PREDICTING DEPRESSION USING PERSONALITY AND SOCIAL NETWORK DATA

by

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ABSTRACT

Over 300 million people worldwide suffer from depression. With the advent of social network, our goal is to apply a novel approach to identify depression by investigating what relationships exist between an individual's social network information and speech features, their personality, and depression levels. The study was conducted using a publicly available dataset, called myPersonality, which contains more than 6,000,000 test results, and over 4,000,000 individual Facebook profiles. From the dataset, we used depression risk and personality assessment scores, Facebook network and linguistic measures. We created a classifier to extract a feature that indicates the speech act of a status update. We applied several machine learning methods and feature sets to predict depression risk based on personality type, speech acts, and network influence. Our results show that the best predictors included personality dimension scores on neuroticism, conscientiousness, and extraversion, and the usage scores for the assertive and expressive speech acts.

ACKNOWLEDGEMENTS

I would first like to thank my MRP supervisor Dr. Morteza Zihayat Kermani of the Ted Rogers School of Management at Ryerson University. Professor Zihayat provided invaluable support and guidance throughout the term. He empowered me to make this research my own, but steered me in the right direction when I needed it. I also appreciate him providing additional researchers to assist with the manual annotation of speech acts of Facebook status updates used to train my speech act classifier, which was critical in completing this paper.

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Thank you.

Liza Robee Ong

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

INTRODUCTION

Depression is the leading cause of disability globally, with more than 300 million individuals of all ages suffering from this common mental disorder [10]. In the USA, studies have shown that the prevalence of depression has significantly increased from 2005 to 2015, with the fastest rate of increase occurring among the youth compared to older age groups [30]. In Canada, 1 in 5 Canadians experience a mental illness or addiction problem, with young people aged 15-24 most likely to suffer from mental health disorders, compared to other age groups. Further, mental illness costs an estimate of $51 billion a year to the Canadian economy [6]. For individuals, depression can cause poor performance at work, school, and with social relationships. At worst, it can lead to suicide, which is the second leading cause of death among 15-29 year olds [10]. However, due to stigma, barriers still exist to effectively diagnose and treat individuals suffering from mental illness. A study in Canada showed that 40% of survey respondents agreed to experiencing feelings of anxiety or depression, but never sought medical help [6].

With the widespread use of social network among individuals and the youth and the increasing amount of information shared by individuals in these platforms in recent years, there is an opportunity to apply a novel approach to using data from these social networks to help identify those at risk of depression. To illustrate, Facebook currently has 2.2 billion monthly active users, with 64% aged 13-34 years old [11]. It may be useful to understand how certain types of behavior and speech on this social network and how individuals' personality types are relevant in detecting depression risk, to provide early warning signs and resources for people who lack awareness of depression symptoms or for those who hesitate to seek medical help.

Studies have shown that depression is associated with the personality traits: neuroticism, extraversion, and conscientiousness [4]. In addition, it has been observed that depressed individuals exhibit more negative statements and sadness, especially with friends [25]. However, existing research has not yet investigated the use of personality traits in conjunction with social network information to predict depression. Related work use mainly semantic and syntactic features from tweets or Facebook status updates to predict depression. Pragmatics, the study of the meaning of language, has not been explored. Pragmatics includes the observation that words can be used to perform an act, known as "speech acts."

In this research, our contribution is to examine the impact of using various types of information such as the speech content and meaning conveyed by Facebook status updates, the influence of an individual's Facebook friends and network, and the relevance of personality dimensions to help predict an individual's risk of depression. We developed models for predicting depression using linguistic, network, and metadata features extracted from individuals' Facebook profiles, and attributes corresponding to their responses to personality and depression risk assessment questionnaires. Further, we added features that indicate the meaning conveyed by Facebook status updates through a supervised speech act classifier developed for this project, that was trained on more than 4,000 status updates. Subsequently, our depression risk prediction models were trained on a dataset of 521 users and on different feature sets to determine the importance of various attributes and identify their relationship with an individual's depression risk. Our test results indicate that the best predictors for depression include personality dimension scores on neuroticism, extraversion, and conscientiousness, and the use of the speech act types assertives and expressives.

The rest of this document is organized as follows: we provide a background on depression and the theories of personality and speech acts, and a review of existing literature and related work. We then share the results of our exploratory data analysis and describe our methodology and experiments. Last but not the least, we present the results of our experiments and our conclusion and discussion on opportunities, implications and potential future work.

BACKGROUND

In this research, our goal is to explore the relationships between an individual's personality traits, and the meaning of their speech on social networks, to an individual's depression risk. In this section, we provide an overview of the definition of depression and the theories on personality and speech acts that were used as basis for this research objective.

Major Depressive Disorder

Depression is formally called Major Depressive Disorder (MDD) in The Diagnostic and Statistical Manual of Mental Disorders (DSM–5). The DSM-5 defines the essential feature of a major depressive episode as "a period of at least 2 weeks during which there is either depressed mood or the loss of interest or pleasure in nearly all activities" [2]. The diagnostic criteria for this disorder are listed in Table 1 [2]. In this paper, we use the terms depression and MDD interchangeably.

Table 1: Diagnostic Criteria for Major Depressive Disorder

A. Five (or more) of the following symptoms have been present during the same 2-week period and represent a change from previous functioning: at least one of the symptoms is either (1) depressed mood or (2) loss of interest or pleasure. Note: Do not include symptoms that are clearly attributable to another medical condition. 1. Depressed mood most of the day, nearly every day, as indicated by either subjective report (e.g., feels sad, empty, hopeless) or observation made by others (e.g., appears tearful). (Note: In children and adolescents, can be irritable mood.) 2. Markedly diminished interest or pleasure in all, or almost all, activities most of the day, nearly every day (as indicated by either subjective account or observation). 3. Significant weight loss when not dieting or weight gain (e.g., a change of more than 5% of body weight in a month), or decrease or increase in appetite nearly every day. (Note: In children, consider failure to make expected weight gain.) 4. Insomnia or hypersomnia nearly every day. 5. Psychomotor agitation or retardation nearly every day (observable by others, not merely subjective feelings of restlessness or being slowed down). 6. Fatigue or loss of energy nearly every day. 7. Feelings of worthlessness or excessive or inappropriate guilt (which may be delusional) nearly every day (not merely self-reproach or guilt about being sick). 8. Diminished ability to think or concentrate, or indecisiveness, nearly every day (either by subjective account or as observed by others). 9. Recurrent thoughts of death (not just fear of dying), recurrent suicidal ideation without a specific plan, or a suicide attempt or a specific plan for committing suicide.

B. The symptoms cause clinically significant distress or impairment in social, occupational, or other important areas of functioning.

C. The episode is not attributable to the physiological effects of a substance or to another medical condition.

Note: Criteria A-C represent a major depressive episode.

Depression is commonly screened with the use of the Center for Epidemiologic Studies Depression Scale (CES-D) [21]. The CES-D is a 20-item questionnaire that asks respondents to rate how often over the past week they experienced situations related to depression (e.g. restless sleep, poor appetite, feeling lonely). Response options range from 0 to 3 for each item (0 = Rarely or None of the Time, 1 = Some or Little of the Time, 2 = Moderately or Much of the time, 3 = Most or Almost All the Time). Scores range from 0 to 60, with high scores indicating greater depression risk. A score of 16 or greater is the commonly used cut-off point to indicate individuals at risk of depression. However, recent research [28] recommended the use of a cut-off point of 20 to provide a better balance between sensitivity and specificity of results.

Five Factor Model of Personality

The relationships between depression and personality have been explored in a lot of psychological research and while there has not been a definitive consensus on this topic, researchers conclude that it is useful to take into account an individual's personality when studying depression and the appropriate treatments for this disorder [4].

In this research, we explore personality using a specific trait theory of personality called the Five Factor Model of Personality. Trait theories often started with the use of words commonly used to describe an individual (e.g. hard-working, shy). The Five Factor Model of Personality summarizes various theories that use different terms and measures for personality traits into five domains or factors, namely, Neuroticism, Extraversion, Openness, Agreeableness, and Conscientiousness [18].

Traits that represent these five factors are listed in Table 2 [18]. In this model, traits are defined as "dimensions of individual differences in tendencies to show consistent patterns of thoughts, feelings, and actions." Individuals are measured on a scale and can be ranked or ordered based on the degree to which they exhibit specific traits.

Table 2: The Five Factor Model of Personality Traits

Factor	Traits (Low – High)
Neuroticism	Calm – Worrying Even-tempered – Temperamental Self-satisfied – Self-pitying Comfortable – Self-conscious Unemotional – Emotional Hardy – Vulnerable
Extraversion	Reserved – Affectionate Loner – Joiner Quiet – Talkative Passive – Active Sober – Fun-loving Unfeeling – Passionate
Openness to Experience	Down-to-earth – Imaginative Uncreative – Creative Conventional – Original Prefer routine – Prefer variety Uncurious – Curious Conservative – Liberal
Agreeableness	Ruthless – Soft-hearted Suspicious – Trusting Stingy – Generous Antagonistic – Acquiescent Critical – Lenient Irritable – Good-natured
Conscientiousness	Negligent – Conscientious Lazy – Hardworking Disorganized – Well-organized Late – Punctual Aimless – Ambitious Quitting – Persevering

One method of measuring the personality traits of individuals is through the use of the International Personality Item Pool (IPIP) version of the NEO Personality Inventory [13]. This questionnaire measures individuals on the five dimensions (Neuroticism, Extraversion, Openness to Experience, Agreeableness, Conscientiousness) of personality defined by the Five-Factor Model. Scores for each dimension range from 0 to 5, with high scores indicating stronger associations with that personality dimension.

