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Associating Internet Usage with Depressive Behavior Among College Students

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Digital Object Identifier 10.1109/MTS.2012.2225462
Date of publication: 19 December 2012

 1932-4529/12/$31.00©2012IEEE

Depression is a serious mental health problem affecting a significant segment of American society today, and in particular college students. In a survey by the U.S. Centers for Disease Control (CDC) in 2009, 26.1% of U.S. students nationwide reported feeling so sad or hopeless almost every day for 2 or more weeks in a row that they stopped doing some usual activities [32]. Similar statistics are also reported in mental health studies by the American College Health Association, and by independent surveys [1], [2].

Students with depressive symptoms used the Internet much more than those without symptoms.

Although there are treatments for depression, many sufferers do not recognize symptoms; others may be reluctant to seek help [24], [25]. If left untreated, depression can cause appetite loss, sleep disorders, fatigue, and anxiety, as well as poor academic performance and higher dropout rates. Detecting depressive symptoms early therefore is a critical need in our colleges today.

In this article, we report our findings from a month-long experiment conducted at Missouri University of Science and Technology on studying depressive symptoms among college students who use the Internet. This research was carried out using real campus Internet data collected continuously, unobtrusively, and while preserving privacy.

Internet Use as a Marker for Depressive Symptoms

Recent studies show that college students are increasingly active on the Internet. A study conducted by Hargittai in 2007 reported that almost 84% of students surveyed are online at-least once a day [26]. A larger scale study among 103 institutions and 27 846 respondents conducted by Salaway, Caruso, and Nelson in 2007 found that college students are online an average of eighteen hours per week, using the Internet in multiple capacities including email, chatting and social networking [23]. While the benefits of the Internet for academic learning, research, business, and social networking are well known, studies conducted by the psychological sciences community have focused on exploring relationships between Internet use and students' mental health. Studies in [3]–[7] demonstrated that students with depressive symptoms used the Internet much more than those without symptoms. It was also shown that when the Internet was utilized for activities like shopping, depressive symptoms among students increased [5]. Excessive online video viewing [18]–[20], social networking [31], gambling [9], [10], frequent visits to health websites [11], late-night Internet use [12], [13] and online chatting [21], [22] have also been associated with symptoms of depression among young people. With excessive Internet use, students may replace real-life interactions with online socializing, leading to increased social isolation and anxiety in their physical environments [8].

While the studies mentioned in the preceding paragraph provide critical insights into how Internet use associates with depressive symptoms among college students, the information the data convey is limited. This is because student Internet use in existing studies has been assessed by means of self-reported surveys only. In other words, students themselves reported their volume and type of Internet activity.

Self-reported data methodology has limitations. First, the volume of collected Internet usage data is limited during surveying because people's memories fade with time. There may be errors and social desirability bias when students report their own Internet use. An accurate characterization of Internet use requires representations of significantly higher dimensionality, and the number of dimensions that can be captured via surveys is limited.

Contributions of this Article

We conducted a study in 2011 to explore whether there is an association between depressive symptoms among college students and their real Internet usage. The data in the study were collected continuously, unobtrusively, and through methods that preserved privacy[1] at Missouri University of Science and Technology (Missouri S&T). To the best of our knowledge, this is the first study to use such methodology. The study consisted of the following steps:

- ***Participant Selection and Surveying:*** We recruited 216 students from three undergraduate classes at Missouri S&T in February 2011. The depressive symptoms of participants were quantified using the Center for Epidemiologic Studies Depression (CES-D) scale [14]. In our survey, 30% of students met the minimum

[1]This research was proposed to the Institutional Review Board (IRB) at Missouri S&T, and received approval under Exempt Category 4: "Research involving the collection or study of existing data, documents, records, pathological specimens, or diagnostic specimens, if these sources are publicly available or if the information is recorded by the investigator in such a manner that participants cannot be identified, directly or through identifiers linked to the participants."

CES-D criteria for exhibiting depressive symptoms, which compares well with many recent mental health surveys [1], [2], [32].

