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Exploring the dominant features of social media for depression detection

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Abstract
Recently, social media have been used by researchers to detect depressive symptoms in individuals using linguistic data from users' posts. In this study, we propose a framework to identify social information as a significant predictor of depression. Using the proposed framework, we develop an application called the Socially Mediated Patient Portal (SMPP), which detects depression-related markers in Facebook users by applying a data-driven approach with machine learning classification techniques. We examined a data set of 4350 users who were evaluated for depression using the Center for Epidemiological Studies Depression (CES-D) scale. From this analysis, we identified a set of features that can distinguish between individuals with and without depression. Finally, we identified the dominant features that adequately assess individuals with and without depression on social media. The model trained on these features will be helpful to physicians in diagnosing mental diseases and psychiatrists in analysing patient behaviour.

Keywords
Depression; Facebook; mental illness; value-added information

1. Introduction

Mental illness is a significant contributor to worldwide disability [1]. It specifically affects an individual's cognitive and language styles, mood, routine activities and ability to work. Universally, medical resources are consumed in high amounts to cope with mental illness. Mental illnesses are categorised as anxiety, bipolar disorder, depression, borderline personality disorder, obsessive-compulsive disorder (OCD), post-traumatic stress disorder (PTSD), schizophrenia and many more. Today, major depressive disorder (MDD) is among the most common mental illnesses, having symptoms including depressed mood, tiredness, sadness, sleep problems, poor concentration, lost interest in activities, feelings of guilt, reduced energy, reduced motivation to work and suicidal ideation [2].

Ingeneral, symptom diagnosis is a fundamental step towards the treatment process of mental illness. Particularly for MDD, timely identification and prevention could be the best strategy because the depression recovery rate has a direct relation with the depressive episode period. Depression is a multifaceted phenomenon that depends on diverse types of information, which are not always directly available. Such information is hard to directly acquire from the subject in an explicit manner. Hence, substantial work has been done to identify and diagnose depression in the general population using different questionnaire-based assessment tools by asking patients to complete depression questionnaires during a routine appointment. Based on the specified threshold score, the patients are evaluated for depression [3]. These questionnaire tools are used for depression assessments and include the Beck Depression Inventory (BDI) [4], the Center for Epidemiological Studies Depression (CES-D) scale [5], the Patient Health Questionnaire 9-item depression module (PHQ-9) [6], the Hamilton Rating Scale for Depression (HRSD) [7] and the Zung Self-Rating Depression Scale (SDS) [8].

Although these questionnaire-based assessment tools are a good step to identify and diagnose depression at early stages, their main drawback is bias and the low interest in completing them among people with depression. In addition, care providers cannot obtain a complete understanding of a person with depression using questionnaire-based self-reported data in a single appointment. For example, explicit interviewing depends on a person's memory, which is subject to bias and inaccuracy [9]. However, medical science lacks reliable techniques for the assessment of MDD. Comprehensive research has been conducted to delineate how people with depression manage their social relationships, as well as to understand how to detect depressive symptoms at an early stage [10,11].

Recently, social networking sites (SNSs) have been used as a social sensor to detect MDD. SNSs provide a platform to share information in a very cost-effective way. People easily express their opinions and share their thinking via social media platforms, which enables researchers to investigate multiple aspects of psychological concerns and human behaviours; Twitter and Facebook are among these platforms. Using these platforms, it is possible to detect an individual's daily life activities, user behaviour, emotions and feelings, and users do not pay for these services. Behavioural data from

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several years now exist through these platforms and can be leveraged to identify changes in an individual's life. These data also have the potential to be harnessed to reveal mental illness [9].

Specifically, recent studies have used SNSs to detect individuals with depression by inspecting textual posts [9,10,12,13], SNS usage [14] and interaction [15]. SNSs are used as a social sensor [9,16,17] to deduce behaviours and ailments in individuals via behavioural markers, which are implicitly biased from an individual's decisions on what to report. SNSs register daily activities and events in a realistic way, which makes them less vulnerable to memory bias or experimenter demand effects [18]. SNSs provide a way of capturing behavioural attributes relevant to an individual's thinking, activities, communication, socialisation and mood. For example, user profiles and postings may indicate feelings of self-hatred, worthlessness, guilt and helplessness, which are symptoms of major depression [9]. The language used in postings predicts depressive markers; for example, depressed persons use more negative words/terms and first-person pronouns compared with people without depression. However, the relationship between SNSs and depression is complicated. It is challenging to predict depression markers based just on the linguistic aspects of posts. However, other attributes such as frequency, inbound and outbound communication and the textual posting on SNSs can efficiently predict mental illness [15,19,20].

Hence, to understand the influence of SNSs as a resource for preventing and intervening with depression, it is important to recognise the meaning of interactions on SNSs and understand how to interpret value-added information or features of SNSs, particularly Facebook. Indeed, more research is required to describe the effects of depression on an individual's behaviour on Facebook. The analysis of SNS users' activities provides a closer look at users' natural behaviour, way of thinking and mental health state. Facebook, for instance, has a comprehensive set of features including demographics, user profiles, status updates, comments, likes, groups, activities and friend networks. These features are used to extract meaningful information such as user personality, depression references, drug usage references, help-seeking references, self-discourse, race/ethnicity and radicalisation for detecting individuals having depression.

SNSs have a potential impact on well-being, so that SNS factors have both positive and negative association with mental health states such as depression. Most studies have identified a relationship between SNS features and depression-related factors that may mediate or moderate this association [21–28]. These factors can be characterised as SNS usage behaviour, individual differences and social interaction.

Regarding SNS usage behaviour, a positive correlation was found with depression [19,29–32]. For example, status update frequency, either positive or negative, has been associated with depression. Frequent negative status updates or negative comparisons with other individuals lead to increased rumination [33,34]. Meanwhile, frequent posting of positive status updates was found for less depressed [35] individuals. Studies show that people with depression share more negative and less positive postings [19,36], and they are less active in posting than those who are not depressed [13]. Previous studies also found that some SNS features have a negative correlation with depression, for example, friend network size [14], location tagging [14] and social support [33]. This is due to social support for individuals accepting friend requests to increase their social circles, sharing more content with friends or engaging in greater interactive communication on SNSs.

In addition, other studies [15,37] show that Facebook activities become more predominant for more depressed individuals. Their findings show that the behaviour might be due to loneliness in online activities [15]. Furthermore, De Choudhury et al. [12] showed that depressed people prefer to use SNSs to express their feelings, get social support and mitigate uncertainty. Therefore, there is a need to further study SNSs to resolve these discrepancies: why are depressed individuals involved in such activities?

The primary goal of this research was to discover dominant Facebook features to help identify users with depression. It was hypothesised that people with depression show more markers related to depression, have a smaller friends network and are less interested in social activities on SNSs compared with people who are not depressed. To test this hypothesis, we created and evaluated a novel framework to identify depressive activities for active social media users, by analysing observable and non-observable variables, including their posts, friend network size and others. This identification process utilises an underlying feature generation engine, the Socially Mediated Patient Portal (SMPP), which identifies the relevant depression markers using state-of-the-art machine learning techniques.

Through our experiments, we were able to identify a predictive set of features in Facebook, which can categorise users based on their mental depressive state. We further explored attributes of depressed individuals regarding data generated by SMPP, including depression markers, help-seeking markers, substance use disorder (SUD) markers and self-disclosure. Towards this end, we analysed 4350 Facebook users for correlation analysis between the Facebook features and CES-D scale [5]. We predicted that depressed individuals were looking for more information on the SNS to cope with depression. However, no previous prediction had been made on this association with SNS in previous studies. We further predicted a positive relation between Facebook activities and depression.