Speech Act theory

A large portion of the content in social network is composed of messages written by individuals, with the use of language. Hence, it is relevant to look at how language is used when trying to understand information presented through social network. The study of language mainly consists of semantics, syntax, and pragmatics. Syntax refers to the rules for forming sentences and phrases from words. Semantics refer to the study of meaning of words and sentences. Meanwhile, Pragmatics refer to the study of the meaning of language considering the context, which includes the observation that words can be used to perform an act, known as "speech acts." Identifying the type of action being accomplished through language provides an additional perspective when exploring the ways individuals manifest their personality and depression.

The five types of speech acts are: Assertives, Commissives, Declarations, Directives, and Expressives [24]. Table 3 lists the definitions and examples of each speech act type.

Table 3: Speech act types

Type	Purpose of the Speech Act	Examples
Assertives	commit a speaker to the truth of an expressed proposition.	statements, descriptions, and predictions, asserting, stating, concluding, boasting, describing, suggesting
Commissives	commit a speaker to some future action	promises, oaths, and bets, promising, pledging, threatening, vowing, offering
Declarations	affect an immediate change of affairs	excommunications, hirings, and declarations of war, declaring, baptising, resigning, firing from employment, hiring, arresting
Directives	used by a speaker who attempts to get the addressee to carry out an action	orders, requests, and direction giving, requesting, advising, commanding, challenging, inviting, daring, entreating
Expressives	express some sort of psychological state	greetings, congratulations, and thanks, condolences, greeting, thanking, apologising, complaining, congratulating

LITERATURE REVIEW

Numerous studies have been conducted to identify an individual's personality and depression risk through the information people share on social network. Most of these studies use syntactic (e.g. punctuation marks, parts-of-speech) and semantic (e.g. LIWC [17], sentiment words) features extracted from the social network messages to identify patterns and build models to predict depression risk or personality type. Meanwhile, some have added the use of pragmatic linguistic features, such as speech acts, to improve the models' performance in detecting personality type or rumors. While semantics helps to understand the meaning of words, and syntax shows how words are combined into a sentence, pragmatics are able to provide more meaning behind a sentence and considers the context [5]. Hence, pragmatics may be useful when trying to better understand the thoughts and intentions of the author of a sentence. This paper also reviews existing research on the relationships between depression and personality, and between depression and communication style.

Predicting depression using social network data

De Choudhury et al. [9] analyzed a year's worth of Twitter posts of depressed individuals prior to the onset of their depression to provide estimates of depression risk before the reported onset. They concluded that features that can be extracted from social network such as the frequency and the emotions of posts, the relational, medicinal, and religious content of messages, and the structure of ego networks, were useful in building a model that can predict an individual's likelihood of depression with 70% classification accuracy.

Schwartz et al. [23] used the Facebook status updates of 28,749 users to predict the degree of depression of individuals. They used the following features extracted from status updates: ngrams, topic models, number of words, usage of LIWC categories, and the season when messages were posted, to create a regression model to predict the degree of depression risk.

Resnik et al. [22] employed several variations of supervised topic modeling algorithms to process the tweets of 2000 users and to identify topics discussed by the users that may be helpful in the assessment of depression. Their results showed that applying more sophisticated topic modeling techniques and analyzing topics over a shorter period of time (i.e. weekly versus longer periods) were helpful in improving the prediction accuracy.

Chen et al. [7] applied a time series analysis of the strength of eight basic emotions extracted from tweets of 585 depressed users and 6596 control group users to create a binary classifier for depression. Among several algorithms used to predict depression, their research showed that accuracy was highest using Support Vector Models with Radial Basis Function, and using Random Forests.

Orabi et al. [20] explored a number of neural network architectures to analyze the tweets of 1145 users and optimized their word embedding process to map words from tweets to a vector representation used by their prediction models. Their results showed that convolutional neural network-based models performed better than recurrent neural network models.

Table 4 summarizes the research conducted on predicting depression using social network and the social network data features, the depression metric, and the algorithms used, as well as the number of users in the data and the performance results of the models.

Table 4: List of published research on predicting depression using social network data

Year	Author (s)	Data & Features	Depression assessment method	# of Users	Algorithm(s)	Accuracy (highest)
2013	De Choudhury et al.	Twitter: number of posts, replies, retweets, links, question-centric	CES-D questionnaire	476	SVM with Radial Basis Function kernel	Precision: 0.74 Recall: 0.63 Acc (+ve): 70.35%

		posts; insomnia index; number of followers and followees, reciprocity, prestige ratio, graph density, clustering coefficient, size of two-hop neighborhood, embeddedness, number of ego components; emotion; linguistic style, usage of depression related terms, usage of antidepressant names				Acc (mean): 72.38%
2014	Schwartz et al.	Facebook status updates: ngrams, topics, LIWC categories, number of words	Depression facet items from an International Personality Item Pool (IPIP) proxy to the NEO-PI-R	28749	Penalized linear regression (ridge regression)	Pearson correlation coefficient r 0.386
2015	Resnik et al.	Tweets: unigram, LIWC categories, topic models	Self-disclosed	2000 (total) 600 (depressed)	LDA, Supervised LDA, Supervised Anchor algorithm, Supervised Nested LDA, Linear Support Vector Regression	R=0.75, 3 of 4 depressed individuals are detected at the cost of roughly 1 false positive per 3 individuals predicted
2018	Chen et al.	Tweets: emotion strength scores, time series statistics per emotions, LIWC categories	Self-disclosed	585 (depressed), 6596	Logistic regression, SVM, Naïve Bayesian, Decision	75/25 Acc: 93.06% Prec: 0.944 Recall 0.901 F 0.918

				(contr ol)s	trees, Random forests	Loo.CV 92.17%
2018	Orabi et al.	Tweets: Word embedding	Self-disclosed	1145 (Contr ol, Depre ssed, and PTSD)	SVM (baseline), Convolutional Neural Network, Recurrent Neural Network	(Highest) Accuracy: 83.12 F1: 82.25 AUC: 0.923 Precision: 81.63 Recall: 84.44

Predicting personality using social network data

Many studies have been conducted in the past decade to determine an individual's personality using their social network data. A summary provided by Laleh et al. [15] shows that the most commonly used features in prediction models are Facebook status updates, followed by ego network then likes. The study also indicated that the most common algorithms used are regression and Support Vector Machine (SVM), followed by k Nearest Neighbors (kNN) and Naïve Bayes (NB). Though these studies have several similarities, it is challenging to make a comparison of their performance results due to wide-ranging differences in the size and content of the training and the test datasets, and their evaluation metrics and processes.

Prediction modelling using speech acts

A few studies have explored classifying speech acts in social network, to be used as features for prediction models.

Appling et al. [3] used a set of Facebook statuses to create an SVM-based classifier of speech acts, using lexical, syntactic, and sentiment features extracted from status updates. The automatically labelled speech acts for each status update were then used for regression analysis to determine the relationships between speech act types and personality dimensions.

Vosoughi [29] analyzed Twitter data and identified assertions using a logistic regression-based speech act classifier. The tweets containing assertions were then provided as input to a clustering module and the resulting clusters were verified for their truthfulness, using a Hidden Markov Model, to determine if the assertion was a rumor or not.

Relationships between depression and personality and communication style

Klein et al. [14] performed a review of existing research that explored the link between depression and personality types. Their study identified three types of proposed relationship between personality and mood disorders. These are: a) depression and personality have common causes but they do not influence each other; b) personality may cause or affect the start and maintenance of depression; and c) depression may influence personality. They concluded that depression is related to the personality traits: neuroticism, extraversion and conscientiousness. While the evidence does not clearly indicate if personality serves as a precursor or predisposition to depression, they show that personality traits may help predict and affect the treatment of depression.

Slonim [26] conducted a review of literature that studied the verbal behavior of depressed individuals. The results showed that the communications of depressed individuals are more self-focused, as indicated by the use of more first person pronouns, and their language express more negative sentiment, as evidenced by the use of more negative emotion words.

Segrin [25] reviewed evidence of relationships between depression and social skills indicators which includes speech content. The results showed that depressed individuals exhibit more negative self-disclosures and negative verbal content, especially when interacting with a friend.

EXPLORATORY DATA ANALYSIS

The datasets on personality type assessment, depression risk assessment, and Facebook information were obtained from the myPersonality project [27].

The depression risk assessment dataset contained the 6,561 responses to the Center for Epidemiologic Studies Depression Scale (CES-D Scale) [21] questionnaire. The CES-D is a 20-item questionnaire that asks respondents to rate how often over the past week they experienced situations related to depression (e.g. restless sleep, poor appetite, feeling lonely). Response options range from 0 to 3 for each item (0 = Rarely or None of the Time, 1 = Some or Little of the Time, 2 = Moderately or Much of the time, 3 = Most or Almost All the Time). Scores range from 0 to 60, with high scores indicating greater depression risk.

The personality type assessment dataset contained the responses of 3,137,694 individuals to the International Personality Item Pool (IPIP) version of the NEO Personality Inventory [13]. This questionnaire measures individuals on the five dimensions (Neuroticism, Extraversion, Openness to Experience, Agreeableness, Conscientiousness) of personality defined by the Five-Factor Model of Personality [8]. Scores for each dimension range from 0 to 5, with high scores indicating stronger associations with that personality dimension.

