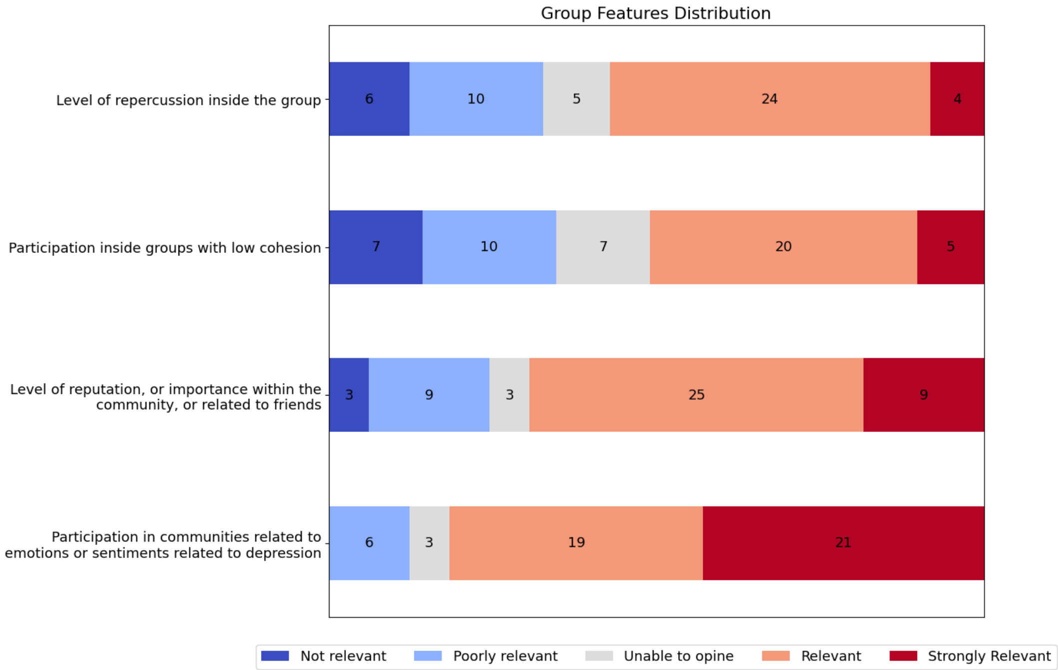

Figure 4. Level of relevance for Group Features.

5. Contributions and Future Steps

In this work, we presented an application scenario of informatics in mental health. Due to the vast implications of depression in people's health and the great use of social media, we should use these data with better precision and reliability. We have presented the scenario of pattern recognition solutions in the scientific community related to identifying the depressive population. We have constructed this scenario using Systematic Literature Review protocols to select the most relevant works. We highlight that most of these works do not consider the knowledge from the health research area when creating solutions.

With the literature review, we have selected the features used for depression identification on social media users from the works in the computer science field. This article has developed an instrument study to interact with health specialists, and this instrument enabled us to investigate more details about detecting depressive disorder. This interaction provides a multi-disciplinary comprehension of the studied phenomena. To validate these features with health professionals, we have constructed a questionnaire instrument to understand professionals' scope of depressive disorder and their approach to identifying when a patient is depressed.

We have applied this questionnaire at two different moments. The first application used the semi-structured interview method with three psychologists, and the latter was applied as a survey to not only psychologists but also to physicians and other health professionals. The survey has reached 49 professionals that are related to depressive disorder diagnosis. With this, we intended to have a broader awareness of depression from the health professional's point of view.

From the interaction with the professionals, we highlight that information about the patient context must be one of the main factors to define if him/she is a depressive patient. Features that are related to the patient discourse tend to be more attractive to the respondents. Since it is with this group of features contains direct data about patient's expressiveness. Thus, the answers for this group of features are higher than the three remaining ones. The features that are related to depression or some symptoms are prone to have higher relevance to respondents. For instance, the information about a user is a member in a group of discussion about depression, and this information seems highly connected to the fact that someone has any affliction caused by depression. From the group of interaction features, the variation in the number of friends is the feature with the higher number of votes for a powerfully relevant score in the relevance scale. Features from User Profile also do not present high scores on the relevance scale. The feature with the most votes in this section is the information about changes in profile information.

This feedbacks reinforce that discourse features are still the most valuable when compared to other types of features. However, as demonstrated by the interviews, combining this type of information with data about the patient's context could help a better understanding of the patient.

