Manifestation of Depression and Loneliness on Social Networks: A Case Study of Young Adults on Facebook

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ABSTRACT
As people around the world are spending increasing amounts of time online, the question of how online experiences are linked to health and well-being is essential. This paper presents how activities on Facebook are associated with the depressive states of users. Based on online logs of 212 young adults, we show not only the sheer size of the network but also the frequency and diversity of interactions on social networks have close associations with depression. Depressed individuals reported smaller involved networks regarding comments and likes, the two popular forms of interactions. In contrast to the decreased level of interactions, depressed individuals showed an increase in the wall post rates and were active online during midday, which can be interpreted as an endemic behavior linked to the perceived degree of loneliness among young adults who are avid users of social media. We discuss these findings from theoretical, empirical, and subjective perspectives.

Author Keywords
Social media; online activities; depression; mental health; Facebook; Web application

ACM Classification Keywords
H.3.4 Systems and Software: User profiles and alert services; J.3 Life and Medical Sciences: Health

INTRODUCTION
Online social networks have become a common part of everyday life. The frequent intermingling of online life and offline life means that social networks can be an appealing platform to study human behaviors and moods. In response, researchers have studied how online experiences affect the daily interactions and well-being of users. A number of studies found online social links help maintain one’s off-line relationships better [2] and increase social capital, for individuals with low self-esteem [47] or among those who live across far geographical distance [51]. However, some have found a detrimental impact: frequent accesses to online social networks was shown to incur addiction and decreased the subjective well-being for young adults [32].

Moving beyond the debate of whether constant use of social networks is a benefit or a harm, recent studies have utilized data from online social networks to predict individual’s well-being. For instance, population happiness [14], reactions to pandemics [17], unemployment or suicide rate [26, 54] can be predicted from sentiments in social media. These studies investigate whether online activities and sentiments indicate the presence of a particular social trend and collective mood of individuals. These efforts help attain a better understanding of individual’s and societal needs and a design of right policies to further promote health and well-being through online experiences.

Continuing on the efforts, this paper seeks to understand how depressive moods and loneliness of young people in their 20s are manifested as online activities on Facebook, one of the most popular Internet destinations. We chose depression because it is the most common mental disorder, affecting more than 350 million people worldwide of all ages [11]. Depression is also the leading cause of death in many developed countries, especially among young adults [54]. Despite the severity of the problem, existing diagnostic tools often face challenges in reaching vulnerable individuals due in part to the perceived stigma of acknowledging depressive symptoms and visiting psychiatrists [46, 57]. Remarkable efforts have been paid to raising awareness to depression, including a social media-based research that guessed the possible depressive state of online friends based on wall posts, network structure, and interactions on Facebook and visualized the prevalence of depression [20].

As a joint effort between psychiatrists and data scientists, we designed a study framework that investigates the relationship between various activity metadata and one’s depressive state. The ultimate goal of this project was to raise awareness to depression at the university where the study was conducted, which had seen an increase in the suicide rate of its students. Because all activities are digitally logged, online social networks can be used to analyze psychological attributes such as mood states [10, 38] as well as any pathological social net-
work use such as Internet addiction [33]. Our project is in line with on-going efforts of online health communities that try to reach and detect a large number of depressed individuals at low cost [24, 37, 39].

Our methodology is based on a Web application implemented within Facebook. The application provides easy access to the Center for Epidemiological Studies-Depression (CES-D) scale, a well-proven self-report test for measuring depressive symptomatology in the general population [41]. The application also contained tips and games that would appeal to young people and gave feedback on the depression test. The users could invite their peers and share test results if they wished. Having the study targeted for one school, we could further conduct face-to-face interviews, through which a psychiatrist supported validity of the online evaluation system.

The application-based methodology is novel in three perspectives. First, compared to offline depression diagnosis, we may correlate one’s online and offline behaviors. Second, compared to the recent papers that infer users’ moods based on snapshot data, our approach considers moods as a dynamic entity. The depression test is designed to measure the past week’s mood and so we examine activities from the corresponding time period, which allows us to separate out the effect of mere topology (i.e., listed as friends) from the involved network (i.e., active interactions). Third, by logging how users answer each depression questionnaire, our approach can gain deeper insight into the precise depression aspects (e.g., somatic and interpersonal affects) and test which online behaviors are prominent. For instance, we can check if users who experienced restless sleep were more active during late hours than usual.

Described below are the key observations and findings from this research.

1. The depressed young adults owned fewer friends and posted fewer logs of physical activity (e.g., geotags) on Facebook. In addition, they constructed smaller ‘involved networks’—the network of friends a user actually interacts with during a given period of time on Facebook (as opposed to the mere number of friends)—than the non-depressed participants.

2. In contrast to the decreased level of interactions, communication intensity was not different between the two groups. Inside the small involved networks, depressed young adults sent a similar number of comments to each interacting friend compared to the non-depressed participants. Yet, in comparing the ratio of inbound and outbound comments, there was a tendency in the more depressed ones to be more passive in communicating with others.

3. The depressed young adults showed an increase in the wall post rates compared to the past months and were active online during the midday. Analysis of each depression statement and face-to-face interviews suggested that these behaviors are linked to compensating for loneliness in the offline world through activities in the online world.

These observations help us to better understand how users interact with features such as ‘likes’ and ‘comments’ on Facebook. Our findings also contribute to understanding users’ needs and psychological states in general within social media platforms—a natural collaborative system for sharing emotional support, which are important lines of research within the computer-supported cooperative work community. For instance, here is some related research: recent research investigated how moods are affected by interactions [34], depression is portrayed within social networks [13, 24], personality traits are discovered from sharing preferences [18], and how people manage vast amount of their digital traces over time [55].