The Facebook datasets included 22,043,394 Facebook status updates from 153,727 users, and demographics information from 4,282,857 users.

In preparation for exploratory data analysis, the datasets were loaded as dataframes in R. Most of the dataframes were merged to select the information relevant to this research. Table 5 shows a summary of the data from the merged datasets.

Table 5: List of datasets used for exploratory data analysis

	Dataset	# of Rows	# of Unique Users
A	Merged: CES-D and Status Updates	16,496,881	115,873
B	Merged: Five Factor and Status Updates	228,761	1,047

C	Merged: Five Factor, CES-D, and Status Updates	216,395	981
D	Merged: CES-D and Demographics	6,242	5,664
E	Merged: Five Factor and Demographics	2,907,658	2,907,658

A. Users who responded to the CES-D questionnaire and who had more than 1 status update

Figure 1 shows a histogram of the number of status updates for these users. It shows that majority of the users in this dataset have less than 100 status updates. Figure 2 shows a histogram of the CES-D questionnaire results for this set of users. The CES-D scores range from 0-60 and the histogram shows a normal distribution across this range.

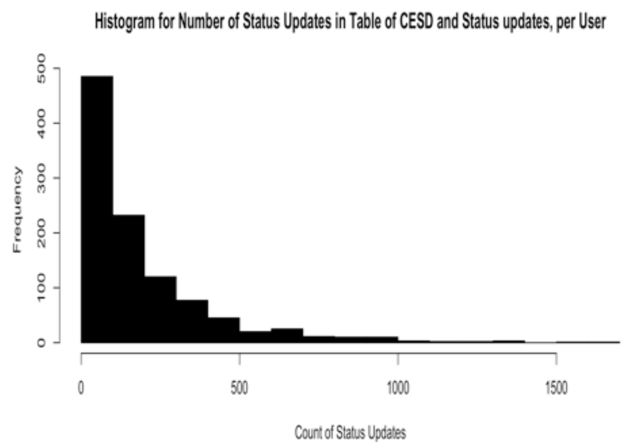

Figure 1: Histogram for the Number of Status Updates

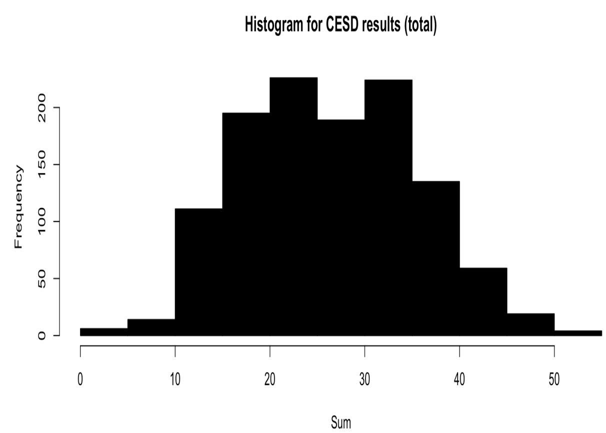

Figure 2: Histogram for the CES-D scores

B. Users who responded to the Five Factor Personality assessment and who had more than 1 status update

Figures 3-7 show the histograms of the Five Factor Personality assessment scores per dimension for these users. All of the histograms show a normal distribution, with most skewing right, on the higher end of the range, with the exception of Neuroticism, which was skewed left. This indicates that most of the users had lower scores on the Neuroticism personality dimension, compared to the other dimensions.

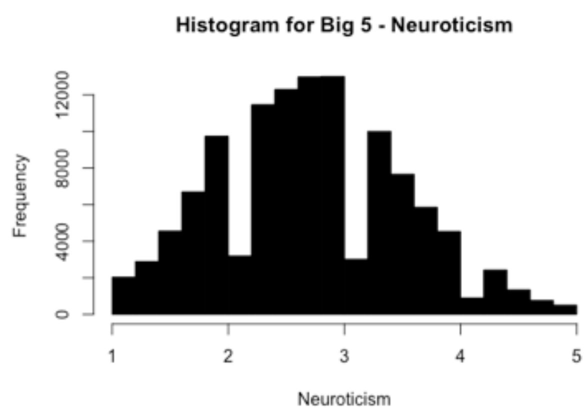

Figure 3: Histogram for Neuroticism

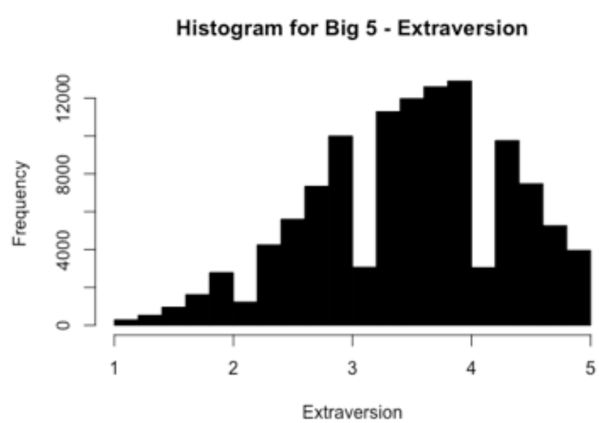

Figure 4: Histogram for Extraversion

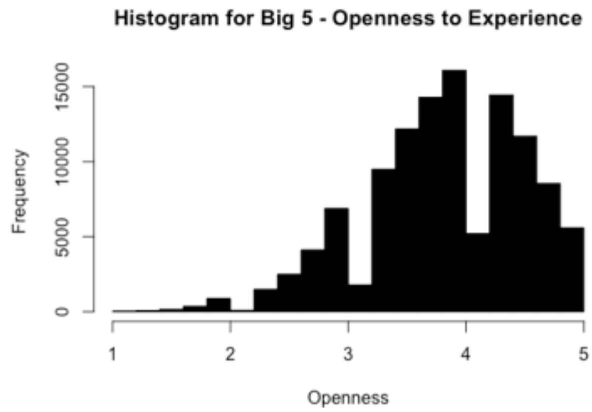

Figure 5: Histogram for Openness to experience

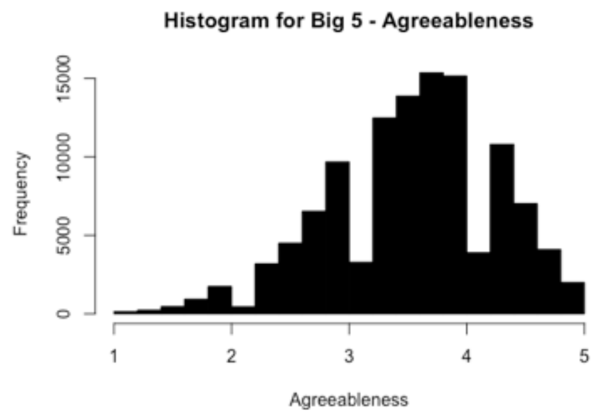

Figure 6: Histogram for Agreeableness

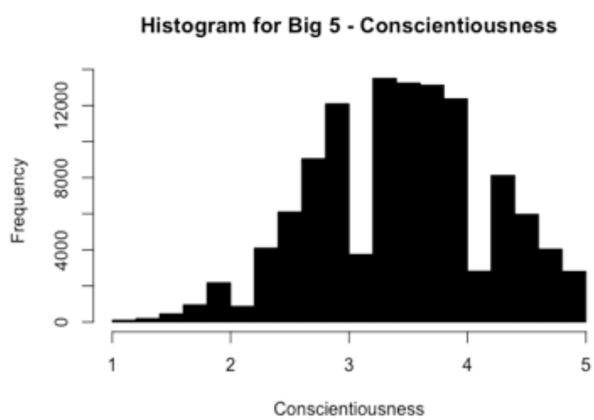

Figure 7: Histogram for Conscientiousness

C. Users who responded to the Five Factor Personality assessment and the CES-D questionnaire and who had more than 1 status update

Figure 8 shows the correlations between the scores for each of the personality dimensions and the CES-D scores for the users in this dataset. This indicates that Neuroticism is negatively correlated with the other personality dimensions, but positively correlated with depression risk. Figure 9 shows that majority of the users in this dataset are at risk of depression. For this analysis, a CES-D cut-off score of 16 was used to indicate the individuals at risk for depression.

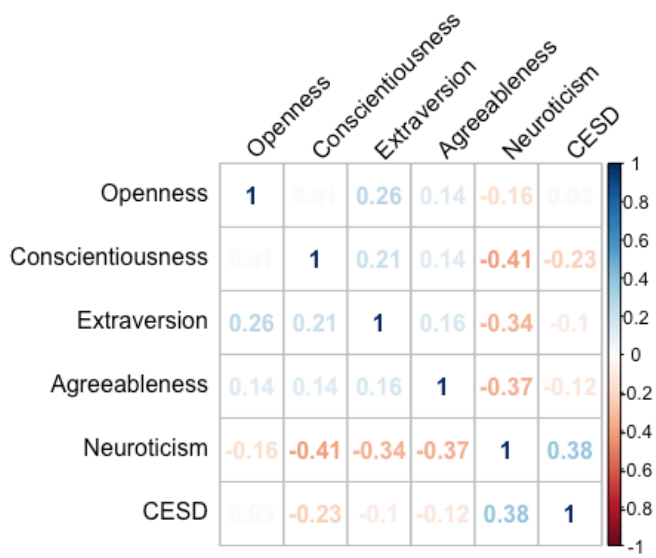

Figure 8: Correlations between the Five Factor personality scores and the CES-D scores

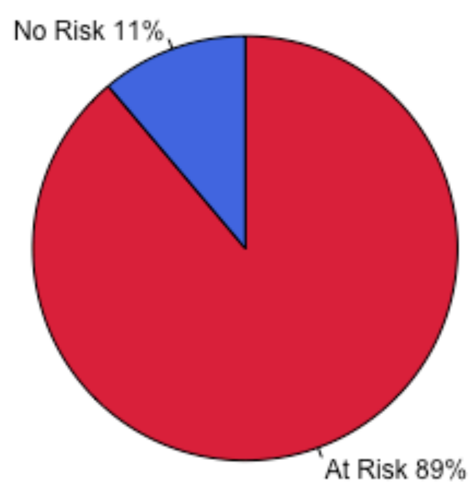

Figure 9: The CES-D score label distribution for the users in the dataset

D. Users who responded to the CES-D questionnaire and who provided demographic information via Facebook

Figure 10 shows the correlations between the CES-D questionnaire scores and Facebook demographic information: age and network size, for the users in this dataset. This indicates that there are no significant correlations between the CES-D scores and age and network size.