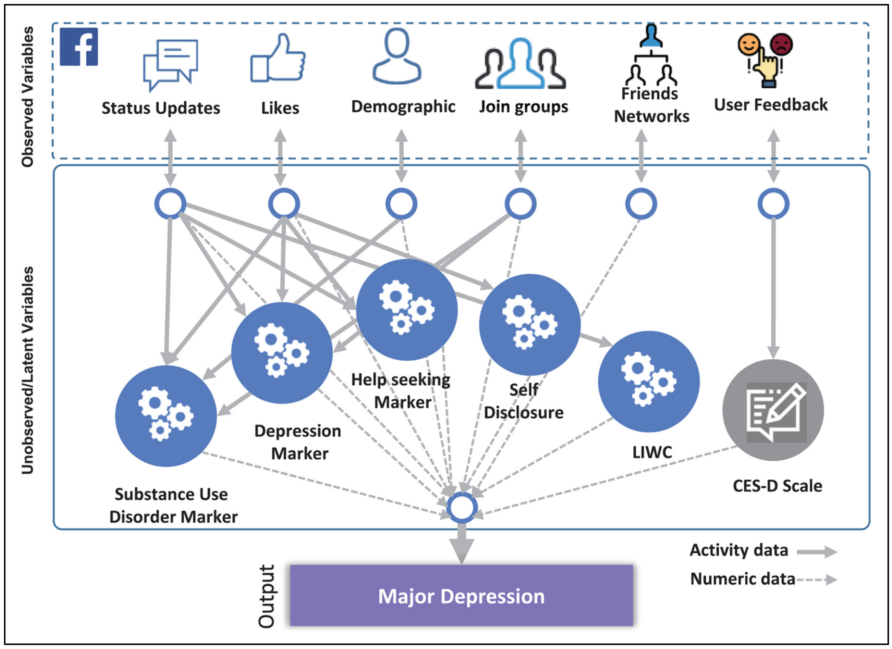

Figure 1. The proposed conceptual framework for depression detection on Facebook.

The rest of the article is structured as follows. In the 'Materials and methods' section, we discuss the materials and methods for analysis. In the 'Results and discussion' section, we describe the results, followed by a discussion of correlation analysis of Facebook predicative features concerning depression assessment, and the 'Conclusion' section concludes the work.

2. Materials and methods

We proposed a conceptual framework that utilises Facebook users' data for the assessment of MDD, shown in Figure 1. We utilised user demographics, activities and information generated by our SMPP application for the improvement of depression assessment methodology. The framework uses both observed and unobserved variables for major depression detection analysis. Observed variables are Facebook features, while unobserved variables are those features produced by the SMPP, Linguistic Inquiry and Word Count (LIWC) and CES-D scale. The dotted lines represent the counts of the observed variable, such as the number of status updates, likes, friend network size and others. Meanwhile, the solid lines represent the latent variables, which are obtained by the classifiers using observed variables. These include depression markers, SUD, help-seeking and self-disclosure. We hypothesised that this information would improve depression prediction because several user characteristics can influence expressed depressive symptoms.

2.1. Data set

The data used in this study were downloaded from the mypersonality project after obtaining access by registering as a collaborator. The mypersonality project was created by David Stillwel and Michal Kosinski and is a Facebook application that collected a vast anonymised data set of more than 6 million Facebook users along with psychological tests [38]. Access was granted from its users to record their activities for research purposes. We analysed a sample set of 6562 users who were evaluated using the CES-D scale for depression, because our intention was to analyse the SNS features related to depression. We selected the CES-D score as a dependent variable for correlation analysis. The CES-D scale is used to quantify depressive disorders using a 5-point Likert-type scale questionnaire. It consists of 20 items related to depressive symptoms that may have been experienced by the participant during the past week. The symptom occurrence is evaluated via user response values for each question on a scale from 0 (rarely or none of the time) to 4 (most or almost all the time). The CES-D total score is between 0 and 60 (non-depressed < 20; depressed > 21), in which a higher score

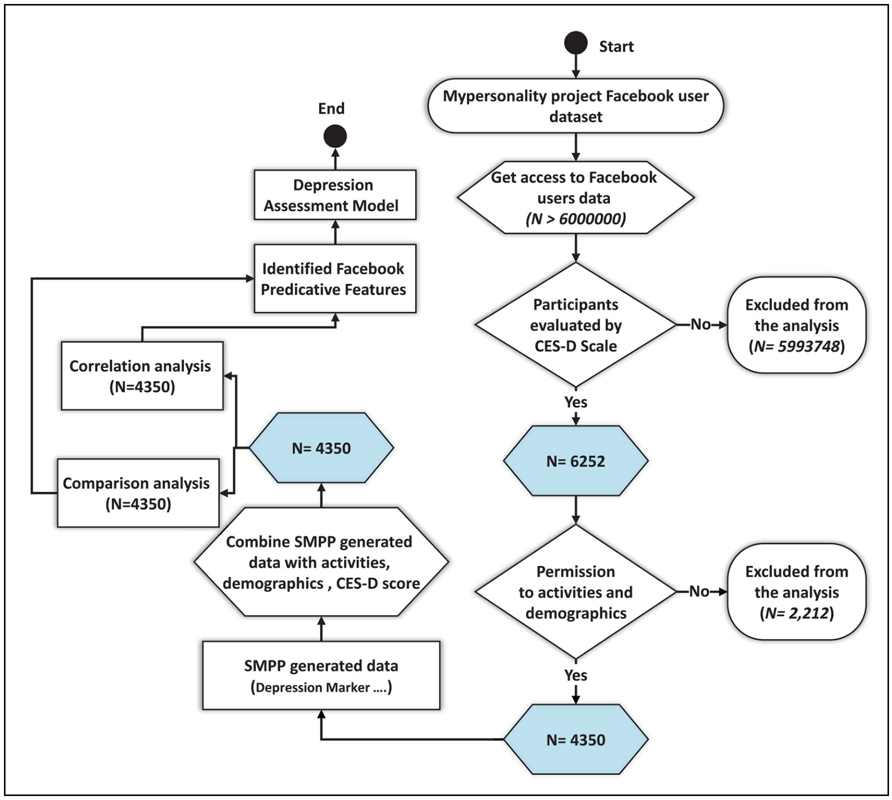

Figure 2. The overall process flow used for the proposed study.

indicates that the person meets the criteria for a major depressive episode. The overall process of inclusion of participants was based on the selected criteria, which is depicted in Figure 2.

2.2. Participants

Out of more than 6,000,000 participants, we examined data from 6252 Facebook users (male = 3445, female = 2807, mean age = 25.36, standard deviation (SD) = 10.378) using the mypersonality data set. Among the 6252 users, 4350 users gave permission to access their activity and demographic information, so 2212 users were excluded from the analysis. Their activity data were gathered in the years before they completed the CES-D depression evaluation. In this sample, the CES-D scale average score was 26.47 (SD = 9.03), having a high Cronbachs alpha value (0.72). The distribution of users over the CES-D scale scores is shown in Figure 3.

2.3. Feature generation via SMPP application

In this study, we utilised the SMPP as a feature generation engine, shown in Figure 4, in order to produce features and data to enable depression identification. SMPP consists of the following seven modules:

1. The *preprocessing* module is used to preprocess raw textual data using natural language processing (NLP) techniques, eventually producing a word vector.
2. The *depression marker tagger* module identifies depression-related symptoms in the word vector.
3. The *help-seeking marker tagger* module is used to identify the individuals who are seeking help to cope with depression.
4. The *SUD* module identifies the individuals mentioning drug experiences.
5. The *self-disclosure* module is used to determine the amount of personal information disclosed by the target user.
6. The *aggregate markers* module is used to aggregate the total number of markers for each user.