Our contributions cover aspects in both computer science and psychology areas. Our findings can serve as a basis for more accurate machine learning and deep learning models, with more relevant features curated by health professionals in the computer science area. Regarding the health research area, we contribute by offering health professionals new insights that can improve the diagnosis of depression in social media users. This work detaches from similar ones in literature review due to its concerns about covering sociotechnical aspects that are not taken into consideration when creating IS solutions. The interaction, even being small, with a part of the health professional community is extremely important to understand what is desirable from a technology solution, to improve the assistance of depressive users.

Since we intend to create a trustworthy classification model, with the information presented in this article, our next steps embrace creating a classification model using the features selected by health professionals. Afterward, it is also essential to validate the model. To accomplish that, we plan a comparative study in order to know how effective the model is. Another critical point is to take information about the patients and understand their vision about social media use. We expect to construct better classification models with valuable features in the computer science area, which comprehends more accurate models that are more relevant for professionals.

6. Acknowledgements

We would like to acknowledge the professionals who participated. This work was supported by the CAPES – Public Notice Number 09/2020 - Prevention and Combat against Outbreaks, Endemics, Epidemics and Pandemics. Process number 223038.014313/2020-19, "Digital Technologies for Monitoring, Mapping and Control of Outbreaks, Endemics, Epidemics and Pandemics", held at the Federal University of Rio de Janeiro. This work was also supported in part by Oracle Cloud credits and related resources provided by the Oracle for Research program (award number CPQ-2160239).

References

[Akay et al. 2016] Akay, A., Dragomir, A., and Erlandsson, B. E. (2016). Assessing Antidepressants Using Intelligent Data Monitoring and Mining of Online Fora. *IEEE Journal of Biomedical and Health Informatics*, 20(4):977–986.

[Andalibi et al. 2017] Andalibi, N., Ozturk, P., and Forte, A. (2017). Sensitive Self-disclosures, Responses, and Social Support on Instagram: The Case of #Depression. In *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing - CSCW '17*, pages 1485–1500, Portland, Oregon, USA. ACM Press.

[Association et al. 2013] Association, A. P. et al. (2013). *Diagnostic and statistical manual of mental disorders (DSM-5®)*. American Psychiatric Pub.

[Bagroy et al. 2017] Bagroy, S., Kumaraguru, P., and De Choudhury, M. (2017). A Social Media Based Index of Mental Well-Being in College Campuses. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, CHI '17, pages 1634–1646, New York, NY, USA. ACM.

[Boscarioli et al. 2017] Boscarioli, C., Araujo, R. M., and Maciel, R. S. P. (2017). *I GranDSI-BR*. Number December.

[Brody et al. 2018] Brody, D. J., Pratt, L. A., and Hughes, J. P. (2018). *Prevalence of depression among adults aged 20 and over: United States, 2013-2016*. US Department of Health and Human Services, Centers for Disease Control and ....

[Cafezeiro et al. 2017] Cafezeiro, I., Viterbo, J., Costa, L., Salgado, L., Rocha, M., and Monteiro, R. (2017). *Strengthening of the Sociotechnical Approach in Information Systems Research*, pages 133–147.

[Chen et al. 2018] Chen, X., Sykora, M. D., Jackson, T. W., and Elayan, S. (2018). What about Mood Swings. In *Companion of the The Web Conference 2018 on The Web Conference 2018 - WWW '18*, pages 1653–1660, New York, New York, USA. ACM Press.

[Chomutare et al. 2015] Chomutare, T., Arsand, E., and Hartvigsen, G. (2015). Mining Symptoms of Severe Mood Disorders in Large Internet Communities. In *2015 IEEE 28th International Symposium on Computer-Based Medical Systems*, pages 214–219, Sao Carlos, Brazil. IEEE.

[Dao et al. 2015] Dao, B., Nguyen, T., Venkatesh, S., and Phung, D. (2015). Nonparametric discovery of online mental health-related communities. In *2015 IEEE International Conference on Data Science and Advanced Analytics (DSAA)*, pages 1–10, Campus des Cordeliers, Paris, France. IEEE.

[Dao et al. 2016a] Dao, B., Nguyen, T., Venkatesh, S., and Phung, D. (2016a). Discovering latent affective dynamics among individuals in online mental health-related communities. In *2016 IEEE International Conference on Multimedia and Expo (ICME)*, pages 1–6, Seattle, WA, USA. IEEE.