- ***Internet Usage Feature Extraction:*** The Internet usage activity of participants was obtained in the form of Cisco NetFlow records collected over the Missouri S&T campus network. For each participant, we derived a number of Internet usage features divided into three broad categories. The *Aggregate* category captures raw aggregates of Internet usage like flows, packets, octets, and durations. The *Application usage* category captures application specific Internet usage features like chatting, peer-to-peer, email, ftp, and http. The *Entropy* based features captures randomness in Internet usage from the perspective of flows, octets, packets, durations etc.
- ***Statistical Analysis:*** Subsequent statistical analysis revealed that the following Internet usage features correlate with depressive symptoms: average packets per flow, peer-to-peer (octets, packets, and duration), chat octets, mail (packets and duration), ftp duration, and remote file octets. Additionally, Mann-Whitney U-tests revealed that average packets per flow, remote file octets, chat (octets, packets, and duration) and flow duration entropy demonstrate statistically significant differences in their mean values across groups with and without depressive symptoms.
- ***Interpretation of Results:*** We present preliminary interpretations to our findings by integrating the results with existing research in psychological sciences on associations between depressive symptoms and Internet usage among college students.

Table I
Summary of our Participant Pool

	Computer science	Psychology	CES-D ≥16	CES-D <16
Male	120	68	54	134
Female	8	20	10	18
Total	128	88	64	152

Participant Selection and CES-D Survey

In our study, the participant pool consisted of 216 undergraduate students at Missouri S&T from three classes: Psych 50 (General Psychology), CS 284 (Operating Systems), and CS 153 (Data Structures). Psych 50 is taken by students from all departments, while CS 284 and CS 153 are taken by students from a number of engineering departments. The survey was preceded by a consent form, and there was a minimum age of at least 18 years to participate. The survey was conducted in February 2011.

The levels of depressive symptoms among participants were quantified with a one-time survey based on the Center for Epidemiologic Studies Depression (CES-D) scale. The CES-D scale was developed by Lenore Radloff of Utah State University and is used to measure depression levels in the general population [14]. It consists of 20 questions rated on a 4-point Likert scale. Possible scores range from 0 to 60, with higher scores indicating greater levels of depressive symptoms. In general, a score of 16 or above on the CES-D scale is considered indicative of depressive symptoms. The CES-D scale is widely used and has been extensively tested and validated. It has been shown to be reliable when testing adolescents in high schools and colleges [15], [16]. In order to minimize demand characteristics (where participants form an interpretation of the experiment's purpose and unconsciously change their behavior accordingly), the survey was titled "Recent Affective Experiences Questionnaire," and additional items were embedded into the original CES-D questionnaire, although only the CES-D items were scored. Table I summarizes our participant pool.

To ensure privacy of participants, appropriate anonymization techniques were enforced during participant selection, surveying, and collecting Internet usage data. The information technology (IT) department at Missouri S&T provided unique pseudonyms for each participant, and the associations were not disclosed to the research team. Students who completed the CES-D survey did so using only their pseudonyms, which were tied to their recorded CES-D scores. The IT department remained unaware of the CES-D scores. Additionally, the IT department provided the on-campus Internet usage data indexed only by pseudonyms. The only associations available to the researchers were between Internet usage data and CES-D scores. In our study, IP addresses were not processed, since the focus was on broad Internet statistics alone.[2] Also, the contents of emails, chat, and ftp uploads/downloads were not recorded due to privacy considerations.

[2]Since we do not process IP addresses, websites visited were not accessed. Hence associations between visits to social networking sites like Facebook, Twitter etc. and depressive symptoms were not investigated in this study. This is part of future research.

> Frequent email checking may relate with high levels of anxiety, which in turn correlates with depressive symptoms.

Internet Data Collection and Preprocessing

The main source of Internet Usage data for this study was NetFlow. Cisco NetFlow technology is a protocol for collecting IP traffic information and is popular. NetFlow data consists of several flows. In our study, NetFlow V5 was used, which contains the following eight fields for each flow after preprocessing: 1) Source IP address, 2) Destination IP address, 3) Source port, 4) Destination port, 5) Protocol, 6) Octets, 7) Packets and 8) Duration.