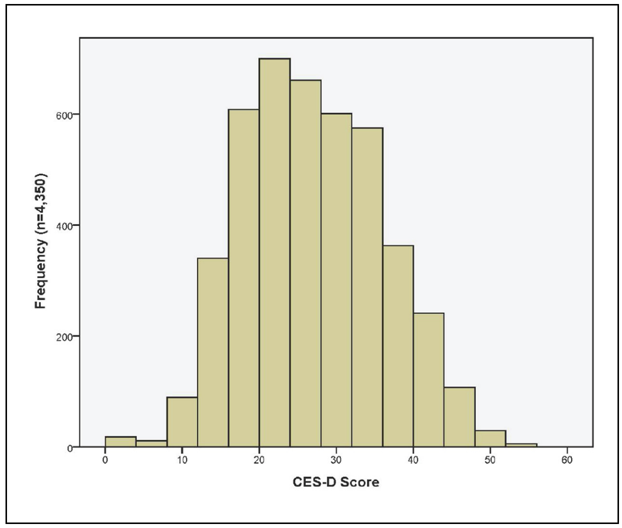

Figure 3. Distribution of CES-D scores for 4350 Facebook users.

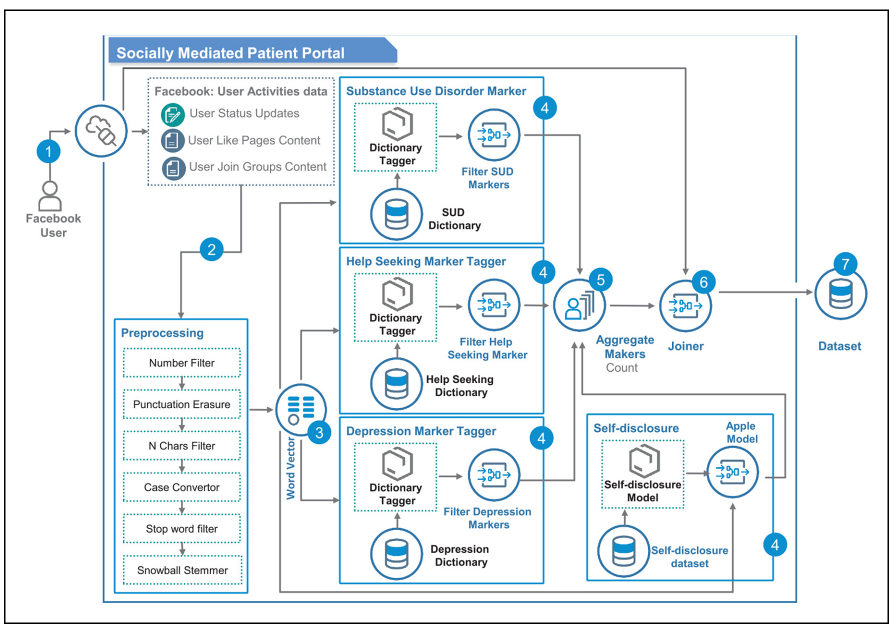

Figure 4. The Socially Mediated Patient Portal (SMPP) application for the detection of depression markers on Facebook.

7. Finally, the *joiner* module is used to combine the SMPP-generated data for each individual for depression analysis.

The detailed algorithm of SMPP is shown in Algorithm 1. SMPP uses classifiers to detect the markers related to depression, help-seeking, SUD and self-disclosure. The machine learning classifiers used by SMPP are given in Table 1. The details of these modules are discussed further in the subsequent section.

2.3.1. Word vector creation process. SMPP considers textual content, which may contain unwanted features. We applied text preprocessing steps before inputting them into the classifier model. We applied the term frequency–inverse document frequency (TF-IDF) vector creation scheme, setting a prune method to an absolute value (below = 2 and above = 100) to remove the least and most frequent words from the input text. The text preprocessing steps consist of

Algorithm 1: Socially Mediated Patient Portal Algorithm

Input: $U_D \rightarrow$ Users Activity Data $\{UD_1, UD_2, UD_3, \ldots, UD_n\}$
Output: $D_T \rightarrow$ Tagged Dataset
Initialization;
for each *User Activity Data* U_Di **do**
  $D_P \rightarrow$ preprocessing(U_Di); //Prepocessing of activity data
  IntermediateResults I_R
  for each *Line* DP_L *of* D_P **do**
    $T_{DM} \leftarrow Depression_{Tagger}(DP_L)$;
    $T_{SUDM} \leftarrow SUD_{Tagger}(DP_L)$;
    $T_{HSM} \leftarrow HelpSeeking_{Tagger}(DP_L)$;
    $T_{SD} \leftarrow SelfDisclosure_{Tagger}(DP_L)$;
    $I_R \leftarrow$ appendToFile(T_{DM}, T_{SUDM}, T_{HSM}, T_{SD}) //append
    Intermediate results
  end
  TaggedRow $\leftarrow$ sumByColumn(I_R); //Aggregate Markers
  $D_T \leftarrow$ Append(TaggedRow) //Join final results against each user
end

Table 1. The machine learning classifiers used by SMPP.

Component	Classification technique	Algorithms
Depression marker tagger	Lexicon-based approach	Lexicon-based classifier
Help-seeking marker tagger	Classification	Support Vector Machine (SVM)
Substance use disorder	Multi-View User Embedding (MUE)	Deep Canonical Correlation Analysis (DCCA)
Self-disclosure	Ensemble learning (voting)	SVM, Naive Bayes (NB) and Decision Tree

SMPP: Socially Mediated Patient Portal.

tokenisation to split the text into a sequence of tokens; a number filter to remove numeric data such as decimal separators, commas, periods and possible leading mathematical symbols (i.e. ' + ' or '–'); punctuation erasure to remove all punctuation characters of terms contained in the input text; an N chars filter to filter all words contained in the input text with less than the specified number N (n = 3) of characters; a stop-word filter to remove the English stop words (e.g. a, the, there, etc.); a case convertor to transform all words contained in the input text to lower case; and a stemmer to apply the snowball stemmer algorithm and reduce each word to its root word.

2.3.2. Depression marker tagger. For the depression marker classifier, a lexicon-based approach was used for the evaluation of depression-related markers against each user's demographics, posts, likes and group membership. The training data set was created using user posts and mood theme tags, collected from depression-related communities and classified using our previous work [39] on LiveJournal (http://www.livejournal.com/).

LiveJournal is a social networking platform that allows its users to identify their moods before sharing their opinions and medical conditions. This also enables identification of the various aspects of user depression and sentiments. In particular, we selected the depressive communities using the 'search communities by interest' option in LiveJournal. The results were then filtered based on the community title and description. Words such as depression, suicide, loneliness, sadness, loss of interest and self-harm were used to select the target communities, which are summarised in Table 2. Using a custom crawling programme, we collected and archived all posts in these communities, which are then used for feature extraction and dictionary creation. Next, we applied the depression degree analysis technique, from our prior work [10], to further filter out non-relevant communities. Furthermore, we classified individual posts, in the remaining subset of communities, as being depressive or non-depressive, using the technique presented in Aldarwish and Ahmad [39]. Finally, for effective detection of depressive markers, we used the proposed depression dictionary creation process on the posts classified as depressive in the previous step. This process is shown in Figure 5 and is described in detail as follows:

Table 2. LiveJournal depression-related categories.