[Dao et al. 2016b] Dao, B., Nguyen, T., Venkatesh, S., and Phung, D. (2016b). Effect of social capital on emotion, language style and latent topics in online depression community. In *2016 IEEE RIVF Int. Conf. on Computing & Communication Technologies, Research, Innovation, and Vision for the Future (RIVF)*, pages 61–66, Hanoi, Vietnam. IEEE.

[De Choudhury et al. 2013a] De Choudhury, M., Counts, S., and Horvitz, E. (2013a). Major life changes and behavioral markers in social media: case of childbirth. In *Proc. of the 2013 conference on Computer supported cooperative work - CSCW '13*, page 1431, San Antonio, Texas, USA. ACM Press.

[De Choudhury et al. 2013b] De Choudhury, M., Counts, S., and Horvitz, E. (2013b). Predicting postpartum changes in emotion and behavior via social media. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems - CHI '13*, CHI '13, page 3267, New York, New York, USA. ACM Press.

[De Choudhury et al. 2013c] De Choudhury, M., Counts, S., and Horvitz, E. (2013c). Social Media As a Measurement Tool of Depression in Populations. In *Proceedings of the 5th Annual ACM Web Science Conference*, WebSci '13, pages 47–56, New York, NY, USA. ACM.

[De Choudhury et al. 2017] De Choudhury, M., Sharma, S. S., Logar, T., Eekhout, W., and Nielsen, R. C. (2017). Gender and Cross-Cultural Differences in Social Media Disclosures of Mental Illness. In *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing*, CSCW '17, pages 353–369, New York, NY, USA. ACM.

[Elkin 2008] Elkin, N. (2008). How america searches: Health and wellness. *Opinion Research Corporation: iCrossing*, pages 1–17.

[Fang et al. 2014] Fang, Y.-E., Tai, C.-H., Chang, Y.-S., and Fan, C.-T. (2014). A mental disorder early warning approach by observing depression symptom in social diary. In *2014 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, pages 2060–2065, San Diego, CA, USA. IEEE.

[Homan et al. 2014] Homan, C. M., Lu, N., Tu, X., Lytle, M. C., and Silenzio, V. M. B. (2014). Social Structure and Depression in TrevorSpace. In *Proceedings of the 17th ACM Conference on Computer Supported Cooperative Work & Social Computing*, CSCW '14, pages 615–625, New York, NY, USA. ACM.

[Horvitz and Mulligan 2015] Horvitz, E. and Mulligan, D. (2015). Data, privacy, and the greater good. *Science*, 349(6245):253–255.

[James et al. 2018] James, S. L., Abate, D., Abate, K. H., Abay, S. M., Abbafati, C., Abbasi, N., Abbastabar, H., Abd-Allah, F., Abdela, J., Abdelalim, A., Abdollahpour, I., Abdulkader, R. S., Abebe, Z., Abera, S. F., Abil, O. Z., Abraha, H. N., Abu-Raddad, L. J., Abu-Rmeileh, N. M. E., Accrombessi, M. M. K., and Acharya, D. (2018). Global, regional, and national incidence, prevalence, and years lived with disability for 354 diseases and injuries for 195 countries and territories, 1990–2017: a systematic analysis for the global burden of disease study 2017. *The Lancet*, 392(10159):1789–1858.

[Katchapakirin et al. 2018] Katchapakirin, K., Wongpatikaseree, K., Yomaboot, P., and Kaewpitakkun, Y. (2018). Facebook Social Media for Depression Detection in the

Thai Community. In *2018 15th International Joint Conference on Computer Science and Software Engineering (JCSSE)*, pages 1–6, Nakhonpathom, Thailand. IEEE.

[Kavuluru et al. 2016] Kavuluru, R., Ramos-Morales, M., Holaday, T., Williams, A. G., Haye, L., and Cerel, J. (2016). Classification of Helpful Comments on Online Suicide Watch Forums. In *Proceedings of the 7th ACM International Conference on Bioinformatics, Computational Biology, and Health Informatics*, BCB '16, pages 32–40, New York, NY, USA. ACM.

[Larsen et al. 2015] Larsen, M. E., Boonstra, T. W., Batterham, P. J., O'Dea, B., Paris, C., and Christensen, H. (2015). We Feel: Mapping Emotion on Twitter. *IEEE Journal of Biomedical and Health Informatics*, 19(4):1246–1252.