**BACKGROUND**

Our study was built upon a large body of relevant research.

**Conventional Studies on Depression**

The following socio-demographic factors have been found to be associated with depression: female gender, young adulthood, old age, single parenthood, social isolation, financial difficulties, and stressful environments [12, 25, 29]. Researchers have also confirmed that psychological factors such as perfectionism, self-criticism, and sensitivity to loss and rejection are important correlates of depression [5].

**Wall Posts & Outbound Interactions Volume, and Active Time**

Loss of interest, lack of energy, and fatigue are the main symptoms that can be detected by the fifth edition of the diagnostic and statistical manual of mental disorders (DSM-5), a popular test widely used for diagnosing mental disorders, including depression, in the psychiatric field [1]. In regard to somatic features, one study proposed that dyssomnia is a major manifestation of depression, mood disorders, and anxiety disorders [49]. Furthermore, another study that assessed 38,000 subjects from ten countries concluded that insomnia and lack of energy are the most common symptoms related to depression [52].

**Networks Size**

Considering the interactions via offline social networks, it has been revealed that depressed people engage in smaller and less supported social networks than non-depressed people. A social psychology research synthesized existing findings on depression to find that depressed people feel uncomfortable interacting and they have fewer meaningful contacts with others compared to non-depressed people [4].

**Personal Traits and Depression Seen from Online Data**

Recent research has utilized the Internet and social network data to find correlates of personal traits and various disorders. One study investigated online surveys such as the Big 5 test to collect personal traits and then suggested the feasibility of predicting participants’ personal traits based on social media posts in Twitter [18]. The study found a relationship between participants’ personal traits and their preferences in sharing the prediction results via social media. Another study observed a strong geographical correlation between the ratio of suicidal tweets (e.g., bullying) and the actual suicide rates at the state level in the United States [26]. Research on the national suicidal rate of South Korea has also revealed one word
Himdeulda, which means tired or exhausted in Korean, to be the most powerful predictor as more people used this word in social media, the national suicide rate has risen [54].

Inbound Interactions Volume
A recent study concentrated on the relationship between the textual expression of loneliness indicating how people perceive loneliness and the number of sent tweets on Twitter [28]. They found that people who wrote about loneliness with transient remarks (e.g., “OMG, I’m so lonely right now.”) and sent more tweets than those who wrote with prolonged remarks (e.g., “I Hate feeling like this, I’m so lonely and depressed all the time.”). Moreover, people who wrote about loneliness with prolonged remarks were much less likely to get responses from others. These findings are in line with conventional studies concluding that language use is closely associated with psychological states.

Not only the raw text, but also Internet metadata or application logs can be used for the same purpose. A study of college students revealed those who exhibited signs of depression were more likely to use file-sharing services, send emails, and chat online than non-depressed students [31]. Depressed students had a tendency to use high-bandwidth applications (such as online videos and games) and showed random behaviors, for instance erratically switching between applications. Another intervention study asked college students to increase their rate of social network usage and found this to decrease the subjective well-being of subjects [32].

Among research that utilizes online social network data, one study examined a list of content that people ‘liked’ on Facebook and found that this information can be used to accurately predict various private traits, such as personality and sexual preference, as well as other demographic variables [30]. Another study found that people who feel lonely tend to disclose themselves more negatively and to establish fewer friends and also have less communication activity on Facebook [27]. This self-disclosure appears to be a common behavior on social media, as Major Depressive Episodes (MDE) could be detected in the wall posts of Facebook [37] as well as on the micro-blog platform Twitter [38].

Wall Posts & Outbound Interactions Volume
Other studies revealed whether people facing psychological anxiety over social interactions tend to cling on to online social media. Unlike the conventional notion that depression is connected to lethargy or loss of interests [1, 52], one study by surveying 568 users of Usenet newsgroups via e-mails found that people who feel lonely or psychological anxiety on social interactions are more likely to express themselves and to form intimate relationships over the Internet in order to dispel loneliness [35]. Another study measured the state of depression and loneliness of 368 undergraduate students by surveying the participants offline [7] and found that depressed individuals tend to prefer interacting online to face-to-face. This finding implies that depressed individuals try to find a safer alternative to the face-to-face interactions, in which they experience the difficulties in overcoming or compensating for social incompetence in their personal lives.

Finally, a recent work discussed the behavioral changes of new mothers who gave birth and had signs of postpartum depression [13], which based on an extensive set of activities within Facebook found clear distinguishing signs of postpartum depression, such as increased use of first person pronoun and reduced activity in general. We extend upon these studies and try to understand which activities within Facebook correlate with depressive moods.

Research Hypotheses
Based on the related literature, we test the following hypotheses to reveal whether depressed peoples’ ways of expressing themselves and interacting with others in social media would be different from those discovered by the previous works in the real world:

H1 (Networks Size): Depressed users have smaller social networks compared to non-depressed users [4].

H2 (Wall Posts Volume): Depressed users write fewer wall posts compared to non-depressed users [28, 35, 52].

H3 (Inbound Interactions Volume): Depressed users receive fewer comments and likes compared to non-depressed users [28].

H4 (Outbound Interactions Volume): Depressed users send out fewer comments and likes compared to non-depressed users [4, 7, 35, 52].