Category	Community name	No. of posts	Description
Depressive	Fight-depression	500	This community is to help people who have any kind of depression
	Depression	605	This community is for those people who are depressed, need support, have depression or are suicidal
	Manic-depression	351	This community is for manic depressive people of all ages, sexes and colours, who are looking to find people just like them to help cope
	Self-injury	365	This community is for people who think of suicide and injuring themselves to discuss problems
	Pain	500	This community is for people who are depressed, are suicidal, are self-injured and feel as if they are alone in the world
	Survivors of suicide	408	This community is used by those people who have lost someone due to suicide
	Everyone needs a friend	356	This community is for anyone who needs a friend to talk to or is just really stressed
	A life interrupted	241	This is a community for teens or any age group who feel as though their life has been interrupted by something. It could be suicide, abuse, drug use or a trauma of some sort
	A refuge for the mentally ill	586	This community was created for people to express their problems (i.e. depression, bipolar disorder, anger and anxiety) and to receive support

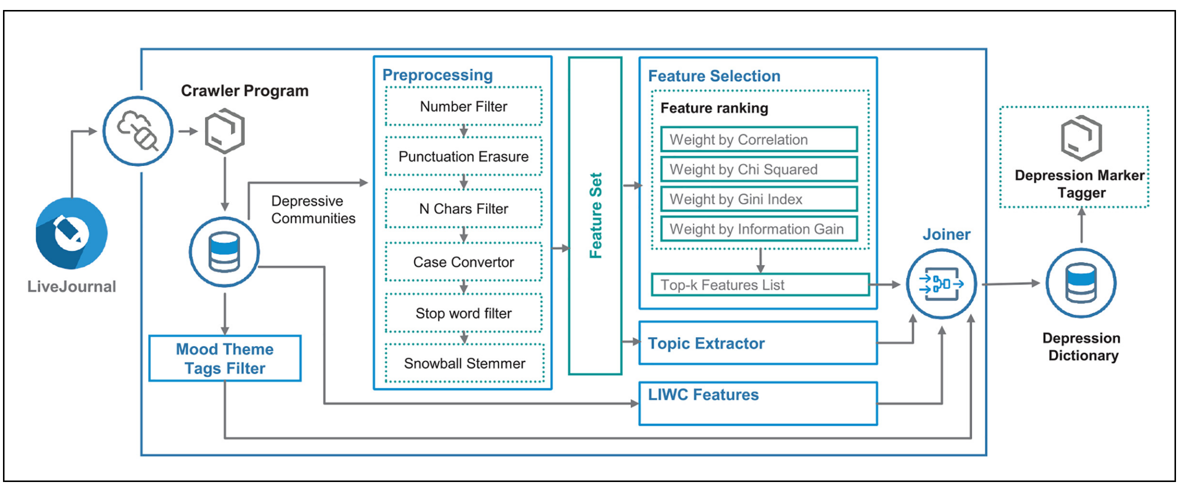

Figure 5. The method and process creating the depression marker dictionary.

Theme moods tag filter: LiveJournal has 132 pre-defined theme moods (https://www.livejournal.com/moodlist.bml?-moodtheme=1) that reveal the post category based on user sentiment in addition to the post text. We filtered out all user moods from the collected posts for both depressive and non-depressive communities. We collected all the theme moods by checking the value of the current mood in each post. We selected those theme moods that appear more than five times in posts from depression communities as a word cloud (see Figure 6).

LIWC features: People discuss different topics in LiveJournal communities related to either positive or negative aspects of life. Mainly, in depression-related communities, people discuss issues related to health, sadness, anger, negative emotions and others. We classified the LiveJournal posts into depressive and non-depressive categories using the LIWC (http://liwc.wpengine.com/) tool, which reveals common thoughts, emotions, feelings, moods, personal and social concerns and motivation. LIWC was used to analyse the given text based on the dictionary. The percentage was calculated based on how well the words of the given text matched the dictionary categories. The selected categories from LIWC were as follows: negate, affect, negemo, anx, anger, sad, social, friend, female, cause, health, sexual, achieve, reward, risk, focus present, work, death, religion and the pronoun ‘I’. We used all the words under the aforementioned categories as the feature set for the depression dictionary.

Figure 6. Word cloud of post theme moods.

Topic extractor: Topics were extracted using the latent Dirichlet allocation (LDA) [40], which is an unsupervised generative statistical model. LDA assumes that each document consists of different topics and word distributions covering each topic. We implemented the mallet topic modelling module for the extraction of topics from the collected posts. All the collected posts were processed by the preprocessor module to remove numerical data, erase punctuation, remove stop words, convert text to lower case and accomplish stemming. We set the number of topics to 30, the number of words per topic to 50 and the number of iterations to 1000 to interpret the results.
Feature selection: We employed the same filter-based approach for feature ranking methods as mentioned in our prior work [41]. The word vector was input into the feature-selection module, and the individual filters assigned weights to each feature using internal logic and selected the initial subset features. We applied the majority voting method for the final feature selection. We set the threshold value to three to check for common features selected by at least three filters. Finally, we obtained a total of 9850 features from LiveJournal communities posting data for our depression dictionary.

As previously mentioned, each module gives depression lexicons. We combined all the depression lexicons extracted from the theme moods, topic words list by LDA and LIWC categories words list (such as affect, risk and personal concerns) to build the final depression dictionary. We removed duplicated words from the final depression dictionary. The final depression dictionary is used by the lexicon base classifier to check Facebook user activity for depression markers as shown in Algorithm 2. The depression marker model is created from an annotated depression dictionary list of words. It expects a list of words with a weight (value) attribute describing how depressive or non-depressive a word is. The depression marker score is calculated based on the polarity value of a user activity textual data modified by the contextual valence. To handle contextual shifting, a negation word seed is used. If the total score is positive, then the posting is classified as depressive; otherwise, it is classified as non-depressive. We then checked for depression-related markers against the target users' Facebook activity (e.g. status updates, likes and joined groups) to further analyse the correlation between depression display markers and scores on the CES-D depression scale.

2.3.3. Help-seeking marker tagger. We measured the help-seeking intention of a user using the help-seeking marker classifier. The classifier evaluated the individual's attitude towards help-seeking behaviour to cope with major depression. This classifier was based on help-seeking measures, which were collected through a systematic review process, shown briefly in Figure 7.

In particular, help-seeking constructs relating to mental health issues were chosen. Starting with a manual search operation, we collected articles relating mental health issues from PubMed, Google Scholar, PsycINFO and EMBASE between 2000 and 2018. To identify the relevant studies, we applied inclusion criteria of the studies published in English and containing quantitative measures. A total of 12,250 studies satisfied the first criteria, which contained 7623 duplications. The remaining 4627 studies were then evaluated for their evaluation measures. In this step, we removed 2589 studies that contained qualitative evaluation measures in their title. We then evaluated the contents of the remaining 2038 studies and found 1947 of these to be outside the scope of the project (containing qualitative evaluations in the body of the studies). The remaining 91 studies were then evaluated for help-seeking measures. From the screening results, we found 35 questionnaires that correspond to help-seeking quantitative measures. These are widely used to

Algorithm 2: Depression Marker Tagger Algorithm

Input: $U_A \rightarrow$ Users Activity Textual Data {*T1*, *T2*, *T3*,…, *Tn*}
Output: Depressive marker score $\rightarrow SCORE_{DEP}$
initialization;
$SCORE_{DEP} \leftarrow 0$;
foreach *activitytext T* **do**
  tokens $\leftarrow$ tokenization(T);
  foreach *tokens* W_i **do**
    score $\leftarrow$ 0;
    if *depressive*(W_i) **then**
      score $\leftarrow$ 1
    end
    if *non-depressive*(W_i) **then**
      score $\leftarrow$ -1
    end
    if *negation*(W_i-1) **then**
      score $\leftarrow$ -1 * score
    end
    $SCORE_{DEP}$ += score
  end
end