[Lech et al. 2014] Lech, M., Low, L.-S., and Ooi, K. E. (2014). Detection and prediction of clinical depression. In *Mental Health Informatics*, pages 185–199. Springer.

[Leitão and Prates 2017] Leitão, C. F. and Prates, R. O. (2017). A aplicação de métodos qualitativos em computação. *Jornadas de Atualização em Informática*, 2017:43–90.

[Li et al. 2016] Li, G., Zhou, X., Lu, T., Yang, J., and Gu, N. (2016). SunForum: Understanding Depression in a Chinese Online Community. In *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing - CSCW 16*, pages 514–525, New York, New York, USA. ACM Press.

[Nakagawa et al. 2017] Nakagawa, E. Y., Scannavino, K. R. F., Fabbri, S. C. P. F., and Ferrari, F. C. (2017). *Revisão sistemática da literatura em engenharia de software: teoria e prática*. Elsevier Brasil.

[Nambisan et al. 2015] Nambisan, P., Luo, Z., Kapoor, A., Patrick, T. B., and Cisler, R. A. (2015). Social Media, Big Data, and Public Health Informatics: Ruminating Behavior of Depression Revealed through Twitter. In *2015 48th Hawaii International Conference on System Sciences*, pages 2906–2913, HI, USA. IEEE.

[Nguyen et al. 2014] Nguyen, T., Phung, D., Dao, B., Venkatesh, S., and Berk, M. (2014). Affective and Content Analysis of Online Depression Communities. *IEEE Transactions on Affective Computing*, 5(3):217–226.

[Nobles et al. 2018] Nobles, A. L., Glenn, J. J., Kowsari, K., Teachman, B. A., and Barnes, L. E. (2018). Identification of Imminent Suicide Risk Among Young Adults Using Text Messages. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, CHI '18, pages 413:1—-413:11, New York, NY, USA. ACM.

[Oyong et al. 2018] Oyong, I., Utami, E., and Luthfi, E. T. (2018). Natural Language Processing and Lexical Approach for Depression Symptoms Screening of Indonesian Twitter User. In *2018 10th International Conference on Information Technology and Electrical Engineering (ICITEE)*, pages 359–364, Kuta. IEEE.

[Park et al. 2015] Park, S., Kim, I., Lee, S. W., Yoo, J., Jeong, B., and Cha, M. (2015). Manifestation of Depression and Loneliness on Social Networks: A Case Study of Young Adults on Facebook. In *Proc. of the 18th ACM Conf. on Computer Supported Cooperative Work & Social Computing*, CSCW '15, pages 557–570, New York, NY, USA. ACM.

[Sadeque et al. 2018] Sadeque, F., Xu, D., and Bethard, S. (2018). Measuring the Latency of Depression Detection in Social Media. In *Proceedings of the Eleventh ACM International Conference on Web Search and Data Mining - WSDM '18*.

[Saha et al. 2016] Saha, B., Nguyen, T., Phung, D., and Venkatesh, S. (2016). A framework for classifying online mental health-related communities with an interest in depression. *IEEE Journal of Biomedical and Health Informatics*, 20(4):1008–1015.

[Silveira Fraga et al. 2018] Silveira Fraga, B., da Silva, A. P., and Murai, F. (2018). Online Social Networks in Health Care: A Study of Mental Disorders on Reddit. In *2018 IEEE/WIC/ACM International Conference on Web Intelligence (WI)*, pages 568–573, Santiago. IEEE.

[Simms et al. 2017] Simms, T., Ramstedt, C., Rich, M., Richards, M., Martinez, T., and Giraud-Carrier, C. (2017). Detecting Cognitive Distortions Through Machine Learning Text Analytics. In *2017 IEEE International Conference on Healthcare Informatics (ICHI)*, pages 508–512, Park City, UT, USA. IEEE.

[Trotzek et al. 2018] Trotzek, M., Koitka, S., and Friedrich, C. M. (2018). Utilizing Neural Networks and Linguistic Metadata for Early Detection of Depression Indications in Text Sequences. *IEEE Transactions on Knowledge and Data Engineering*, page 1.