H5 (Active Time): Depressed users are more active during night compared to non-depressed users [49, 52].

METHODS

Application Design
We developed a Facebook web application for this study. The main purpose of the application was to measure depressive states of users by an authorized psychological questionnaire and to cull user data. Upon accessing the application for the first time, users were shown a consent form asking permission to access personal data. When users agreed, the application provided depression questionnaires, gathered data from Facebook, and stored it on the application server. For those users who did not give consent, the application terminated. Participants were recruited from a large university through online and offline advertisements, where the application could be accessed from both mobile devices and desktop computers.

The application is designed for both desktop computer and mobile environments, and it therefore has two different versions, one for the desktop computer and one for the mobile device. The two versions share the same database; thus, if a user completed the depression test on a mobile device, he or she cannot do this on a desktop computer later, and vice versa. We designed the application to be compatible with both environments to guarantee that users can access the application anywhere and at any time. There were no differences in the user interfaces of the desktop computer and mobile versions.
Once users took the depression test, the application provided three types of feedback according to the depression scale: non-depressed, mild depression, and severe depression. The feedback was carefully designed by psychiatrists to inform users of the depression test results and suggest guidelines that promote healthier psychological state. The screen snapshots in Figure 1 illustrate the process for asking user consent, the front page of the application, the flyer used to gather participants, and the test results.

The application provided another function, learning general knowledge about depression (100 facts and tips). We embedded this function not only to raise the awareness of users but also indirectly to measure the interest level of users toward depression. The main menu of the front page contains buttons to bring up the depression test and tips and facts page simultaneously so that users can freely access both pages without any given directions. However, once users access the depression survey, the corresponding button disappear from the main menu. Thereby, users can complete the depression test only one time whereas they can repeatedly access other functions. The application offered a points system to motivate users, where users could accumulate points every time they clicked on any function within the application.

Once getting permission from the participants we acquired users’ access tokens on Facebook and stored them into the database of our application. With the access tokens, we could directly access additional information stored on Facebook by utilizing FQL (Facebook query language). Also, some additional information such as the texts of wall-posts, was collected through the application and stored in the database of the application server. Therefore, additional information was collected through both Facebook and the application.

### Depression Survey

The application provided the Center for Epidemiological Studies-Depression (CES-D) scale [41], a test widely used in epidemiological studies. It is a self-report scale and contains 20 simple statements, each designed to identify markers of somatic, positive, and interpersonal affects related to depression. The test questions are shown in Table 1, which is re-organized to highlight three major subscales of depression. Participants were asked to judge each statement based on experience from the previous week. The items of the CES-D test were presented in a regular sequence from question #1 to #20 to follow the general surveying method used in the psychiatric field.

The degree of depressive symptom for each statement is rated from 0 (weak) to 3 (strong) scores, except for the positive affect subscale, whose severity is in reverse order from 3 to 0. The total score range of the CES-D is between 0 and 60 and cutoffs of 16 and 25 have been suggested in various literature to detect depression [22]: a score up to 15 indicates low probability of depression, a score between 16 and 24 indicates mild depression, and a score of 25 or above indicates a major depressive disorder. We followed this guideline to provide feedback to users. For presenting findings, however, we used different cut-off values and categorized participants into two groups: depressed and non-depressed. We chose the cutoff value 21 because it is a commonly used threshold with adequate sensitivity and specificity in community or school settings [3, 8].

In this study one explicit consideration went to preventing potential bias in data. Crowdsourced surveys often suffer from inaccurate data [15], because users participate for monetary rewards and could fill in answers inaccurately. Our survey was hence designed as voluntary-based and offered no explicit reward. To further ensure reliability of the depression test, a subset of users (115 participants) were asked to additionally take an alternative depression test (Beck Depression Inventory, BDI) and their scores were checked for consistency [56]. We did not find any abnormal trends between the CES-D and BDI results. Another subset of users were invited to perform the depression test in a laboratory setting (e.g., a desktop computer was provided) and data from these users were later used to check bias.

### Participant Recruitment

A total of 234 participants were recruited from a large university among users who had Facebook accounts for at least a year. Participants were gathered over two periods of time, April and December in 2013, during which they did not overlap with major exams. Three distinct methods were utilized: (1) flyers distributed across the campus, (2) online advertisements at the school’s bulletin board system, and (3) a survey booth installed at the largest cafeteria. Recruited participants showed a high response rate and a large majority of 212 (90%) completed the depression test; 161 (76%) were males aged between 19 and 38 (Mean=25.61, SD=3.72) and
The CES-D score

participants with fewer than five friends and two participants compared to common users [39]. As a consequence, three would show extraordinary behavioral patterns on Facebook absolutely no activity on Facebook—to filter out outliers who the participants whose friends numbered less than five did ab-
of +3SD while five was chosen based on the observation that to 1,000—the threshold 1,000 was chosen based on the value set up a range for the number of Facebook friends from five interacted with others during the past six months. Then we set of likes, comments, and wall posts through which they them, we further asked for agreement to access more detailed approved this study.

We explained the purpose of study and the list of personal data fields that we planned to analyze. The application explicitly cited the name of the hospital in charge of the study, should participants have any question about how the data was used. Informed written consent was obtained prior to participation and the school’s Institutional Review Board approved this study.