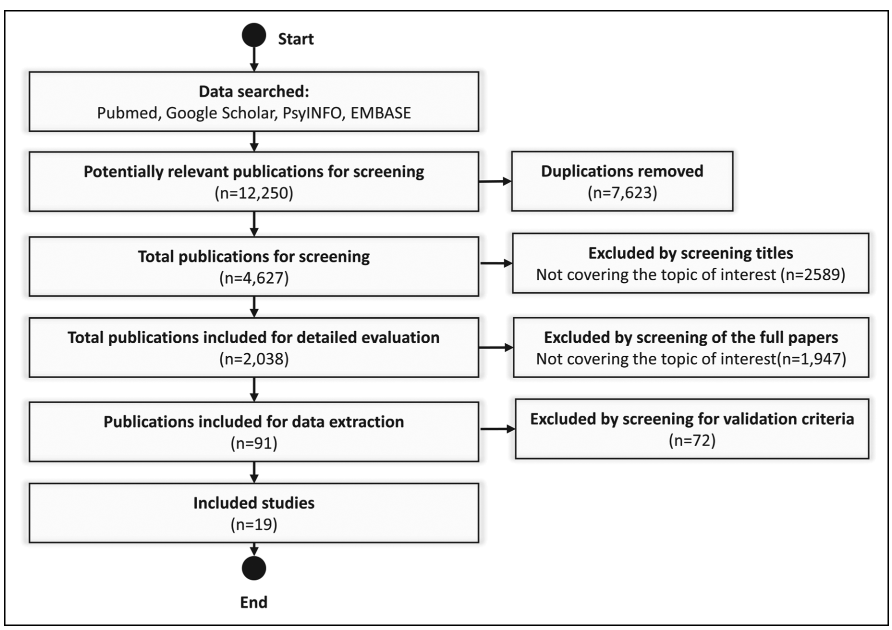

Figure 7. Help-seeking measures selection criteria process flow chart.

quantify help-seeking behaviour for coping with mental health problems. However,among these, only 19 studies contained at least one validation criterion, which is very important for comparing the results of the proposed and existing approaches. Consequently, we selected 19 studies, which provided us with 10 questionnaires, along with some validation criteria, as shown by Table 3.

Finally, we identified and consolidated the help-seeking aspects from these questionnaires and selected four help-seeking features, as shown in the Figure 8. These features include Direct Questions (DQ), Implied Help-Seeking (IHS), Help-Seeking Source (HSS) and Help-Seeking Concern (HSC). These features cover a wide range of help-seeking behaviour employed by users suffering from depression (Table 4). These features are also able to detect help-seeking behaviours of the individual by analysing the various sentiments that may have been expressed in a single post.

Table 3. Help-seeking measures.

Measures	Validity	
1	ATSPPH-SF [42]	FA; CS
2	Intention of Seeking Counselling Inventory (ISCI) [43]	FA; CS
3	General Help-Seeking Questionnaire (GHSQ) [44]	FA
4	Jorm Mental Health Literacy Survey (items on attitudes/beliefs towards treatment) [45]	P; CV; DV
5	Help-Seeking Intentions [46]	FA
6	The New Inventory of Attitudes towards Seeking Mental Health Services (IASMHS) [47]	FA; CS
7	Help-Seeking Attitude Scale (HSAS) [48]	CC
8	Scale of Attitudes towards Seeking Psychological Help for Secondary Students (ASPH-S) [49]	FA
9	Help-Seeking Acceptability (HSA) [50]	FA; CS
10	Parental Attitudes towards Psychological Services Inventory (PATPSI) [51]	FA; CS

FA: factor analysis; CS: construct validity; P: predictive validity; CV: convergent validity; CC: concurrent validity; DV: divergent validity; ATSPPH-SF: Attitudes towards Seeking Professional Psychological Help Scale Short Form.

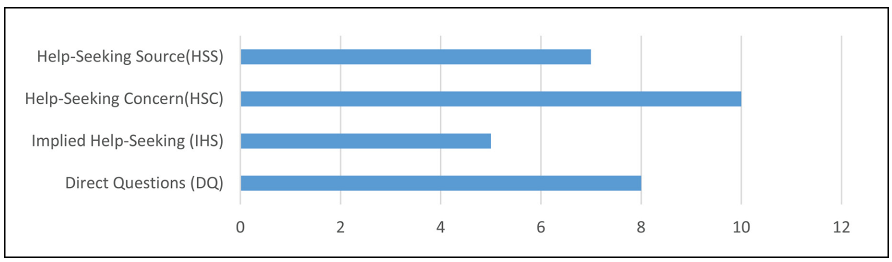

Figure 8. Help-seeking aspects.

The DQ and IHS features were used to identify if an individual was seeking help by asking direct questions or indirect questions, respectively. The HSS feature has been established in the literature as a useful indicator for detecting help-seeking behaviour [52]. HSS refers to the resource from which an individual gets assistance to cope with depression. Resources for help-seeking can be formal, semiformal and via self-help, depending on an individual's expertise and their social circle. The HSC feature represents a type of mental health problem for which help is required, such as an emotional problem, mental health problem or distress. We used three models for detecting the presence of the aforementioned features by consolidating the DQ and IHS detection processes into one model and using an independent model for HSS and HSC. The model for the DQ and IHS features was trained on a publicly available data set [53] to detect the direct and implied questions asked by a user in their status updates. In the given data set, we used the sentences along with their labels as training data for both DQ and IHS features detection. In addition, we also included the LIWC2015 dictionary 'Interrog' category into the DQ feature to detect the five 'W's' to their original data set to enhance the training data set. We tested the performance of different classifiers (Decision Tree, *k*-Nearest Neighbour, Naive Bayes (NB) and Support Vector Machine (SVM)) for classifying the status updates into DQ, IHS or other. We found that a classifier based on the SVM model gives a best average accuracy of 91.4% for detecting the DQ and IHS features. For the HSS feature, we used the LIWC categories, namely, family, friends and health, from LIWC2015 dictionary to identify the resource from which an individual gets assistance to cope with depression. The HSC feature is related to mental health problems, which are detected by the depression marker classifier already discussed in the depression detection marker section. We fed the features presence identifier module with preprocessed user status updates to check for the presence of the four relevant features (DQ, IHS, HSS and HSC). In the case of positive results, the feature presence identifier returns 1, indicating the presence of at least one of these features. This overall process is shown in Figure 9.

Based on this result, an identifier vector is formed, which is used by our model to classify the status update, after aggregating all its individual parts. If the result is greater than or equal to 1, then the status updates are enriched with help-seeking references.

Finally, we summed the total number of help-seeking references of each user to further analyse and assess a correlation with the depression CES-D scale score.

Table 4. Selected features for coding.