The Information Technology department at Missouri S&T collects NetFlow data of all users for troubleshooting network connections and policy enforcement. The Missouri S&T campus has a connection to both the standard commodity Internet and the Internet 2 education research network. Both Internet and Internet 2 traffic pass through the same router where NetFlow statistics recording and exporting are enabled. Every five minutes, these flows are exported from the router to a collector where they are stored for a period of 45 days for analysis purposes before being discarded automatically.

In order to obtain the NetFlow data of participants, the flows pertaining to each participant were identified based on the source IP field, and subsequently filtered and logged to a secure remote server at the end of every month. As the Missouri S&T campus uses a Dynamic Host Configuration Protocol (DHCP) to provide the IP address, the IP address used by a participant at one time could be used by someone else later. Therefore, the extraction process begins by creating a mapping file and associating each user with a set of assigned IP addresses, along with the start and end time stamps. This information is used by a backup daemon to extract user-specific NetFlow information by filtering flows based on the source IP field. The mapping file is created by analyzing DHCP logs that include a participant's user-id, which is that participant's campus email address. Note that this process, summarized in Figure 1, was executed by the Missouri S&T campus IT department. This process was completely automated. Subsequently, the Internet usage of each participant indexed by appropriate pseudonyms (as

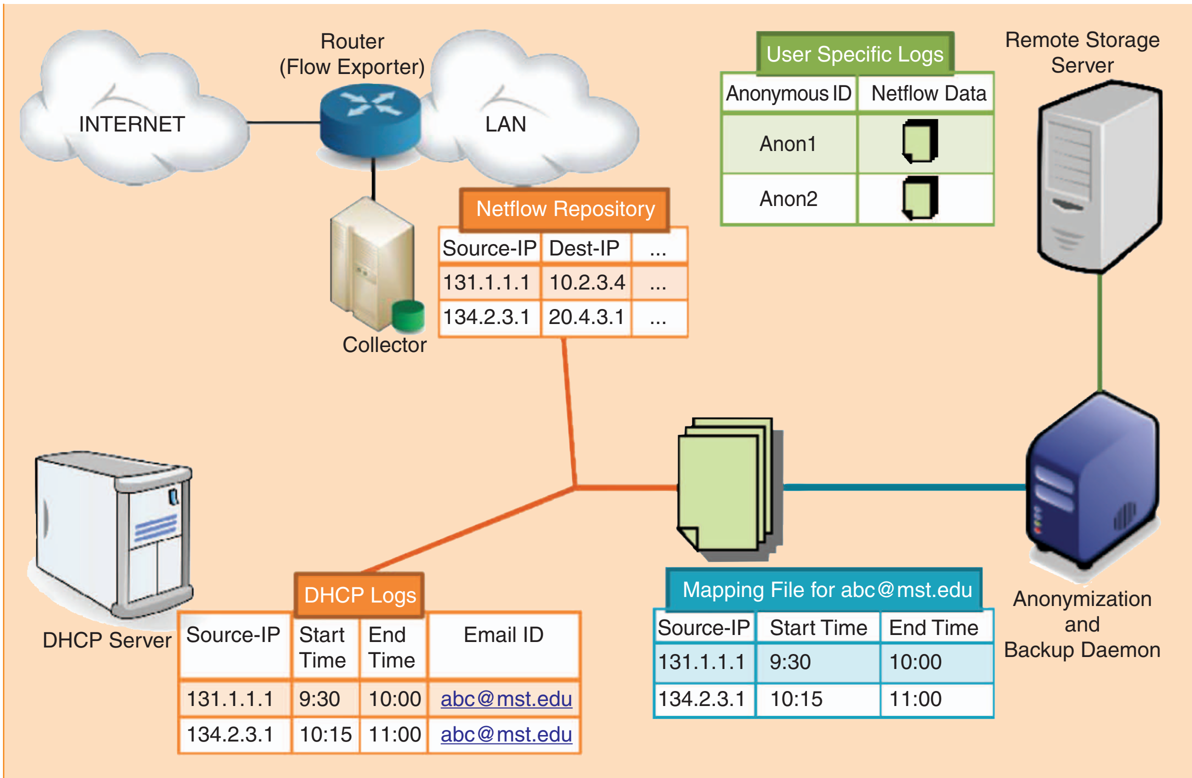

Fig. 1. Illustration of the overall NetFlow data logging process.