For 212 participants, we had access to all activities over the recent two weeks that appeared on their walls. For 129 of them, we further asked for agreement to access more detailed information on their Facebook usage, including the complete set of likes, comments, and wall posts through which they interacted with others during the past six months. Then we set up a range for the number of Facebook friends from five to 1,000—the threshold 1,000 was chosen based on the value of +3SD while five was chosen based on the observation that the participants whose friends numbered less than five did absolutely no activity on Facebook—to filter out outliers who would show extraordinary behavioral patterns on Facebook compared to common users [39]. As a consequence, three participants with fewer than five friends and two participants

with more than 1,000 friends were excluded. The eventual data of 124 participants (i.e., 53% of the 212 participants) accounted for a total of 17,157 activities. We used everyone’s data (i.e., 212 participants) for most of the analyses and we limited the focus to the 124 participant subset when detailed information was necessary.

We particularly paid attention to ‘likes’ and ‘comments’ as a proxy of lightweight and effort-taking interactions respectively. These two functions are the two most popular forms of interactions on Facebook, and hence have received much attention. For instance, a recent study demonstrated that the two functions serve different purposes: relationships grew closer from composed content (e.g., writing on the timeline or leaving comments) than from simple on-click features (e.g., likes) [6].

RESULTS

Out of the 212 participants, 170 (80%) of them obtained a CES-D score of between 0 and 20 indicating a low probability of depression. The remaining 42 obtained a CES-D score of between 21 and 60, which means a high probability of depression. For convenience, we simply refer to these two groups as non-depressed and depressed, respectively. The overall CES-D distribution is shown in Figure 2.

We checked the efficacy of online depression screening through both quantitative and qualitative approaches. The quantitative approach involved comparing the CES-D score with an alternate test, BDI [56], and the qualitative approach involved face-to-face interviews. The application sent a personal invitation message to all participants who obtained a personal invitation message to all participants who obtained a high CES-D score (i.e., 21–60) and offered free counseling at the university’s hospital. The turnout rate was low. Only six participants out of 42 corresponding individuals agreed to meet, for whom a psychiatrist assessed their depressive symptoms through the Hamilton Depression Rating Scale (HAM-D), a widely practiced structured interview for determining one’s depression level [21].

Three participants reported chronic depressive symptoms that
Table 2. The depressed and non-depressed participants are compared (1) at the individual level through the Pearson’s test and (2) at the group level through the two sample t-test. Significance of the results are marked (*p<.05, **p<.01, ***p<.001).

<table>
<thead>
<tr>
<th>Feature &amp; App Activity</th>
<th>Individual level(N=212) Pearson’s r</th>
<th>p-value</th>
<th>Group level(N=124) Depressed(N=90)</th>
<th>Non-depressed(N=34)</th>
<th>Ratio</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Friends</td>
<td>-0.25**</td>
<td>&lt;.01</td>
<td>190.57 141.59 336.26</td>
<td>183.71 0.57***</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td>Tips checked</td>
<td>0.39***</td>
<td>&lt;.001</td>
<td>3.65 4.07 1.02</td>
<td>2.37 3.58***</td>
<td>&lt;.01</td>
<td></td>
</tr>
<tr>
<td>Geotags</td>
<td>-0.16</td>
<td>.48</td>
<td>1.5 0.58 4</td>
<td>3.89 0.38*</td>
<td>.01</td>
<td></td>
</tr>
<tr>
<td>Area of gyration</td>
<td>-0.20</td>
<td>.16</td>
<td>560.26 1942.74 5385.28</td>
<td>23534.49 0.10</td>
<td>.24</td>
<td></td>
</tr>
<tr>
<td>Wall posts</td>
<td>0.16</td>
<td>.17</td>
<td>1.85 3.16 1.74</td>
<td>3.58 1.06</td>
<td>.92</td>
<td></td>
</tr>
<tr>
<td>Wall post rate</td>
<td>0.26*</td>
<td>.02</td>
<td>0.21 0.28 0.10</td>
<td>0.17 2.13</td>
<td>.18</td>
<td></td>
</tr>
<tr>
<td>Fan pages</td>
<td>0.14</td>
<td>.11</td>
<td>73.96 256.51 44.55</td>
<td>69.12 1.66</td>
<td>.59</td>
<td></td>
</tr>
</tbody>
</table>

Inbound Likes

| Total                  | -0.11                             | .34     | 18.80 26.25 44.60                | 69.18 0.42*          | .03   |         |
| Distinct friends       | -0.23                             | .05     | 13.60 15.52 29.25                | 29.30 0.46*          | .01   |         |
| Avg per friend         | 0.07                              | .60     | 1.23 0.41 1.31                   | 0.50 0.94           | .56   |         |

Inbound Comments

| Total                  | -0.17                             | .52     | 8.60 10.68 22.49                | 38.55 0.38*          | .02   |         |
| Distinct friends       | -0.13                             | .28     | 6.20 5.75 12.42                 | 4.60 0.50*           | .01   |         |
| Avg per friend         | -0.13                             | .34     | 1.25 0.30 1.52                   | 0.61 0.82*          | .04   |         |

Outbound Comments

| Total                  | -0.24*                            | .01     | 5.04 5.08 8.24                   | 5.78 0.61*           | .01   |         |
| Distinct friends       | -0.27***                          | <.001   | 3.83 3.65 7.14                   | 5.18 0.54***         | <.001 |         |
| Avg per friend         | 0.17                              | .09     | 1.28 0.36 1.19                   | 0.31 1.07           | .34   |         |
| In-Out ratio           | 0.16                              | .08     | 0.87 1.62 0.42                   | 0.82 2.07           | .21   |         |

Table 3. Scatter plot of the depression test result (CES-D) along with major features on Facebook.