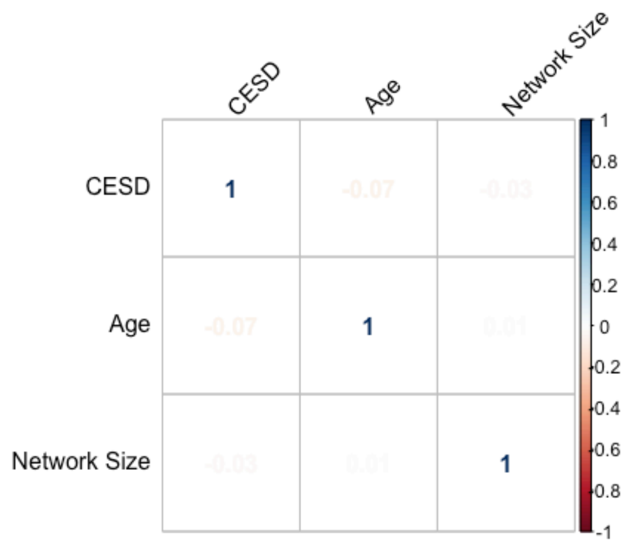

Figure 10: Correlations between CES-D scores and Age, Network Size

E. Users who responded to the Five Factor Personality assessment and who provided demographic information via Facebook

Figure 11 shows the correlations between the Five Factor personality dimension scores and Facebook demographic information: age and network size, for the users in this dataset. This indicates that there are no significant correlations between the Five Factor personality scores and age and network size.

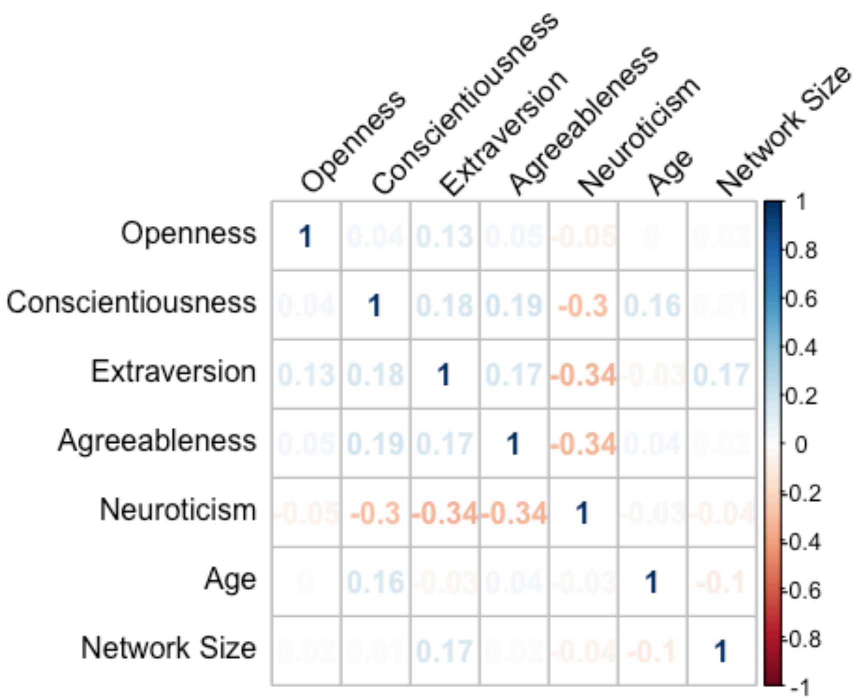

Figure 11: Correlations between Five Factor personality scores and Age, Network Size

METHODOLOGY

The over-all process followed to create a predictor of depression risk based on Facebook user information and status updates, and depression and personality scores, is shown in Figure 12.

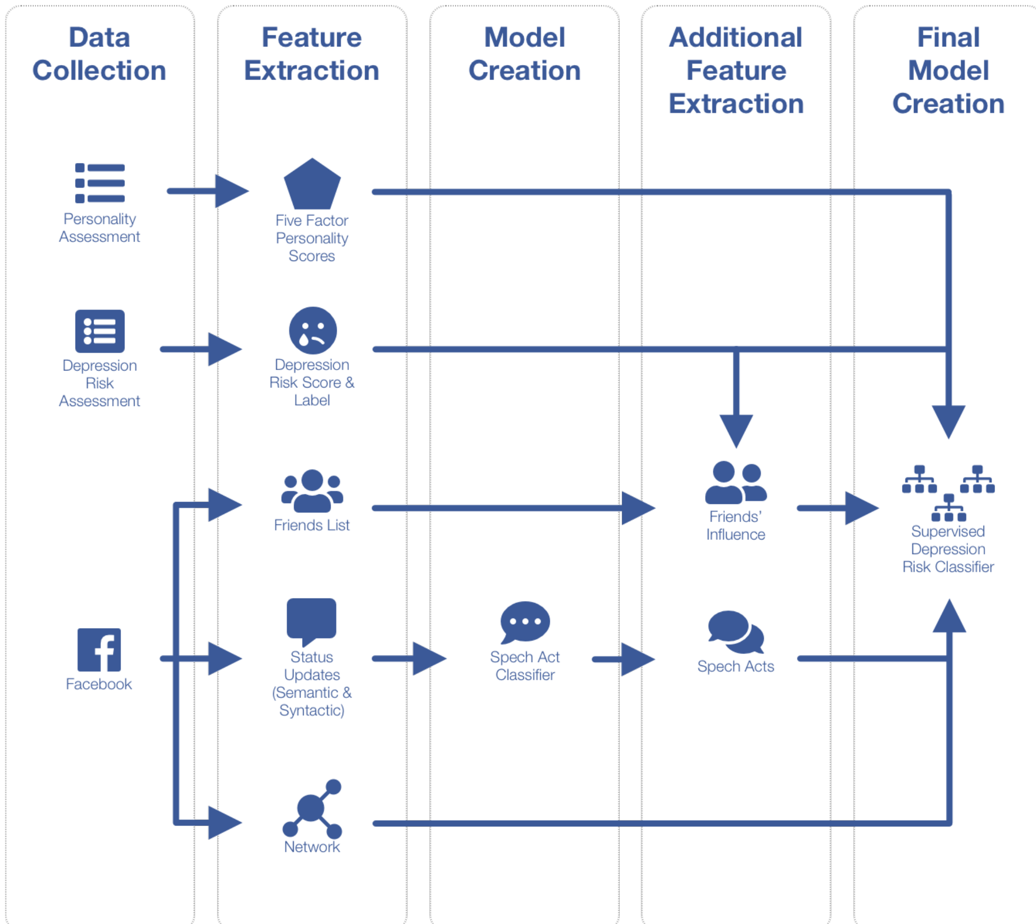

Figure 12: Methodology followed for this research

First, we collected datasets from the myPersonality project [27] that included individual's Facebook information and their responses to the International Personality Item Pool (IPIP) version of the NEO Personality Inventory, and to the Center for Epidemiologic Studies Depression Scale (CES-D Scale) questionnaire. From these datasets, we extracted features, specifically personality dimension scores, depression risk scores and labels, list of friends, demographic information, network measures, and semantic, syntactic, and pragmatic attributes from Facebook user status updates.

These features were used to train a speech act classifier to label the speech acts of Facebook status updates, and a supervised depression risk classifier, using several algorithms.

Supervised Speech Act Classifier

Based on our literature review, numerous studies have built models to predict depression or personality using social network information, using mainly syntactic and semantic linguistic features from tweets or from Facebook status updates. Semantic features include n-grams, appearance of specific word categories (e.g. sentiment words, swear words, pronouns, articles) such as those classified using the Linguistic Inquiry and Word Count (LIWC) program [17]. Based on a text, LIWC provides the percentage of words that fall under types of emotions, linguistic styles, and social concerns. Meanwhile, syntactic features include the use of punctuation marks, social network platform-specific characters (e.g. "#", "@"), and parts-of-speech.

For our research, we added pragmatic linguistic features in the analysis of Facebook status updates by identifying the speech act that a message reflects, through a supervised speech act classifier. To train the speech act classifier used to label the speech acts of status messages, which will serve as an additional feature to our depression risk classifier, we used the datasets on depression risk assessment, and a sample of Facebook users' status updates. To create this sample of status updates used to train the speech act classifier, we identified users at risk of depression and who had at least 5 status updates in our dataset. This resulted to 879 users, and out of these, we randomly sampled 5 status updates from each user. This yielded a total of 4395 status updates that were manually annotated by 2 researchers with the speech act category illustrated by each status update. The label of "N/A" was assigned to status updates that were not written in the English language, or those that only contained punctuation marks. The distribution of the speech acts for the labelled status messages is shown in Figure 13. Examples of status updates for each speech act category are listed in Table 6.