Table II
Sample NetFlow Data Per Participant

srcIP	dstIP	Prot	Srcp	dstp	oct	pkts	Dur
131.151.x.x	208.78.x.x	6	65055	80	1187	13	158
131.151.x.x	208.78.x.x	6	65058	80	1141	12	166
131.151.x.x	208.78.x.x	6	65042	80	402	5	67
131.151.x.x	208.78.x.x	6	65062	443	1533	9	196

discussed earlier) was delivered to the research team. In this study, the Internet data used was that collected in February 2011, the month in which the depressive symptoms of participants were surveyed.

Internet Features Extraction

A sample of NetFlow data for a single participant is shown in Table II. Each row in the table corresponds to a flow.

NetFlow data in its natural form is unsuitable for statistical analysis. In order to derive meaningful statistics, we have to preprocess NetFlow data $D=\{\mathrm{flow}_i\}_{i=1:k}$ for each participant into an N-dimensional feature vector. Also, as the number of rows associated with a participant approaches millions when aggregated over a month, preprocessing also compresses the data into manageable proportions. As the space of all possible feature vectors is large, care must be taken to extract features that are likely to associate with depressive symptoms. Inspired by related research in the psychological sciences community, we derived three broad features of Internet usage.

Aggregate Traffic Features

The simplest feature is a representation of overall aggregate traffic statistics, such as total packets, flows, and octets. Although the granularity is low, these features can be used to answer questions like: "Does more Internet usage associate with increased depressive symptoms"? In our study, aggregate flow statistics were derived using the flow-report in the flow-tools suite. Additionally, bash scripting was used to extract the data and convert it into a feature vector, one per participant. In total, 14 features were derived as summarized in Table III.

Application Level Features

Traffic aggregation alone has low granularity. For example, an aggregate of high email and low chatting may appear similar to an aggregate of low email and high chatting. Application-level statistics capture more information by sub-categorizing aggregate traffic features by application. In other words, traffic features such as flows, octets, packets, and duration are derived per application such as http, email, peer-to-peer (p2p), and chat.

A total of 61 applications were identified by filtering flows based on set combinations of destination port and destination protocol fields, as allocated by the Internet Assigned Numbers Authority

Table III
Aggregate Features

Feature	Description
flows	Total flows
oct	Total octets
pkts	Total packets
timeflows	Total time (1/1,000 s) (flows)
durreal	Duration of data (real time)
durdata	Duration of data (1/1,000 s)
aftime	Average flow time (1/1,000 s)
apsize	Average packet size (octets)
afsize	Average flow size (octets)
apflow	Average packets per flow
afsec	Average flows/s (flow)
afsecreal	Average flows/s (real)
akbits	Average kb/s (flow)
akbitsreal	Average kb/s (real)

Table IV
Categories of Application Features

Category	Applications
p2p	File-sharing applications based on peer-to-peer architecture (edonkey, neomodus, winmx)
http	HyperText Transfer Protocol applications (http, https)
streaming	Stream media applications (shoutcast, real, winmedia, stream-works, audiogalaxy)
chat	Instant messaging applications (aim, irc, carracho)
email	Email traffic (IMAP, POP3, SMTP)
ftp	File transfer applications (snmp, ftp)
gaming	Massively multiplayer online games (battlenet, quake, starseige, portzero, halflife, gamespyarcade, directx)
remote file access	Remote file system access (afs, nfs)

Table V
Internet Usage Features that Statistically Correlate with Depressive Symptoms (CES-D scores ≥16)

Internet features	Pearson	Spearman ρ	Kendall tau-b
Average packets per flow	0.056	0.137*	0.198*
p2p octets	0.173*	0.075	0.111
p2p packets	0.236**	0.106*	0.160*
p2p duration	0.265**	0.098	0.143
chat octets	0.267**	0.100	0.145
mail packets	0.164*	0.050	0.068
mail duration	0.202**	0.048	0.064
ftp duration	0.267**	0.100	0.145
remote file octets	0.281**	0.117*	0.172*

**Correlation is highly significant at 0.01 level (two-tailed)
*Correlation is significant at 0.05 level (two-tailed)

(IANA) [17]. Since NetFlow data was only logged for on-campus Internet usage, some application categories like socks, squid, and blubster, showed little or no activity. Universities tend to block such services due to security and copyright issues, and students also tend to limit such activities on campuses. In our study, 25 applications were hence retained. These applications were further grouped into eight categories, as summarized in Table IV.