Code	Feature name	Feature description
DQ	Direct Questions	This feature is related to a direct question, for example, question marks, does, how, the five W's (who, what, where, when and why); how do I get rid of emotional problems?
IHS	Implied Help-Seeking	This feature is related to confirmation help-seeking and indirect questions, for example, 'I was curious'; 'I might want to have psychological therapy in the future'
HSS	Help-Seeking Source	This feature is related to help-seeking sources like a formal source (psychiatrist, practitioner, etc.) or informal sources such as friends, parents or a partner. For example, 'I am planning to see a psychiatrist to overcome my sleeping problem'
HSC	Help-Seeking Concern	This feature is related to mental health problems such as sleeping problems, sadness, loss of interest, helplessness and self-hatred. For example, 'I dont understand why its so easy to nap during the day but so hard to fall asleep at night'

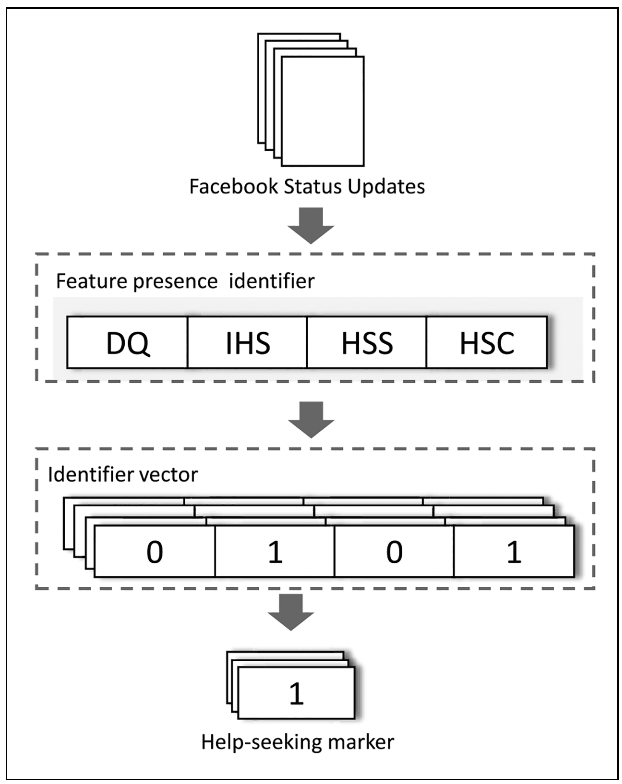

Figure 9. Help-seeking marker overall detection process.

2.3.4. SUD marker tagger. SUD is a recurrent habit of substance (tobacco, alcohol and drugs) use, which can cause physical or psychological impairment in the affectee's life. To train the model for the SUD predictor, we used the SUD status data set from the 'mypersonality' project, which has collected data from 13,557 participants related to smoking, drinking and drugs behaviour using three different types of questionnaires. The Cigarette Dependence Scale (CDS-5) [54], Alcohol Use Questionnaire (AUQ) [55] and Assessment of Substance Misuse Questionnaire (ASMA) [56] were used by the project team to collect information from users relating to their smoking, drinking and drug behaviours during a week. The results for each of these questionnaires are consolidated by the mypersonality project, producing a matrix of abuse type and its numeric intensity (1 being never, 2 being less than daily and 3 being daily or more).

For each user, we further consolidated the results by adding together the scores for each abuse type and producing one number. This output is then classified in a binary format, with values under 4 being labelled as '0', while others are labelled as '1' (indicating that the participant experiences the SUD). We then augmented this relatively small amount of labelled data with status updates and likes data against each user by employing the Multi-View User Embedding (MUE) technique [57]. MUE uses Deep Canonical Correlation Analysis (DCCA) [58] to combine both status updates and likes data, which are, in turn, produced by two unsupervised feature learning processes, Single-View Post Embedding (SPE) and Single-View Like Embedding (SLE).

Internally, SPE is calculated for all posts by each user, by employing the Document Embedding with Distributed Bag of Words (D-DBOW) method [57]. In contrast, SLE creates an adjacency matrix between users and their likes, by setting the corresponding cell to 1, if there is an association between the two, and 0 otherwise. We then applied the singular value decomposition for dimensionality reduction. The average accuracy of the SUD marker tagger was 85.02%.

From the set of 13,557 users suffering from SUD and 4350 users identified by CES-D, a total of 1230 users were found in the intersection of these two sets (SUD CES-D). For the remaining 3120 users, we applied the SUD marker prediction model to identify the SUD markers from their status updates and likes.

Finally, we classified the target user's posts and likes for SUD markers. We counted the SUD markers and noted if any marker was found in user posts or 'likes'. We added that data to each target user to test whether there was a relationship between SUD and depression.

2.3.5. Self-disclosure. Self-disclosure is related to how much personal information each individual is comfortable with publicly reporting. Self-disclosure is an important method to learn about users, especially when building relationships [59]. Using correlation analysis, similar to other studies [59,60], we identified the relationship between self-disclosure and depression. The features required for this analysis were produced using annotated data, originally produced by Wang et al. [61] for self-disclosure. These features were then applied on non-annotated test data through the application of a machine learning model to predict self-disclosure from user status updates. In its original form, Wang et al. created and applied their model on the annotated data, using four linguistic features as independent variables. These features include post length, positive and negative emotions, social distance and topics features. The results produced by their models are also included in the mypesonality data set, whereby 341 users were matched with those users who were evaluated by the CES-D scale.

Our model extends their data set while using the same features to determine self-disclosure for the rest of the users from their status updates for correlation with depression. Our novelty lies in conversion of the self-disclosure numerical values into labels (high, low or no self-disclosure) for model training and classification. We assigned 'no' to the values in the range of 0–2.5, 'low' to 2.5–4.5, and 'high' to 4.5–7. To validate our model, we used 10-fold cross-validation, through which, we were able to characterise test status updates to be of high, low or no self-disclosure. To improve the prediction performance, we used the ensemble learning technique, which combines the predictions of multiple base learners over a single learner. In this research work, we have employed a majority voting technique in conjunction with three base learners, namely, SVM, NB and Decision Tree. Based on the majority voting of the base learners, the user status updates are classified into either high, low or no self-disclosure. The performance of a self-disclosure marker ensemble learning classifier in terms of accuracy was 94%. To measure the self-discourse of the testing data set, corresponding to the remaining non-annotated users, from their status updates, we employed the same preprocessing and feature extraction process as the original study [61]. We applied the post filter criteria to include Facebook status updates, where the length of the content is greater than 10 words. Here, it is pertinent to mention that the relative size of the post length is directly proportional to the automated self-disclosure reveal (a longer post is more likely to produce an accurate result than a shorter post). For the emotion feature, we considered the count of positive and negative tokens in the status update. We employed the LIWC positive and negative categories along with Wikipedia emoticons. For the social distance feature, as performed in the original study, we measured the average distance between the poster and any mentioned user in their post using EntityRecognizer of SpaCy API (https://spacy.io/api/entityrecognizer), augmented by LIWC category. For our study, we identified the value of this feature between an integer range of 0–2, depending on the likelihood of a personal relationship ('0' if the status updates correspond to the 'LIWC I' category, '1' when the reference person is belonging to the 'LIWC family' or 'LIWC we' category and finally to cover the bigger social circle, we also considered the 'LIWC friend' category and assigned it the value '2').

We calculated the topic features based on word frequency in post-processed data and the original topic features dictionaries (created by Wang using LDA and annotated by an expert).

We then extracted these features from the remaining user status updates and combined them into the word vector, followed by its application on the trained model for prediction of self-disclosure. Finally, we added self-disclosure extracted data for further analysis to assess the correlation between self-disclosure and depression.

Table 5. Facebook participants information (n = 4350).