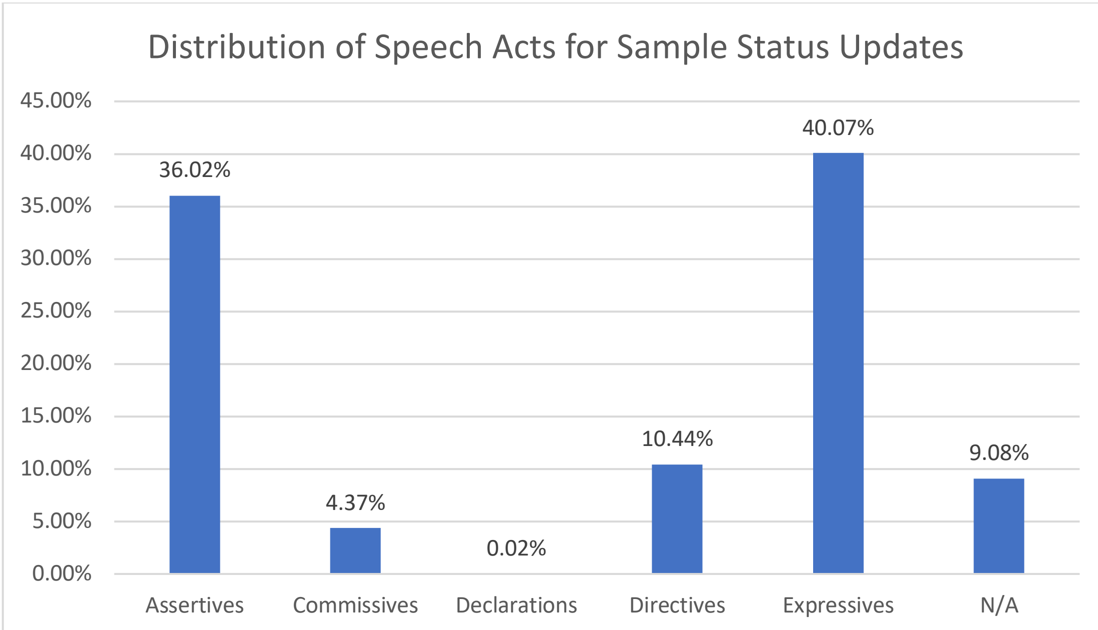

Figure 13: Distribution of speech acts used to train the speech act classifier

Table 6: Examples of status updates for each speech act category

Speech Act	Example Facebook Status Update
Assertives	is back in Notts and had to put the heating on.
Commissives	is off on vacation in Florida until Tuesday August 10. First, going to a wedding, then exploring Disney World!
Declaratives	Duck, meet grinder. Hehehe
Directives	Please vote today :) The pollsters think that only 1 in 3 young people will bother. Prove them wrong and get more attention on youth issues (do you remember those questions about student fees and youth unemployment in the TV debates? Nope. Me neither).
Expressives	Hugs to Liv Lee, Zuzannah, Michal Kosinski, Luning , Iva Cek, Ning and everyone else there this weekend! :o)

Features for the Supervised Speech Act Classifier

For this research, we used several attributes that provide an indication of the speech act type of a Facebook status update.

A. Swear words

We used an online list of 351 swear words [16] to provide additional indication of emotions expressed in a status update. A binary feature was added to represent whether a vulgar word appeared in a status update or not.

B. Speech act verbs

We used a collection of 229 English speech act verbs that were identified by Wierzbicka [31] to represent speech act types. Binary features were added to represent whether a speech act verb falling under specific categories appeared in a status update or not.

C. Punctuations

Specific punctuations such as "?" and "!", may indicate certain speech act types. We added two binary features to specify the appearance of these punctuation symbols.

D. Number of Characters

The number of characters used in a status update was also used as a feature to indicate a speech act type.

Supervised Depression Risk Classifier

To train the supervised depression risk prediction model, we used the datasets on depression risk assessment, personality assessment, and Facebook users' status updates and LIWC scores, demographics information, and network measures that were obtained from the myPersonality project. In addition to these, the speech act labels of the users' status messages, and the number of friends a user has, who were also at risk of depression, were added as features for this dataset. This dataset consisted of 521 users, and 133,657 status updates. For this dataset, the threshold used to identify an individual as at risk for depression was a CESD score of greater than or equal to 23, which is 3 points higher than the cut-off point of 20, recommended by recent research [28]. The threshold was increased to achieve a more balanced dataset of 63% of users identified as at risk of depression, and 37% identified as having no risk of depression.

Each of the features used to train the supervised depression risk prediction model are described in the succeeding section.

Features for the Supervised Depression Risk Classifier

For this research, we used several sets of attributes that provide an indication of the actions of individuals at risk of depression.

A. Personality dimensions

The personality type assessment dataset contained the responses of individuals to the International Personality Item Pool (IPIP) version of the NEO Personality Inventory. This questionnaire measures individuals on the five dimensions (Neuroticism, Extraversion, Openness to Experience, Agreeableness, Conscientiousness) of personality defined by the Five-Factor Model of Personality. Scores for each dimension range from 0 to 5, with high scores indicating stronger associations with that personality dimension.

B. Linguistic features from Facebook status updates

Semantic and Syntactic features

We used LIWC [17] category scores to identify an individual's use of specific types of parts-of-speech, such as articles and pronouns, and use of words that are associated with psychologically relevant categories, such as positive and negative emotions. In the myPersonality project, the source of Facebook data used for this research, scores for each user and each LIWC category were calculated by "aggregating all the status updates of every participant into a single file and executing a LIWC analysis on each user's combined status updates. The LIWC software reported the percentages of the words in each LIWC category out of all of the words used in the combined status updates" [12].

Pragmatic features from Facebook status updates

We used the speech act classifier created for this research to label the speech acts of the status messages. For each speech act type, a score was generated for each user that aggregates the use of each type then divides it by the total number of status updates written by the user. These scores were used as features to indicate the prevalence of the speech act category in the user's status messages.

C. Meta-data from Facebook status updates

We used features extracted from users' status updates, specifically: i) the total number of status updates in the dataset for each user, ii) mean number of characters used by the user across all their status updates. In addition, we calculated an insomnia index, similar to the one used by De Choudhury et.al. [9], to indicate the percentage of a user's status updates that were posted at night. To calculate this metric for each user, we aggregated the number of status updates posted during the day, specifically between 6 AM and 9 PM, Eastern time, and subtracted this from the total number of status updates created at night, specifically between 9 PM and 6 AM, Eastern time.

D. Network information from Facebook

We used features based on Facebook network measures: betweenness, density, and transitivity, that may indicate the strength of an individual's relationships.

E. Influence of Facebook friends

To provide an indication of the influence of Facebook friends to an individual's depression risk, for each user, we counted the number of their friends who also completed depression assessment questionnaire and who were determined to be as at risk of depression.

In summary, our study aims to contribute to the growing research area of predicting depression using social network through analyses and models that consider the relationship between depression and personality, the influence of an individual's social network connections, and the associations between specific speech act types and an individual's psychological state.

EXPERIMENTS

Supervised Speech Act Classifier

We used R to train four different prediction models on our features using the following algorithms: Classification and Regression Trees (CART), k Nearest Neighbors (kNN), Random Forest (RF), and linear Support Vector Machine (SVM). We compared these models using a baseline model that assigned the majority class (Expressives speech act type) to all data points. We used the metrics precision, recall, and accuracy to evaluate these models.

Supervised Depression Risk Classifier

We used R to train eight different models to classify individuals based on depression risk on our features using the following algorithms: classification and regression tree (CART), k nearest neighbors (KNN), logistic regression (LR), multi-layer perceptron (MLP), Naïve Bayes (NB), neural network (NN), random forest (RF), and linear support vector machine (SVM). We compared these models using a baseline model that the majority class (At risk of depression) to all data points. We used the metrics precision, recall, F1, AUC (area under the ROC curve), accuracy, and kappa to evaluate these models.

Using the best performing algorithm from the prior set of experiments, we then used R to train 9 models using different sets of features to predict depression risk. We used the following feature sets: a) All features (ALL) – includes meta-data on status messages such as insomnia index, number of updates, mean number of characters, network measures such as transitivity, betweenness, density, linguistic features including speech acts, personality scores, and number of friends at risk of depression, b) PCA - Dimension-reduced feature set (PCA) - applies Principal Component Analysis on all the features, c) Linguistic (LING) – includes semantic and syntactic features, excludes speech acts, d) Meta-data on status updates (META) – includes number of characters, number of updates, and insomnia index for each user, e) Network measures (NET) – includes network features such as transitivity, f) Personality (PERS) – adds the personality type assessment scores, to the meta data, linguistic and network features, g) Number of depressed friends (DEP) – adds the number of friends at risk of depression to the meta data, linguistic and network features, h) Personality and speech acts (PERS_SP) – includes only the personality dimension scores and use of the speech act types, and i) Top 10 features (TOP 10) – includes only the top 10 features in terms of variable importance, that provides an estimate of the contribution of each feature used in the models. We used the metrics accuracy, kappa, and area under the curve (AUC), precision, recall, and F1 measures to evaluate these models.