(a) Number of friends
(b) Number of inbound likes
(c) Number of in- & outbound comments

Profile and Application Activities

Among various relationships that our research allows us to explore, we focused on user-level metadata related to interpersonal activities such as likes and comments. The relationship between online social activities and the CES-D scores was measured by the Pearson’s correlation coefficient as well as simple linear regression analysis. The difference between the depressed and non-depressed groups was measured by independent two-sample t-test as well as the calculated mean, standard deviation, and ratio of the means.

As a first step, we examined the mere counts as a function of the participant’s depressive state. Table 2 indicates that depressed participants (1) owned fewer friends, (2) shared fewer geolocation tags, and (3) covered a smaller area of movement...
based on geotags compared to non-depressed participants; on
the other hand, they (4) viewed more tips about depression
through the application, (5) liked more pages on Facebook,
(6) updated as many wall posts in total, and (7) even showed
an increase in wall post rates compared to the past months.
We note that the described correlations are specific to the par-
ticipants and the choice of statistical test.1

As these results can be influenced by samples, we do not
bring into focus on the specific values in the regression anal-
ysis but rather focus on the overall trend of the features. For
instance, geotags may be a proxy that represents a user’s ac-
tivity scope in the real world. On average the area of gy-
ration of the non-depressed individuals was wider than that
of the depressed participants, where the area of gyration was
calculated by utilizing the geolocation tags posted by users
over the past six months and then finding a radius that covers
all geotagged locations from the mean location of that user.
While it is debatable whether depressed participants traveled
shorter distances or simply they did not post updates fre-
quently enough than the non-depressed participants, a lower
rate of physical activity is related to the common signs of de-
pressive symptoms (e.g., lethargy, fatigue, weariness) [1, 52].

Wall Posts Activities
Updating posts on the wall page is one of the basic functions
on social networks. A post, which can be of various forms
(e.g., texts, photos, web links), serves as the medium through
which other social interactions begin (e.g., comments, likes).
We examined how many wall posts participants shared during
the two-week period and how much interaction they evoked.
Some participants did not update any wall posts: 34.7% and
41.5% of participants in the depressed and non-depressed
groups, respectively, posted none. Among the rest of the users
who posted at least once, on average depressed participants
wrote as much wall posts as the non-depressed participants.

Since the mere number of postings gives limited information,
we normalized the posting rate for participants for whom we
had longitudinal trace and defined a metric termed ‘wall post
rate’, which compares the posting rate from the recent two
weeks against that of the previous six months. This mea-
sure is useful for tracking behavioral changes of individuals
with acute depression (as opposed to those with chronic de-
pression), which typically takes up the majority of depressive
symptoms among young adults. Because acute depression
develops suddenly, it could leave a visible activity marker
over time. We may now examine whether acute depression
increases or decreases one’s wall post rate.

The data showed that wall posting activity became more
prevalent for depressed participants. For increment of 1 unit
in the depression test result (i.e., higher likelihood of depres-
sion), the wall posting rate increased 0.26 times over a six
month period (p=0.02). At the aggregate level, on average the
depressed group increased the wall post rate more quickly
than the non-depressed group. These observations rejects the
second hypothesis, which assumes that depressed users write
fewer wall posts compared to non-depressed users.

Likes Interactions
The likes activity is a popular way to express a relatively
positive reaction to a story that one has just read on Face-
book. Likes are lightweight because they are an alternative
to taking time to deploy mental energy in giving a written
response [19]. The likes activity showed several meaningful
relationships with depression.

Depressed participants received 4.2 likes for every 10 likes
that non-depressed participants received during the observed
two-week period (see the row termed Total in the Inbound
Likes category of Table 2). Normalizing the number of in-
bound likes per wall post gives a similar picture: on average the
depressed participants received fewer likes for every wall
post they wrote (see Avg per wall post). Moreover, the de-
pressed participants owned 0.46 times fewer distinct friends

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1When we use the Mann-Whitney U test, which has greater effi-
ciency than the t-test on non-normal distributions, the following five
features can be interpreted as significant: Friends and Tips checked
from the Profile & App Activity category as well as Total, Distinct
friends, and In-Out ratio from the Outbound Comments category.

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Figure 4. The relative amount of likes and comments activities on Face-
book by participants in the depressed group compared to those in the
non-depressed group for the observed two-week period: x-axis is the
value of the ratio where 1.0 indicates an equal quantity and y-axis is the
title of each activity feature. For visual clarity, we grouped activity fea-
tures into similar categories and added space between them: Inbound
Likes, Inbound Comments, and Outbound Comments.
Comments Interactions

Users can interact with one another through writing or replying to comments on a wall post. As one might imagine, the correlation between inbound likes and inbound comments was prominent (Pearson $\rho=0.91$); those who received many comments received many likes. In addition, the number of inbound comments was predictive of owning depression (see the Inbound Comments category). Perhaps because writing each comment takes more thought and energy than pressing the like button, its relative quantity was more pronounced between the depressed and non-depressed groups. Depressed participants received 3.8 comments for every 10 comments that non-depressed participants sent and had a 50% smaller involved network that sent comments during the two-week period.

We next looked into the effect of giving a comment as opposed to receiving one (see the Outbound Comments category). Giving was as rewarding as receiving: the number of outbound comments was a meaningful indicator of depression. For the two weeks depressed participants sent 6.1 comments for every 10 comments that non-depressed participants sent and had a 54% smaller involved network that received comments. In contrast, the correlation between the inbound and outbound comments was relatively low ($r=0.02$), indicating that those who write many comments on wall post of others do not necessarily receive back many comments on their wall posts. The conversation intensity, measured as the average number of comments sent for each interacting friend, was not meaningfully different between the depressed and non-depressed participants.