Entropy Based features

Difficulty concentrating or making clear decisions is a symptom of depression among college students [27]. We capture randomness in Internet usage via Shannon Entropy (H). Intuitively, entropy estimates the average uncertainty of a series of discrete events. Given a discrete random variable X, Shannon entropy $H(X)$ is:

$$H(X) = {}_x P(x)\log(P(x)) \qquad (1)$$

where $P(x)$ is the probability that X is in state x.

In our study, we compute the Entropy for all eight fields in a NetFlow record: 1) Source IP address, 2) Destination IP address, 3) Source port, 4) Destination port, 5) Protocol, 6) Octets, 7) Packets and 8) Duration.

Results from Statistical Analysis

Statistical analysis was performed to correlate the Internet usage data collected, with CES-D scores (both collected in February 2011). For each feature derived, Pearson's, Spearman Rho, and Kendall tau-b correlation, coefficients were determined. Additionally, T-tests were attempted to identify Internet usage features that significantly differentiated participants exhibiting depressive symptoms from those that did not. The T-test assumes a normal data distribution and homogeneity of variance. Normality was verified by observing P-P plots, while Levene's test was used to assess the equality of variance. If the data deviated from a normal distribution, the non-parametric Mann-Whitney U-test was used.

Table V contains Internet usage features that correlate statistically with depressive symptoms (i.e., CES-D score ≥ 16).

Mann-Whitney U-Test Results

Mann-Whitney U-test results revealed a statistically significant difference in the mean values of average packets per flow across subjects with and without depressive symptoms ($U(216) = 2231$, $Z = -2.384$,) ρ ($2-$tailed) $= 0.017$). Subjects with depressive symptoms have higher average packets per flow ($\mu = 168.47, \sigma = 46.11$).compared to those without symptoms ($\mu = 110.91, \sigma = 14.51$).

Among application features, the Mann-Whitney U-test revealed statistically significant differences in the mean values of remote file octets across participants with and without depressive symptoms ($U(216) = 2343$, $Z = -1.989$, $\rho(2-$tailed$) = 0.047$). Participants with depressive symptoms have higher remote file octets ($\mu = 1.17 \times 10^{10}, \sigma = 1.88 \times 10^{10}$). when compared to those without symptoms ($\mu = 5.90 \times 10^{9}, \sigma = 5.97 \times 10^{9}$). Additionally, Mann-Whitney U-test results revealed significant mean value differences in internet relay chat (irc) octets ($U(216) = 2602$, $Z = -2.225$, $\rho(2-$tailed$) = 0.026$); packets ($U(216) = 2596$, $Z = -2.269$, ρ ($2-$tailed) $= 0.023$); and duration ($U(216) = 2608$, $Z = -2.182$, ρ ($2-$tailed) $= 0.029$

For the entropy based features, Mann-Whitney U-test results revealed statistically significant mean value differences for flow duration entropy across subjects with and without depressive symptoms ($U(216) = 2337.5$, $Z = -2.008$, ρ ($2-$tailed) $= 0.045$). The results are summarized in Table VI.

Interpretations and Possible Applications of Findings

***Average Packets per Flow*: The** average packets per flow is high when a large number of packets are generated per flow. Larger number of packets per flow is typical under Internet streaming and downloading, which is common when watching videos and gaming. This is intuitive so, as gaming and video watching are common symptoms of Internet addiction that have been shown to associate with depressive symptoms [18]–[20].

***Peer-to-Peer Usage*:** The correlation observed between peer-to-peer usage and depressive symptoms is also intuitive. Sharing files like music, movies, and photos are primary reasons for using peer-to-peer services. Students are notoriously drawn and possibly excessively engaged in such types of content, which may explain this trend.