RESULTS

Supervised Speech Act Classifier

We used the R Caret package [1] to train four different classifiers on our data consisting of 4395 Facebook status updates and 9 features. We used the following methods: classification and regression tree (CART), linear support vector machine (SVM), random forest (RF), and k nearest neighbors (KNN). We randomly split our dataset by allocating 80% for our training set and 20% for our hold out test set. On the training set, we used 10-fold cross validation for all methods. We compared the performance of the four classifiers with a baseline classifier that assigns the most frequently occurring speech act (expressive) in our dataset as the speech act type for all the status updates.

Tables 7,8,9 show the performance of the five classifiers on the hold out test dataset, after training. We used the measures balanced accuracy, precision, and recall to evaluate the performance of the classifiers.

Table 7: Balanced Accuracy results for the Supervised Speech Act Classifier

	Assertive	Commissive	Declaration	Directive	Expressive
Baseline	0.5	0.5	NA	0.5	0.5
CART	**0.6250**	0.5	NA	**0.6774**	0.5290
KNN	0.5950	0.5	NA	0.6036	**0.5877**
RF	0.5950	0.5	NA	0.6036	**0.5877**
SVM	0.6165	0.5	NA	0.6639	0.5876

Table 8: Precision results for the Supervised Speech Act Classifier

	Assertive	Commissive	Declaration	Directive	Expressive
Baseline	NA	NA	NA	NA	0.4587
CART	**0.4934**	NA	NA	**0.4444**	**0.7644**
KNN	0.4623	NA	NA	0.4138	0.5976
RF	0.4623	NA	NA	0.4138	0.5976
SVM	0.4830	NA	NA	0.4130	0.3924

Table 9: Recall results for the Supervised Speech Act Classifier

	Assertive	Commissive	Declaration	Directive	Expressive
Baseline	0	0	NA	0	1
CART	0.7203	0	NA	**0.4255**	**0.4196**
KNN	**0.7299**	0	NA	0.2553	0.4087
RF	**0.7299**	0	NA	0.2553	0.4087
SVM	**0.7299**	0	NA	0.4043	0.3924

The results show that the measures for the Commissive and Declaration speech act categories are mostly 0 or NA. This is mainly due to the lack of data from the labelled speech acts dataset that belong to these categories, compared to the other categories. Specifically, out of the whole dataset of 4395 status updates, used to train and test the models, only 192 (4%) were labelled Commissive and only 1 (0.0002%) was labelled a declaration. The results also indicate that the CART method performed best for 2 out of 3 speech act categories (excluding Commissive and Declaration) for all the measures - balanced accuracy, precision, and recall. Based on these results, the CART model was used to classify the speech acts of the status updates that were used in the depression risk prediction model.

The distribution of the speech acts of the 133,657 status updates used in the depression risk prediction model, as labelled by this supervised speech act classifier, is shown in Figure 14.

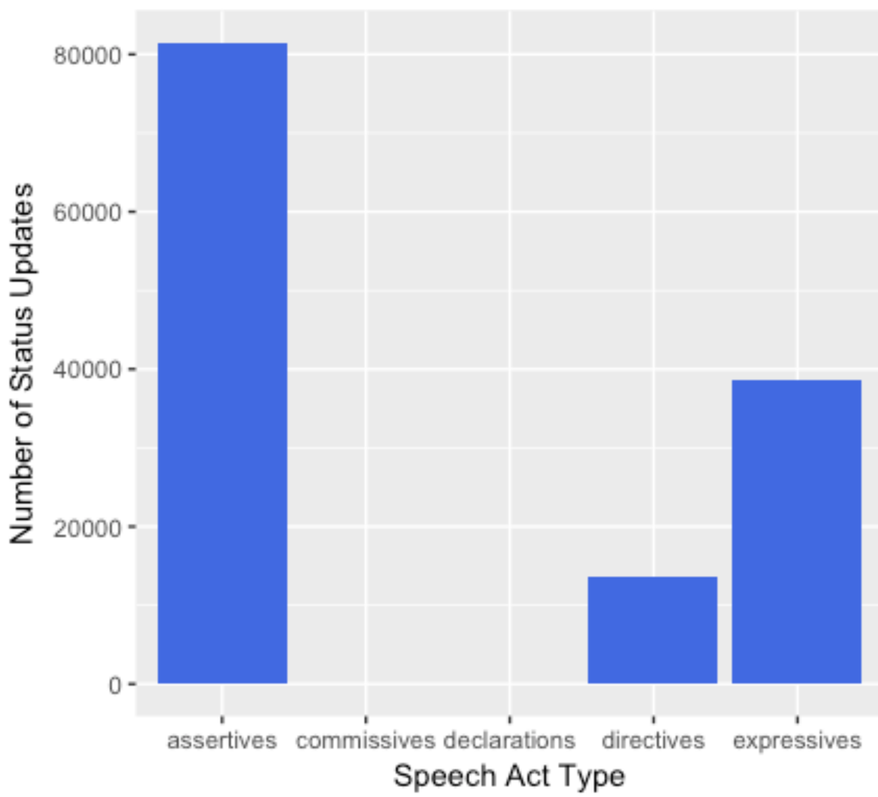

Figure 14: Distribution of speech acts for the status updates used in the supervised depression risk classifier

Supervised Depression Risk Classifier

We used the R Caret package [1] to train eight different classifiers on our data consisting of 521 Facebook users and 21 features. The data consists of users that had complete data for the features we considered, specifically, depression risk assessments, personality assessments, network measures, and meta-data and linguistic features (LIWC, syntactic, semantic, speech acts) of status updates. We used the following methods: classification and regression tree (CART), k nearest neighbors (KNN), logistic regression (LR), multi-layer perceptron (MLP), Naïve Bayes (NB), neural network (NN), random forest (RF), and linear support vector machine (SVM). We randomly split our dataset by allocating 80% for our training set and 20% for our hold out test set. On the training set, we used 10-fold cross validation for all methods. We compared the performance of the classifiers with a baseline classifier that assigns the most frequently occurring depression risk label (at risk) in our dataset as the prediction for all the users.

Table 10 shows the performance of the nine classifiers on the hold out test dataset, after training. We used the measures accuracy, balanced accuracy, precision, and recall to evaluate the performance of the classifiers on the hold out test set. We also show a plot of the models' specificity versus sensitivity measures on Figure 15.

The results indicate that, on the hold our test set, the Random Forest (RF) model yields the best performance in all measures, with a balanced accuracy of 62%, a precision of 64% and a recall of 83%. Meanwhile the Logistic Regression (LR) model follows as the next best performing model with 59% balanced accuracy at a precision at 62% and recall of 81%.

Table 10: Supervised Depression Risk Classifier Results on the hold out Test Set

Methods	**Accuracy**	**Balanced Accuracy**	**Precision**	**Recall**
Baseline	0.5619	0.5	0.5619	1
CART	0.6095	0.5951	0.6364	0.7119
KNN	0.5619	0.05311	0.53571	0.76271
LR	0.619	0.5916	0.6234	0.8136
MLP	0.5429	0.5286	0.5846	0.6441
NB	0.5905	0.5661	0.6081	0.7627
NN	0.5905	0.5829	0.6333	0.6441
RF	**0.6476**	**0.6218**	**0.6447**	**0.8305**
SVM	0.6095	0.5807	0.5926	0.8136