There was no obvious trend related to depression in (1) the time difference between inbound and outbound comments (i.e., how quickly one comments back) or (2) the time interval between two consecutive outbound comments (i.e., how frequently one leaves comments) at both individual and group level tests. This means diversity and intensity of interaction with the involved network are key predictors of depressive moods, rather than immediacy of interactions.

To further investigate what happens to the depressed participants’ involved networks, we examined the ratio of inbound and outbound comments for the depressed and non-depressed groups (see the In-Out ratio row). In calculating this ratio, we divided the number of inbound comments by the square of the outbound comments, as the latter quantity was usually far smaller than the former. The in-out ratio would be 1.0 should one receive and send the same number of comments. The ratio showed a marginally significant positive correlation to the depression score, whereas its average ratio for the depressed participants was greater than that of the non-depressed ones. We discuss implications of these findings in the later section.

Manifestation of Perceived Mood

Depression is a complex disorder that involves various somatic and emotional affects. Having analyzed the user metadata, we now attempt to understand how the self-perceived mood states are manifested as online activities on Facebook. This analysis is possible because the application stored information about how participants judged each statement in the depression test. We demonstrate the idea with three cases: the 12th, 14th, and 19th statements in Table 1.

The first statement we consider is, “My sleep was restless”. While giving a high score (2–3) generally increases the probability of depression, the depressed participants had

from whom they received likes (see Distinct friends). However, on average the number of likes received from each interacting friend was similar between the two groups (see Avg per friend).
posted almost the same number of text-based wall posts as listed in Table 2. Then, to investigate the trend in detail, we checked whether participants who identified themselves as “having talked less” showed slower wall post rates. After grouping participants based on their scores (by two groups: 0–1 and 2–3), an opposite trend emerged as indicated in Figure 6: participants who answered 2–3 (i.e., talked less than usual) currently posted more text-based wall posts than usual when compared to those participants who answered 0–1 (i.e., did not talk less).

The final statement we examined is “I felt that people dislike me”, which we associated with the aggregate number of comments and likes that participants received from friends over a two-week period. We classified users into two groups based on their answers: the first group who answered 0–1 (rarely or some) and the next group with answer of 2–3 (occasionally or most). While none of the non-depressed students gave a score of 3 (i.e., most of the time), none of the depressed students gave a score of 0 (i.e., rarely). Figure 7 shows the trend between the aggregate number of likes and comments students received for their text-based wall posts as a function of their perceived feeling toward others. Those who perceived that others disliked them (i.e., 2–3) in fact received fewer comments and likes than those who did not indicate so (i.e, 0–1).

DISCUSSION
Principal Findings
While we do not attempt to claim a causality between online activities and depression, we discuss how shrinking of interpersonal relationships and loss of interests, which are common factors linked to depression in the real world, correlate with depression through the medium of social media. One of our research achievements is to quantify the interpersonal relationships by utilizing social media data because it has been a difficult task with conventional offline studies. We found certain traits of online interactions (e.g., a small involved network and a large value of the in-out ratio of comments on Facebook) are highly associated with a person’s depressive moods. We revisit the five main hypotheses that we discussed earlier and provide possible explanations.

H1: Depressed users have smaller networks — Supported
The size of a person’s network had a strong correlation with depressive moods. Even the mere number of friends had an association with depression, which was similarly shown in related studies on depressive symptoms, dysthymia, and loneliness [27, 42]. While these studies considered a single snapshot of the network (i.e., the total number of friends), our work considered a temporal aspect and focused on how many peer users interacted over a short period of time. We found that the depressed participants reported qualitatively and quantitatively smaller involved networks through which they interchanged thoughts and emotions with peers via likes and comments.

There are two possible ways of explaining why the size of network is related to depression: one is that participants with a larger involved network may find more opportunities for support from friends and hence are less inclined to be depressed [50]. For instance, receiving positive feedback (i.e., likes) on one’s social network profile may enhance self-esteem and the sense of well-being, as a study of older adolescents demonstrated [47]. On the other hand, another explanation is that participants who are suffering from depression may experience difficulties in engaging and maintaining a social network. However, providing the causality will require qualitative interviews over a long period of time and is beyond the scope of this study.

H2: Depressed users write fewer wall posts — Rejected
Depressed participants showed an increased rate of wall posts compared to the past months, not in line with our expectation. Face-to-face interviews and surveys provided possible reasons for this behavior. A more frequent posting pattern is a specific feature of young adults who are avid users of social media, and this trait may be linked with loneliness—a signal shown in those who fail to express themselves; the depressed users may be eager to compensate for loneliness in the offline world by activity posting updates in the online world [53].

Unfortunately, the one way communication did not reciprocally trigger sufficient positive feedback to the depressed participants from friends, and hence could not ameliorate depressive moods. In the real world, the depressed individuals did not converse actively with their friends due to loss of energy and interest. However, they found it easy to be active in online...
platforms like Facebook, because of the high accessibility and ease of interactions such platforms provide. Thus, our finding is an endemic trait of the depressed young adults on social networks, which designers of the future social networks and health care policy makers may be interested in.