Feature	Mean (standard deviation)	Count
User demographic		
Gender		Male = 2532; female = 1818
Age	25.91 (10.059)	
Relationship status		Single = 1053; married = 756; in a relationship = 452; engaged = 221; it's complicated = 268; widowed = 346; divorced = 219
Network size	133.23 (135.461)	
Race		White = 1852; Black = 987; Asian = 685; Middle Eastern = 221
Facebook activity		
Likes	358.41 (511.953)	
Status updates	204.58 (238.727)	
Event	12.12 (23.591)	
Concentration	2.01 (1.417)	
Group	39.82 (48.445)	
Work	1.87 (1.551)	
Education	2.13 (1.152)	
Tags	116.93 (179.112)	
SMPP application data		
Depression marker	1.60 (3.361)	
Drugs marker	5.98 (6.424)	
Help-seeking marker	2.26 (4.321)	
Self-disclosure	2.195 (0.3880)	
Survey		
CES-D Label		Non-depressed = 1235; depressed = 3115

SMPP: Socially Mediated Patient Portal; CES-D: Center for Epidemiological Studies Depression.

2.4. Statistical analysis

To identify the correlation between the Facebook data set and the CES-D labels for the 4350 users, we utilised the factors indicated in Table 5. In particular, the selected factors were divided into three clusters pertaining to demographics, activities and SMPP application data. For each cluster, individual attributes have been abstracted by applying a count or mean (M)/SD function. This abstraction allows us to make general observations and map the impact of the feature on the CES-D-identified labels.

The demographic feature set of the selected participants shows a good mix in terms of their gender, age, relationship status, network size (friends) and race. Similarly, the activities performed by users on Facebook and in real life also compliment the fairness of our selection. This is also evident by the M and SD values calculated for the participants in terms of the pages liked by the participants, posted status updates, events attended, concentration, joined groups, disclosed workplaces (from a maximum of five allowed on Facebook), educational institutes (from a maximum of five allowed on Facebook) and tagged items (such as posts, images, videos and others).

We performed a correlation analysis between a Facebook feature set and the depression CES-D score. For Facebook activities, we used two types of data for variables (likes, status updates and groups), the textual content and their frequencies. This textual content was used by the SMPP to generate the SMPP variable data as discussed earlier. For the remaining Facebook activity variables, we counted the number of events, concentration, work, education and tags.

First, we evaluated the Spearman's correlation of the LIWC features, Facebook features and SMPP-generated data with the depression CES-D score. Second, we performed chi-square and Mann–Whitney tests to identify the difference between people with and without depression based on feature sets. The feature set used in the analysis is shown in Table 5. The Facebook features and SMPP-generated features were considered observed variables, and the CES-D depression scale scores were used as dependent variables in the analysis.

3. Results and discussion

Foremost, we considered users of the mypersonality project who had completed the CES-D scale survey. Furthermore, we set different screening filters for the users, such as friend network size (0–2000), group membership (0–100) and events that the user showed interest in (0–150). Finally, we considered 4350 users for further analysis. Information from

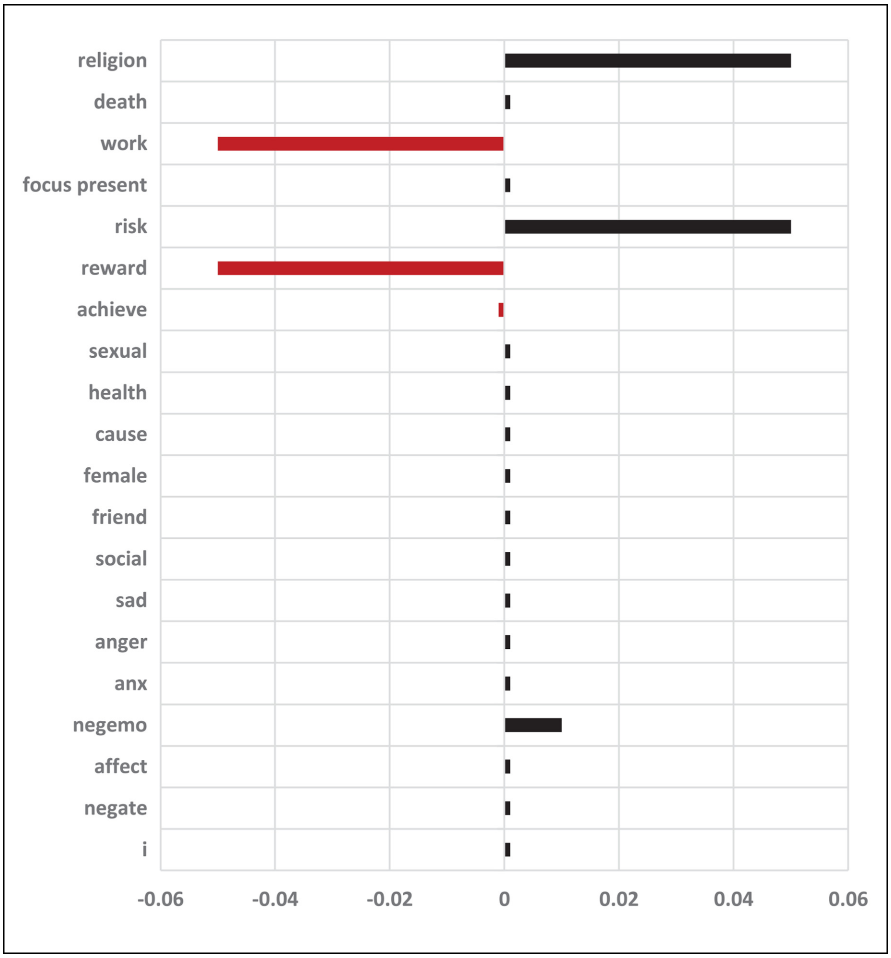

Figure 10. LIWC features that are most significantly correlated with depression.

the subset of participants is provided in Table 5 in three feature categories: user demographics, activity and SMPP-generated data.

3.1. Depression and SMPP-generated data

First, we tested the Spearman's correlation of the LIWC feature of the users' status updates with CES-D scores ($p < 0.05$), and the results are shown in Figure 10. There are some interesting results; for example, a focus on the present, death, health, sad and use of the pronoun 'I' were positively correlated with depression, while achievement and reward were negatively related to depression. Thus, our findings suggest that people with depression tend to think about the present and death and exhibit less motivation.

To identify the value of the added features of Facebook, such as a depression predictor marker, we computed a correlation between Facebook features and SMPP-generated data with the depression CES-D score using the Spearman's rank correlation. The results are shown in Table 6. Among the listed features, nine features revealed significant correlations with the CES-D score. Age, friend network size, events and work were negatively correlated with depression, whereas gender, likes, depression markers, help-seeking markers and SUD markers had positive correlations ($p = 0.004$, $p = 0.014$, $p = 0.005$, $p = 0.005$ and $p = 0.006$, respectively).

The Mann–Whitney test and chi-square test were performed to identify the difference between people with and without depression, and the results are shown in Tables 7 and 8, respectively. The chi-square test for categorical variables was utilised to test the correlation. It is used to find whether there is a significant correlation between the two variables. In our data set, few variables were categorical, so we tested the correlation between those categorical variables with depression using chi-square test, for example, to determine if either marital status or gender is related to depression.

Table 6. Spearman's correlation between Facebook features and the depression CES-D scale score.

Features	Spearman's rank correlation coefficients	Significance (two-tailed)
Gender	0.226**	0.004
Age	–0.123*	0.031
Relationship status	0.099	0.074
Interested in	–0.014	0.891
Race	–0.003	0.955
Friends	–0.126*	0.012
Likes	0.135*	0.014
Status	0.048	0.383
Events	–0.186**	0.001
Concentrations	–0.130	0.181
Groups	0.014	0.807
Work	–0.134*	0.016
Education	–0.045	0.433
Tags	0.042	0.482
Diads	–0.060	0.304
Self-disclosure score	0.027	0.624
Depressed marker	0.427**	0.005
Help-seeking marker	0.386**	0.005
SUD marker	0.522**	0.006

CES-D: Center for Epidemiological Studies Depression; SUD: substance use disorder.
* Correlation is significant at the 0.05 level (2-tailed).
**Correlation is significant at the 0.01 level (2-tailed).