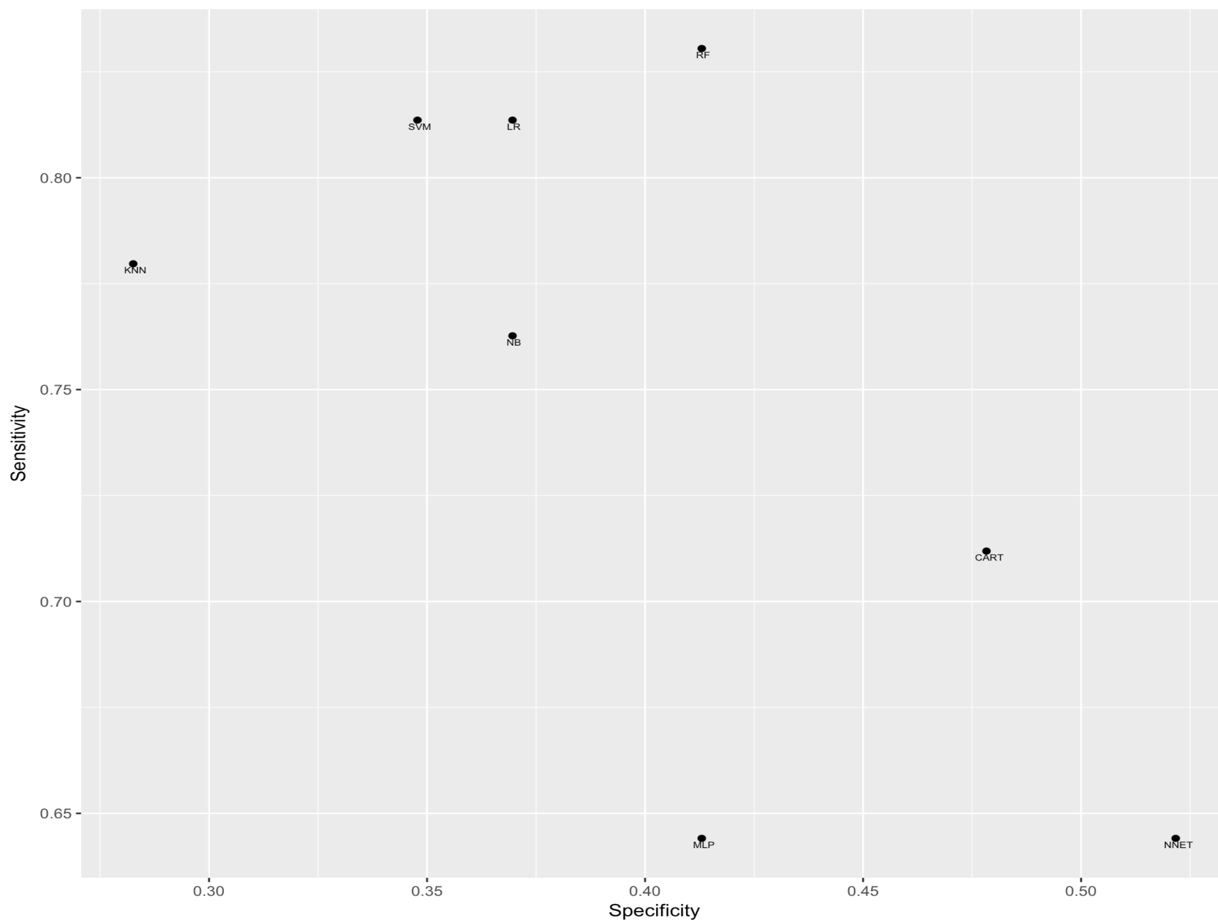

Figure 15: Specificity versus Sensitivity Results of the Supervised Depression Risk Classifiers on the hold out Test Set

We ran another set of experiments to explore the features that will yield the best prediction performance for our models. For these experiments, we used the Random Forest method, which yielded the highest balanced accuracy and precision and recall measures from table 10. We ran the models using the following feature sub sets: a) All features (ALL) – includes meta-data on status messages such as insomnia index, number of updates, mean number of characters, network measures such as transitivity, betweenness, density, linguistic features including speech acts, personality scores, and number of friends at risk of depression, b) PCA - Dimension-reduced feature set (PCA) - applies Principal Component Analysis on all the features, c) Linguistic (LING) – includes semantic and syntactic features, excludes speech acts, d) Meta-data on status updates

(META) – includes number of characters, number of updates, and insomnia index for each user, e) Network measures (NET) – includes network features such as transitivity, f) Personality (PERS) – adds the personality type assessment scores, to the meta data, linguistic and network features, g) Number of depressed friends (DEP) – adds the number of friends at risk of depression to the meta data, linguistic and network features, h) Personality and speech acts (PERS_SP) – includes only the personality dimension scores and use of the speech act types, and i) Top 10 features (TOP 10) – includes only the top 10 features in terms of variable importance, that provides an estimate of the contribution of each feature used in the models.

Variable importance for features in random forests is calculated in the R Caret package [1] as follows: "For each tree, the prediction accuracy on the out-of-bag portion of the data is recorded. Then the same is done after permuting each predictor variable. The difference between the two accuracies are then averaged over all trees, and normalized by the standard error."

For our experiment, we obtained the variable importance from the model that used all features, and used the top 10 features for one of our experiments. The top 20 variables and their importance scores are listed in Table 11.

Table 11: List of top 20 features in terms of variable importance

#	Variable Name	Variable Importance	Variable Description	Feature Type
1	**neu**	13.685	Neuroticism score	Personality
2	**assertives**	9.449	Use of Assertives speech act type	Speech act
3	**con**	9.086	Conscientiousness score	Personality
4	**negemo**	8.797	Use of Negative emotion words	Linguistic
5	**ext**	8.671	Extraversion score	Personality
6	**you**	7.981	Use of the pronoun "You"	Linguistic
7	**expressives**	7.823	Use of Expressives speech act type	Speech act
8	**they**	7.699	Use of the pronoun "They"	Linguistic
9	**transitivity**	7.673	Network transitivity metric	Network
10	**article**	7.585	Use of articles	Linguistic
11	i	7.3	Use of the pronoun "I"	Linguistic

12	directives	7.265	Use of Directives speech act type	Speech act
13	insomnia_index	7.085	Prevalence of messages posted at night versus day	Metadata
14	posemo	7.02	Use of Positive emotion words	Linguistic
15	agr	7.013	Agreeableness score	Personality
16	we	6.876	Use of the pronoun "We"	Linguistic
17	shehe	6.815	Use of the pronouns "She" and "He"	Linguistic
18	ope	6.706	Openness score	Personality
19	brokerage	6.646	Network brokerage metric	Network
20	nupdates	6.556	Number of status updates posted	Metadata

The variable importance scores show that, among the top 5 most important features are the personality scores on neuroticism (1^{st}), conscientiousness (3^{rd}) and extraversion (5^{th}). These results show consistency with the conclusion of Klein et al. [14] that depression is related to the personality traits: neuroticism, extraversion and conscientiousness. In addition to this, the speech act types assertives (2^{nd}) and expressives (7^{th}), as well as negative emotions (4^{th}) also rank high in variable importance. These provide support to the conclusion of Segrin [25] that impaired social skills, which include speech content composed of mostly negative statements and sadness, are associated with depression.

A comparison of the results of the performance of the models based on the different feature sets, using the hold out test data, are listed in Table 12. The top 5 best performing feature sets in terms of Accuracy, Kappa, and AUC measures are: 1) All features, 2) Personality dimension scores added to the linguistic, network, and metadata features, 3) Top 10 features, 4) PCA on all features, and 5) Personality dimension scores and use of speech act types. Meanwhile, the best feature set in terms of F1 measure is the use of Personality dimension scores added to the linguistic, network, and metadata features. These results illustrate the improvement that personality dimensions and use of speech act types contribute to the prediction of depression risk, when used in conjunction with commonly used features such as syntactic, semantic, and network attributes.

A comparison of the results of the performance of the models based on the different feature sets, using the data from cross-validation, are illustrated in Figure 16 and Table 13. The ROC curves and AUC measures are illustrated in Figures 17-25. The top 3 best performing feature sets in terms of Accuracy, Kappa, and AUC measures are: 1) Personality dimension scores and use of speech act types, 2) Top 10 features, and 3) Personality dimension scores added to the linguistic, network, and metadata features. Meanwhile, the top 3 feature sets in terms of F1 measure are: 1) Top 10 features, 2) Personality dimension scores and use of speech act types, and 3) All features. These results further demonstrate the relevance of personality dimensions and use of speech act types to assessing an individual's depression risk.

Table 12: Precision, Recall, F1, AUC, Accuracy, Kappa measures for the models using different feature sets on the hold-out test set

Features	Precision	Recall	F1	AUC	Accuracy	Kappa
All features	**0.6494**	0.8475	0.7353	**0.6303**	**0.6571**	**0.2722**
Personality, linguistic, network, metadata	0.642	**0.8814**	**0.7429**	0.6255	**0.6571**	0.2649
Top 10 features (4 personality, 2 speech acts, 3 LIWC, 1 network)	0.6301	0.7797	0.697	0.5964	0.619	0.1994
PCA on all features	0.6301	0.7797	0.697	0.5964	0.619	0.1994
Personality, Speech acts	0.6286	0.7458	0.6822	0.5903	0.6095	0.1854
Meta-data	0.6125	0.8305	0.705	0.5783	0.6095	0.1649
Network	0.6027	0.7458	0.6667	0.5577	0.581	0.1193
Number of depressed friends, linguistic, network, metadata	0.5862	0.8644	0.6986	0.5409	0.581	0.0877
Linguistic	0.5833	0.8305	0.6853	0.5348	0.5714	0.0741

Table 13: Precision, Recall, F1, and AUC measures for the models using different feature sets on cross-validation results

Feature Set	Precision	Recall	F1	AUC
TOP10	0.7320261	0.8389513	**0.7818499**	0.6443
PER_SP	**0.7491409**	0.8164794	0.7813620	**0.6633**
ALL	0.6925373	0.8689139	0.7707641	0.5888
DEP	0.6802326	**0.8764045**	0.7659574	0.5691
PCA	0.7055085	0.8263027	0.7611429	0.6125
PERS	0.7119741	0.8239700	0.7638889	0.6133
LING	0.6993464	0.8014981	0.7469459	0.592
NET	0.7060811	0.7827715	0.7424512	0.5994
META	0.6687898	0.7865169	0.7228916	0.5443