H3: Depressed users have smaller inbound interactions such as receiving likes and comments from peers — Supported
H4: Depressed users engage less in outbound interactions such as sending likes and comments to peers — Rejected

We examined social activities in the form of comments and likes. Although the depressed group had fewer friends who sent likes, their average number of likes received for each interacting friend was close to that of the non-depressed group. However, the depressed users had fewer aggregate friends who sent comments and further received a smaller number of inbound comments per friend than the non-depressed users. These observations together indicate that friends of the depressed users tend not to send comments to the depressed friends, while they do not hesitate to send likes. The reason for this behavior may be either that it is difficult to make comments on content the depressed users typically share or simply they do not wish to expend more energy than that involved in merely sending likes, which is a kind of threshold. From the result, we may state that, for receiving traits, the depressed participants’ friends might have the perception that ‘likes’ is a lightweight interaction while ‘comments’ is a more energy-driven interaction.

Meanwhile, outbound activities demonstrate the opposite trend from receiving activities. The depressed users sent almost the same volume of comments (1.07) for each interacting friend. Unfortunately, due to the limitation of the Facebook API (application programming interface) we cannot cull the correct data of outbound likes. The result may mean that depressed participants interact through comments at a level of effort similar to the non-depressed participants.

Indeed, if we only looked at the number of comments and likes it would be difficult to find any differences. However, since we deeply investigated the interaction that occurs inside the involved network, we could find endemic traits of the likes and comments features and surmise that users perceive the likes and comments functions on Facebook differently based on their depressive states.

Moreover, the proportion of inbound comments to outbound comments grew as a person had a higher likelihood of depression, meaning that a depressed user sends fewer comments than he or she receives. At first glance, the depressed participants’ intention to actively communicate with focused friends—although they are fewer—is not profoundly different from non-depressed participants. Yet, analysis of the interaction intensity implies that the communication tendency of depressed participants is still passive. This may be linked to a previous study that found that spending money (i.e., an outbound activity) on others as a method of social support makes the spender more happy and improves his or her social well-being [16].

H5: Depressed users are more active on late at night than non-depressed users — Rejected

The depressed group showed a peak at the working hour of around 5 p.m., in contrast to the non-depressed group who showed the highest activity at around 11 p.m. We have two explanations for why the depressed participants used Facebook during working hours, which in the real world are commonly used for studies or social interactions. One explanation is that the depressed participants do not have enough energy to engage in real social interactions. Loss of interest and energy are main symptoms of depression, and thus the depressed participants might give more attention to easy interactions that can occur on social networks. They might replace the real world activities with social network activities, which could also be confirmed through qualitative analysis. This pattern was more prominent for those who indicated restless sleep, suggesting that a sleep problem can aggravate their lack of energy and the day time activities.

An alternative explanation is related to a deficit in real social relationships that could mitigate depressive symptoms [36]. Lack of social support is a main risk factor of depression [40], and depression can reduce the breadth of a social network [48]. Depressed participants in our study may not have received enough support from their real world network, and hence they might have tried to interact with friends through online social networks to compensate for their deficits in social support. This may also explain why participants who answered “having talked less than usual” in the CES-D scale had in fact posted more (text-based) wall posts online.

Interestingly, the depressed individuals without sleep problems had more activities in the middle of the night than the depressed individuals with sleep problems. Subjective satisfaction of sleep quality and duration did not always align with the objective findings; this can be influenced by the individuals’ differences in the composition of sleep [43]. Thus, the subjective sleep problem cannot reflect their behavior directly, but the problem can be influenced by individuals’ physical and cognitive states.

Some of our observations are unexpected and would not have been found if we had not checked the individual CES-D statements. Moreover, for those observations showing unexpected outcomes we could provide reasonable explanations and novel insights with the presented methodologies for investigating profiling frequencies and interacting patterns on Facebook as well as with qualitative analysis.

Feedback on User Experience

The application we developed raised awareness of depression among students, most of whom had no experience of visiting a psychiatrist. The application identified other unexpected findings, for example, depressed participants were eager to view tips provided about depression. In discussing implications, it is important to consider how participants perceived the application.

We conducted a survey a week after the test, asked the participants to complete four questionnaires: the first two were objective and the other two were descriptive. The objective
questionnaires asked for a general assessment of the application and whether a participant intended to seek a psychiatrists’ support if they had emotional difficulties in the future. The descriptive questionnaires asked participants to write about whether the application was helpful and how it could be improved. We asked participants to give the feedback in detail. Regarding the scales used in the survey, participants were asked to estimate general assessment of the application by rating it on a scale of 0 to 10 and to provide information on the preference of psychiatrists’ support with a Likert-like scale of one to five: never; don’t want; don’t know; want; actively want.

In the overall result, 63% of the participants responded to the survey. On the objective questions, 48% from the responding participants evaluated the application as good (7–10), 11% of respondents evaluated it as bad (0–3), while the rest of respondents evaluated it as average (4–6). In addition, 67% from the responding participants indicated that they did not want psychiatrists’ support, whereas 18% of the respondents intended to ask psychiatrists for help if they suffered from emotional problems. Therefore, it is a crucial future task to design a user experience so that users feel comfortable in contacting and getting aid from psychiatrists through the application when they are in need.

Considering positive feedback from the descriptive questionnaires, while most participants answered that they found the application to be useful in learning about their depressive moods, others found it useful in ways that we did not expect. For instance, several participants mentioned that the experience of self-awareness was rewarding in a manner similar to meditation. Below are some sample quotes from the positive responses.

“The app made me think about my emotions, which I liked. Perhaps periodically using this app will help me know about myself better.”