Table 7. The Mann–Whitney test result between participants with and without depression (n = 3115).

Features	Non-depressed mean rank	Depressed mean rank	z-score (two-tailed)	p value
Depressed marker	161.48	173.89	−1.217467838	0.0050
Help-seeking marker	135.76	226.52	–8.67933121	0.0050
SUD marker	124.71	250.50	−11.30104572	0.0060
Friend network size	135.20	127.01	–0.818861499	0.4129
Likes	160.20	175.09	−1.326515516	0.1847
Status updates	164.16	166.75	–0.231994686	0.8165
Events	181.28	132.62	–0.574451164	0.5657
Concentrations	56.16	49.75	−1.000475855	0.3171
Groups	159.98	158.46	–0.13759294	0.8906
Works	76.82	74.19	–0.380302182	0.7037
Educations	152.87	145.62	–0.711660575	0.4767
Tags	139.65	145.73	–0.576604176	0.5642
Self-disclosure	163.06	170.59	–0.671166374	0.5021

SUD: substance use disorder.

From the results, we found that some features of Facebook uncovered ways to distinguish between individuals with and without depression.The individuals with depression reported more depression markers, more help-seeking markers, more SUD markers, a smaller network size and less interest in events compared with the controls.

The help-seeking marker showed a significant difference (p = 0.005) between the two groups, because the depressed groups were looking for information to cope with depression. Previous studies showed that people suffering from depression were more frequently looking for mental health–related information [62,63]. Seeking more information related to depression (liked pages and joined groups) to overcome their depression may be a useful marker for depression detection. In addition, the p value for the SUD marker was 0.006, which shows a statistical significance between the two groups. Thus, the group of users with depression might be more willing to use drugs in order to alleviate their depression.

We performed a chi-square test to determine whether there was a relationship between SUD and depression as shown in Table 8. The SUD category status varied with age in people with depression. The smoking status of participants with depression for age groups 1 (10–20 years), 2 (21–30 years) and 5 (51–60 years) exhibited significant p values of 0.013, 0.003 and 0.011, respectively. The age groups 3 (31–40 years), 4 (41–50 years) and 6 (above 60 years) had insignificant p values of 0.840, 0.143 and 0.338, respectively. However, no association was seen between smoking status and

Table 8. The chi-square test result of independence for categorical variables.

Variables	*N* (depressed)	*p* value (chi-square)
Gender		
Male	1973	0.001
Female	1142	
Marital status		
Single	985	0.032
Married	685	
Divorced	183	
Widowed	245	
Smoking status		
Age group 1 (10–20)	33	0.013
Age group 2 (21–30)	116	0.003
Age group 3 (31–40)	44	0.840
Age group 4 (41–50)	18	0.143
Age group 5 (51–60)	89	0.011
Age group 6 (above 60)	10	0.338
Alcoholic status		
Age group 1 (10–20)	97	0.533
Age group 2 (21–30)	274	0.206
Age group 3 (31–40)	69	0.298
Age group 4 (41–50)	30	0.032
Age group 5 (51–60)	45	0.018
Age group 6 (above 60)	20	0.338
Drug status		
Age group 1 (10–20)	42	0.004
Age group 2 (21–30)	85	0.001
Age group 3 (31–40)	140	0.144
Age group 4 (41–50)	54	0.461
Age group 5 (51–60)	85	0.001
Age group 6 (above 60)	20	0.582

depression for participants in these age groups. The participants with alcoholism in age groups 4 (41–50 years) and 5 (51–60 years) were more likely to be diagnosed with depression (*p* values of 0.032 and 0.018, respectively). For age groups 1 (10–20 years), 2 (21–30 years) and 5 (51–60 years), participants with drug usage behaviour were more likely to be diagnosed with depression (*p* values of 0.004, 0.001 and 0.001, respectively). The likelihood of depression increased for participants having drug usage behaviour, with a larger chi-square value and a very significant *p* value at less than 0.001.

3.2. Depression and demographics

We found that level of education, ethnicity/race, gender, relationship status and Facebook activities (likes, status updates, events and tags) were a more valuable marker for the detection of depression than other Facebook features. For analysis, we performed Spearman's tests to assess the correlation between the number of educational institutes/schools/universities a user has added into their profile and depression, as show in Table 9. We found that a smaller number of educational institutes/schools/universities mentioned in their Facebook profile exhibited a strong negative correlation with depression (*p* value of 0.001). In addition, our finding showed that the users who mentioned more education with depression had fewer thoughts of self-harm and were more occupied with anhedonia [64]. We believe that education level might have an effect on the public expression of depressive signs and symptoms. Further research is required to assess which aspects of education relate to depressive symptoms. We used a chi-square test for independence to determine whether age, marital status and gender are related to depression, as shown in Table 8. Regarding age and relationship status, the risk of depression increased with age for single people and those in a relationship compared with those who were married. Previous studies also have shown that married people have a lower prevalence of depression compared with other relationship statuses [65], and depression level increases with age in single people. Age may have an effect on depression in those who are separated, divorced or widowed. In terms of gender, our results show that depression ratios for males were smaller than females. Because the gender *p* value (0.001) was below the significance level, we conclude that there is a

Table 9. Spearman's correlation between education level and the depression CES-D scale score.

Number of educational institutes/schools/universities	*N* (depressed)	*p* value
< 2	1232	–0.001**
< 3	915	–0.076**
< 5	553	0.01*

CES-D: Center for Epidemiological Studies Depression.
*Correlation is significant at the 0.05 level (2-tailed).
**Correlation is significant at the 0.01 level (2-tailed).

relationship between gender and depression. Facebook demographics have gender information, so gender can be a good predictor for depression in a SNS model for depression identification.

3.3. Depression and activity

The results suggest that users who have smaller friends' networks and post more depression markers are more likely to have depression. People with depression usually do not increase the size of their friends' network and tend towards loneliness. Previous research shows that depressed people have a smaller friend network [66]. Having a larger friend network may allow users to get support from their friends and reduce their loneliness [14,67]. Our findings also show that friend network size is an important marker for depression predication. The number of attended events is negatively correlated with depression, having a *p* value of 0.001. Indeed, people without depression are more likely to attend social events. The event feature is a common function in Facebook and is used to invite people to attend upcoming events such as a party or social gathering. Showing interest in attending an event was revealed to be a key marker of mental health, because people with depression lose interest in life events. Loss of interest is an important symptom of depression [68], thus few or zero events might reveal anhedonia-related signs of depression. In addition, this measure indicates social withdrawal, loneliness and isolation from society. The number of Facebook activities, such as events, is related to Facebook usage; a longer Facebook usage duration might correlate with a greater number of invites. However, our findings suggest that the raw number of events is a good predictor of depression. Interestingly, the results reveal that a person with depression is less likely to use the like feature and not be interested in a friend's activities. Indeed, the like feature can reveal the engagement level of a person in their social circle.

4. Conclusion

Due to extensive use of SNSs for depression detection, this research proposed a framework to explore SNS as a screening tool for depression in individuals. To make an effective screening tool, our goal was to identify predictive correlative Facebook attributes of depression. We developed the SMPP application that utilises Facebook features to detect important markers (depression, help-seeking behaviour and SUD) related to depression. We performed a correlation analysis between the Facebook features and CES-D scale scores. From the analysis, we identified key Facebook features that have the power to distinguish individuals with and without depression in a cost-effective way. In addition, we found out that SNSs information and activities of the user are helpful to identify the tendency of a user towards depression.

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