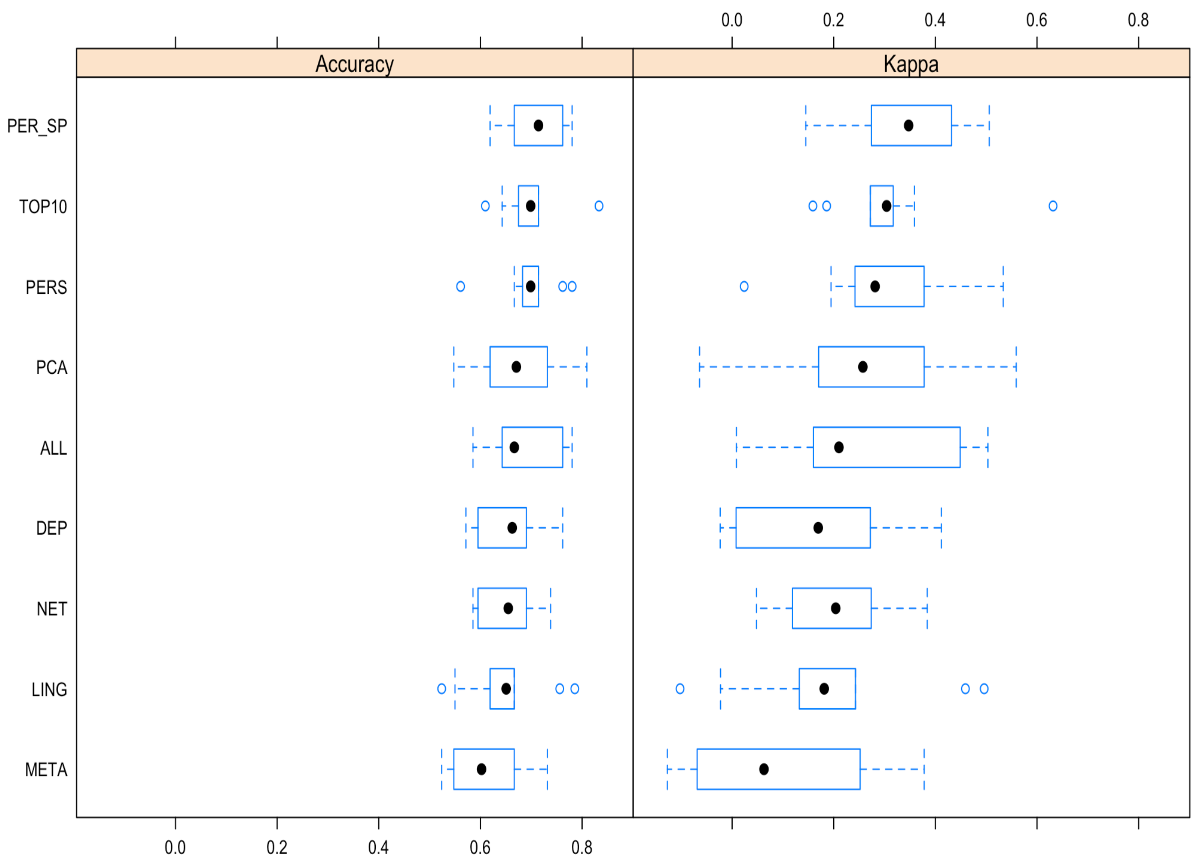

Figure 16: Box plot of the models' performance on different feature sets on cross-validation results

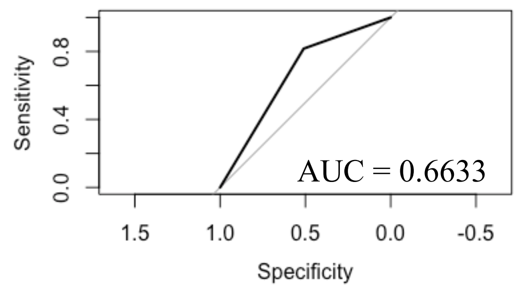

Figure 17: ROC for feature set PERS_SP

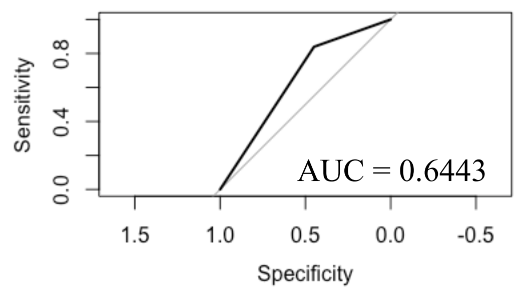

Figure 18: ROC for feature set TOP10

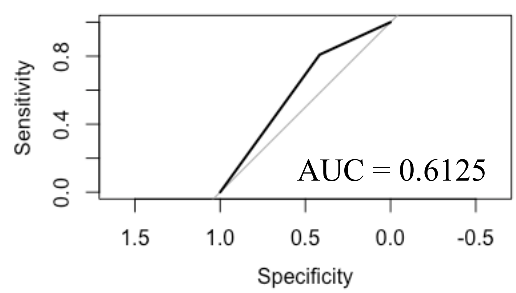

Figure 19: ROC for feature set PERS

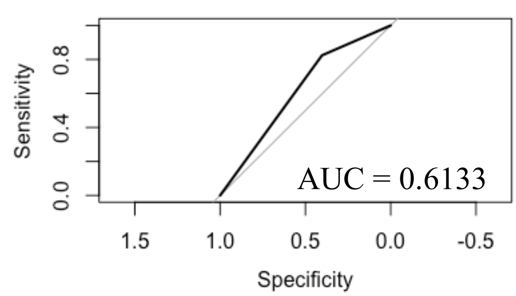

Figure 20: ROC for feature set PCA

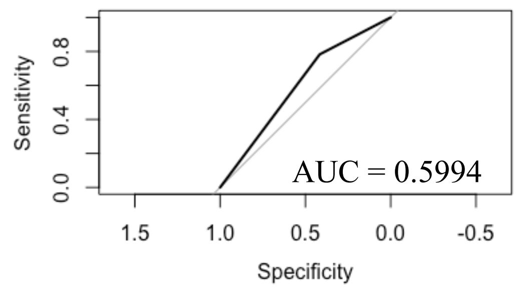

Figure 21: ROC for feature set NET

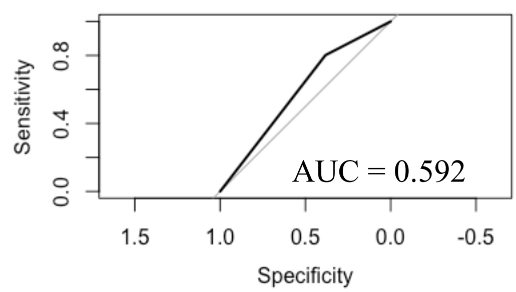

Figure 22: ROC for feature set LING

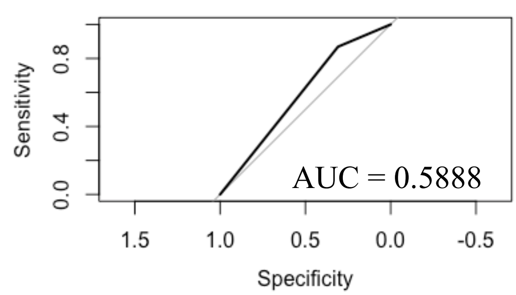

Figure 23: ROC for feature set ALL

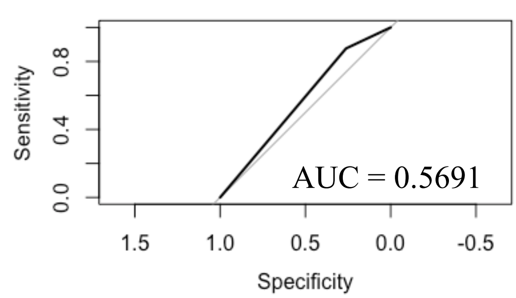

Figure 24: ROC for feature set DEP

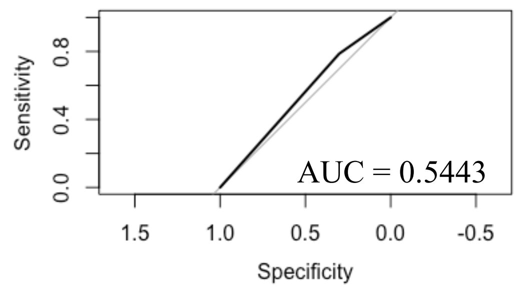

Figure 25: ROC for feature set META

CONCLUSION

In this research, we explored the impact of using an individual's personality dimensions, the meaning of their speech via speech acts of Facebook status updates, and the influence of their Facebook network to predict their depression risk. We conducted this using a publicly available dataset, called myPersonality, which contained more than 6,000,000 test results, together with more than 4,000,000 individual Facebook profiles. From the dataset, we used depression risk assessment and personality assessment scores, Facebook network and linguistic measures. We also extracted semantic, syntactic, and meta-data features from Facebook status updates. Then we created a speech act classifier to add a pragmatic linguistic feature that indicates the speech act of a status update. After which we applied several machine learning methods and feature sets to use the data to predict depression risk based on personality type, speech acts, and network influence.

Our results show that the prediction model that achieved the best performance used features related to the personality dimension scores and prevalence of specific speech act types in addition to features used in existing research such as syntactic, semantic, meta-data, and network attributes. Further, the features related to personality traits for neuroticism, conscientiousness, and extraversion, and the use of assertive and expressive speech acts were found to be among the top 10 most important variables among all the attributes used in the models. These results show consistency with the conclusion of Klein et al. [14] that depression is related to the personality traits: neuroticism, extraversion and conscientiousness. These results also provide support to the conclusion of Segrin [25] that impaired social skills, which include speech content composed of mostly negative statements and sadness, which may manifest in assertives and expressives type of speech acts, are associated with depression.

Our findings suggest that there is value in utilizing various relevant sources of information such as the meaning of Facebook status updates, the influence of their network, and personality assessments, to improve the prediction of depression risk. Given the relatively limited and basic data used in this research to assess speech acts and the influence of a Facebook's network and the promising relevance of these attributes to depression, there is an opportunity to use more extensive data and explore novel ways to use these features to more significantly contribute to the prediction of depression risk. In addition, given our imbalanced dataset, it would be beneficial to explore methods of handling the imbalance and investigating the impact to the prediction results.

Our results also indicate the possibility of using the relevant information such as personality assessments and status updates to facilitate a system to provide early warning signs and referrals to resources to individuals who may not be aware of depression symptoms or those who may hesitate to seek medical attention. However, the consent, privacy, and confidentiality of this information and assessment must be ensured due to the sensitivity of individual's health information.

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