“The feedback shown after the test was useful. It showed an emotional state that I was not well aware of in daily life. Easy-to-try recommendations were given, which I found practical.”

“I took this app as an opportunity to sit quiet and look back on myself. As I took the test, I thought deeply about which elements affect my emotion.”

“I became more aware of the current feeling than feelings from the past week [which the app asked]. Maybe the application can provide more directions to help users focus on feelings from the past week.”

We also received non-positive comments, which we plan to utilize to improve the system. One participant said it was difficult to focus on the past week’s experience (which the depression test is based on), as he became constantly aware of the instantaneous feelings. Another user found the user interface could be designed better.

**Limitations**

This study is limited and can be extended in several ways. First, the findings are dependent on the participants’ demographics, and hence they cannot be generalized. Most online surveys are known to suffer from potential bias [15] in that respondents are found to be in a more educated and affluent group and also disproportionately in male. However, our data showed a different bias: the proportion of females (26%) was marginally higher than the rate of overall female students (21%). One approach to alleviate this bias is to increase the number of participants of the online survey, for instance, by including it on a voluntary basis in a school’s yearly physical check-up service for students. We hope to address the sampling bias and investigate how cultural specifications come into play in the future.

Second, our findings are limited to the particular platform used in this study and any change in the platform may make some correlations weaker or stronger. The way Facebook activities are designed and the level of social interactions promoted will affect how users perceive and behave. For instance, social networks such as Tumblr or Snapchat, where social interactions are more focused on smaller groups, could incur different user behaviors. In order to address this concern, we hope to replicate the study in a number of different platforms. The methodology and high-level implications, however, will remain consistent. For instance, certain interactions require heavier or weaker attention to users (e.g., comments versus likes), for which we found different level of correlations. Although we examined a single platform, its activities, such as wall posting and photo tagging, are easily found in most social networks.

Third, we are not sure whether depression is a unique trait associated with online behaviors and interactions. Other personal categories such as personalities, interests, and other mental as well as physical diseases may be linked to users’ online behaviors and interactions as well. Hence, we need to investigate the relationships of other categories and carefully compare them to the trait of depression.

Fourth, we have not checked the users’ amount of time spent on Facebook. Since time spent on Facebook may influence various actions that can be taken, the amount of time spent can be a confounding variable to consider. However, we were focusing on not just passively consuming the content on Facebook but actively uploading content and sending out likes and comments to interact with others; these active behaviors may or may not be correlated with the time spent on Facebook. We also considered receiving feedback from a user’s friends, and it is also unclear whether these features are related to the user’s time spent on Facebook. Therefore, more research needs to be conducted to reveal the relationship between the amount of time spent and the volume of online inbound and outbound activities to contemplate the confounding variable.

In regard to the confounding variable, there are other factors, such as various demographics and offline user activities, that should be looked at as well. Considering other demographic and offline user activity variables like age, occupation, social status, and specific time events, we think we have relatively
homogeneous participants because we recruited young adults at a single university. Furthermore, we could not find any significant correlations between the CES-D scores and the listed variables in our participants. Consequently, we believe we have removed some major confounding variables.

Lastly we did not examine any linguistic features or content shared by users, an area that future studies can look into. In particular, sentiment and topic analysis may reveal clues as to why the depressed users receive fewer comments and likes than the non-depressed [44]. Such an investigation may help us understand the potential factors that could play a role in making friends hesitate to respond in online interactions.

CONCLUDING REMARKS
Recent studies have proposed the potential for utilizing data from social network sites to identify references for well-being of people. This paper investigated what kinds of interaction metadata of Facebook is related to depressive moods and identified several strong associations between the social network usage patterns and depression symptoms. The research was conducted by an interdisciplinary group and took a mixed methodology and conducted both qualitative and quantitative analyses. Some of our findings are new in the sense that they have not yet been shown in previous studies, for which we provided explanations.

The 212 study participants, recruited from a single university through fliers, covered various levels of depression from mild and moderate to severe. Overall, 20% of the participants were judged to be depressed based on the CES-D screening and the remaining 80% were judged as non-depressed. The overall depression level in our sample was 1.18 times higher than the nation-wide average of people in their 20s and 30s (which was based on offline diagnostic studies [9]). Whereas our analysis was limited to the dataset of a single university, a similar level of prevalence between the studied demographics and the nation-wide sample suggests that online screening is a viable approach to reaching vulnerable individuals, especially young adults.

While this research is observational, the presented research methodology and findings have implications for future intervention designs that can improve the well-being of users. Among various possible directions, one can envision designing a cost-effective online campaign that increases awareness to depression by providing a diagnostic tool that alleviates the stigma associated with offline detection methods [57]. Online social media-based diagnostic tools may be particularly useful in countries, where open discussion of depression is suppressed. One can also envision an application that regularly monitors users and their online behaviors such as wall-posting over time to summarize users’ mood states, which can then be provided to health professionals during hospital visits to help diagnose symptoms more thoroughly. By this method, the application may be an effective communication channel between users and psychiatrists.

Young adults make up the largest population on Facebook; those aged between 18 and 34 are the largest proportion (47.7%) among all age groups [45]. Moreover, 48% of them report reading Facebook streams is the first activity to do in the morning as soon as they wake up [23]. Hence, young adults might find a Facebook application-style screening less intrusive (compared to visiting and taking written screening tests), who are as well the group that could potentially benefit the most from online depression screening. We hope observations from our research contribute toward building mental capital of cognitive and emotional resources that influence well-being of young adults in the future [11].

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