Chatting: Excessive online chatting can affect the psychology of young people in terms of causing social isolation and loneliness in the real world, potentially leading to depressive symptoms [21], [22]. People with depression are also known to join "depression chat rooms" to overcome feelings of isolation. This may explain chat octets being significantly high for students with depressive symptoms.

Email: Excessive email usage identified in our study as statistically correlating with depressive symptoms is supported by studies in [22]. Frequent email checking may relate with high levels of anxiety, which in-turn correlates with depressive symptoms. It is also theorized that email addiction is a form of obsessive-compulsive disorder in the sense that victims (especially young people) suffer from a compulsive and irresistible need to check messages (often even in the middle of the night).

Flow Duration Entropy: Difficulty concentrating or making clear decisions are symptoms of depressive behavior among students [27]. When flow durations have high entropy, it is likely a result of frequent switching among multiple Internet applications, which is likely to result in highly variable flow durations, and hence high entropy. Frequent switching may also reflect an attempt to elevate feelings in the face of anhedonia, when there is desperation to find something - an interesting article, an e-mail, a pleasing video, etc., to derive a momentary spark of pleasure and elevate mood.

Table VI
Internet Usage Features with Significant Mean Value Difference Across Subjects with and Without Depressive Symptoms from Mann-Whitney U-test

Internet features	U (216)	Z	ρ (two-tailed)
Average packets per flow	2231	−2.384	0.017
Remote file octets	2343	−1.989	0.047
IRC (Chat) octets	2602	−2.225	0.026
IRC (Chat) packets	2596	−2.269	0.023
IRC (Chat) duration	2608	−2.182	0.029
Flow duration entropy	2337.5	−2.008	0.045

Ftp and Remote File Usage: It is not completely clear why ftp duration and remote file octets correlate with depressive symptoms. One interpretation could be that since excess ftp usage and remote file octets are indicative of excess file transfers, this could indicate addiction to certain types of files that may associate with depressive symptoms. In our study, we do not access the content of files exchanged, and hence we are limited in the nature of conclusions derived here. Interestingly though, ftp packets and ftp octets did not show statistically significant correlations; only the ftp duration did. Our on-going studies attempt to further explain these trends based on more discussions with counselors, clinical psychologists, and educators, and with more experiments with larger numbers of subjects.

Applications

***Investigating associations between other mental health disorders and Internet usage*:** Our methodology is general and can be used to study associations between Internet usage and other mental health disorders like anorexia, bulimia, ADHD, schizophrenia, etc. We could also investigate associations between other Internet features such as visits to social networking sites, late-night Internet use, and randomness in Internet usage times, with depressive symptoms.

Our methodology is general and can be used to study associations between Internet usage and other mental health disorders like anorexia, bulimia, ADHD, schizophrenia, etc.

Proactively discovering depressive symptoms from passive and unobtrusive Internet usage monitoring: Using the correlating Internet usage features derived in our study, we are currently investigating algorithmic techniques to proactively discover depressive symptoms among students by passive, unobtrusive, and run-time monitoring of Internet usage. To do so, we plan to conduct more large scale studies. However, there are practical concerns in terms of false positives and negatives, along with concerns regarding ethics and privacy of subjects in the realm of detection. While we believe that the techniques developed can assist in early, personalized, and (possibly) in-home mental health care, we believe that a number of stakeholders from multiple disciplines and organizations need to be involved prior to their practical deployment.

Designing Internet (or computer) based interventions for depression: There are many recent studies exploring Internet based intervention strategies for alleviating depression [28]–[30]. Our findings in this paper could yield new insights for designing and administering effective Internet-based interventions for mental disorders. Our work can also enable run-time adaptation of intervention strategies based on severity of symptoms for a subject. Furthermore, our findings will impact the evaluation of Internet-based intervention strategies. With our findings, one could easily test the efficacy of Internet-based intervention strategies by verifying corresponding changes in correlating Internet usage features identified in this study. This, we believe will positively impact the design of effective Internet-based interventions in the future.

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Acknowledgment

Partial support of the National Science Foundation, the Missouri University of Science & Technology Intelligent Systems Center, and the Mary K. Finley Missouri Endowment is gratefully acknowledged. The authors also thank Mr. Levi Malott for executing a number of scripts for Internet data processing.

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