[Tsugawa et al. 2015] Tsugawa, S., Kikuchi, Y., Kishino, F., Nakajima, K., Itoh, Y., and Ohsaki, H. (2015). Recognizing Depression from Twitter Activity. *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems - CHI '15*, pages 3187–3196.

[Vedula and Parthasarathy 2017] Vedula, N. and Parthasarathy, S. (2017). Emotional and Linguistic Cues of Depression from Social Media. *Proceedings of the 2017 International Conference on Digital Health - DH '17*, pages 127–136.

[Wang et al. 2020] Wang, C., Pan, R., Wan, X., Tan, Y., Xu, L., Ho, C. S., and Ho, R. C. (2020). Immediate psychological responses and associated factors during the initial stage of the 2019 coronavirus disease (covid-19) epidemic among the general population in china. *International journal of environmental research and public health*, 17(5):1729.

[Weiss 1995] Weiss, R. S. (1995). *Learning from Strangers: The Art and Method of Qualitative Interview Studies*.

[Wilson et al. 2014] Wilson, M. L., Ali, S., and Valstar, M. F. (2014). Finding Information About Mental Health in Microblogging Platforms: A Case Study of Depression. In *Proceedings of the 5th Information Interaction in Context Symposium*, IIiX '14, pages 8–17, New York, NY, USA. ACM.

[Wohlin et al. 2012] Wohlin, C., Runeson, P., Höst, M., Ohlsson, M. C., Regnell, B., and Wesslén, A. (2012). *Experimentation in software engineering*, volume 9783642290.

[Wongkoblap et al. 2018] Wongkoblap, A., Vadillo, M. A., and Curcin, V. (2018). A Multilevel Predictive Model for Detecting Social Network Users with Depression. In *2018 IEEE International Conference on Healthcare Informatics (ICHI)*, pages 130–135, New York, NY. IEEE.

[Yazdavar et al. 2017] Yazdavar, A. H., Al-Olimat, H. S., Ebrahimi, M., Bajaj, G., Banerjee, T., Thirunarayan, K., Pathak, J., and Sheth, A. (2017). Semi-Supervised Approach to Monitoring Clinical Depressive Symptoms in Social Media. In *Proceedings of the 2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2017*, ASONAM '17, pages 1191–1198, New York, NY, USA. ACM.

[Zhao et al. 2018] Zhao, X., Lin, S., and Huang, Z. (2018). Text Classification of Microblog's "Tree Hole" Based on Convolutional Neural Network. In *Proceedings of the 2018 International Conference on Algorithms, Computing and Artificial Intelligence*, ACAI 2018, pages 61:1—-61:5, New York, NY. ACM.

	Textual				Content Metadata	User Profile	Interactions Data			Group Charac.	Longitud. Variation
Reference	Emot./ Sent.	Linguis.	Topic	Other			Platform	Other Users	Both		
[Fang et al. 2014]	x										
[Nguyen et al. 2014]	x	x	x								
[Larsen et al. 2015]	x	x									
[Nambisan et al. 2015]							x				
[Chomutare et al. 2015]			x	x							
[Dao et al. 2015]	x		x								
[Dao et al. 2016b]	x						x				
[Dao et al. 2016a]	x	x	x								
[Saha et al. 2016]	x	x	x								
[Akay et al. 2016]	x	x						x		x	
[Simms et al. 2017]	x	x									
[Oyong et al. 2018]		x		x							
[Katchapakirin et al. 2018]	x	x			x	x			x		
[Silveira Fraga et al. 2018]				x					x	x	
[Wongkoblap et al. 2018]	x	x			x	x			x		
[Trotzek et al. 2018]	x	x			x						
[De Choudhury et al. 2013b]	x	x							x		
[De Choudhury et al. 2013a]	x	x		x	x				x		
[De Choudhury et al. 2013c]	x	x					x				x
[Homan et al. 2014]								x		x	
[Wilson et al. 2014]		x									
[Tsugawa et al. 2015]	x		x	x	x				x		
[Kavuluru et al. 2016]	x			x							
[De Choudhury et al. 2017]	x	x	x								
[Vedula and Parthasarathy 2017]	x	x							x	x	
[Yazdavar et al. 2017]	x	x	x								x
[Bagroy et al. 2017]				x							x
[Nobles et al. 2018]	x	x		x							
[Chen et al. 2018]	x										x
[Sadeque et al. 2018]		x		x							
[Zhao et al. 2018]				x	x						

Table 3. SLM Works classification using the types of features.