



Profiling depression and anorexia in Social Media

David E. Losada

CiTUS USC

profiling
depression

depression

Eating
Disorders

ED
profiling

eRisk

ethics

acks

depression

common mental disorder

persistent sadness self-harm

hopelessness loss of energy

restlessness indecisiveness

loss of interest change of appetite suicide

sleeping problems worthlessness

inability to carry out daily activities

reduced concentration anxiety

guilt



key facts

300 MILLION people

ALL ages



more women than men



800k people die
due to suicide

suicide: 2nd leading cause
of death in 15-29 year-olds



**leading cause of
disability**

▼ 50% receive treatment
(in many countries ▼ 10%)



and the burden
of depression is
on the rise





Profiling depression and anorexia in Social Media

David E. Losada

CiTUS USC

profiling
depression

depression

Eating
Disorders

ED
profiling

eRisk

ethics

acks

profiling depression

online profiling
as a **complementary** tool

lack of access to qualified **assessments**
report inaccurately or **underreport** symptoms
e.g. to avoid negative consequences
(active duty soldiers, child custody evaluations)

key
components

refs

key components



text/content analysis: extraction of symptoms, detection of depression, doc search, ...



network/phone **usage** statistics



resources/data: LIWC, ontologies, discussion boards, support communities, questionnaires, ...

profiling depression - refs



construction of a
depression lexicon
(assisted by experts)



to evaluate the level of
depression in texts

harvest the web for **metaphorical relations** in which depression is embedded (e.g. "Depression is like Y")

extracts **relevant concepts** related to depression

Artificial Intelligence in Medicine 56 (2012) 19–25

Contents lists available at SciVerse ScienceDirect

 Artificial Intelligence in Medicine

journal homepage: www.elsevier.com/locate/aim

Proactive screening for depression through metaphorical and automatic text analysis

Yair Neuman^{a,*}, Yohai Cohen^{b,1}, Dan Assaf^a, Gabbi Kedma^a

^a Department of Education, Ben-Gurion University of the Negev, Beer-Sheva 84105, Israel

^b Gilasio Coding, Tel-Aviv, Israel





consultation records



semantic-based approach
extracts depressive **symptoms**
(depressed mood, suicide
ideas, anxiety, ...)



concept hierarchies, Hamilton Depression Rating Scale (HDRS)
KBs (HowNet), domain ontology



Experiments done with **PsychPark**,
a virtual psychiatric clinic maintained
by a group of volunteer professionals

Using Semantic Dependencies to Mine Depressive Symptoms from Consultation Records

Chung-Hsien Wu and Liang-Chih Yu, National Cheng Kung University

Fong-Lin Jang, Chi-Mei Medical Center

HAMILTON DEPRESSION RATING SCALE (HAM-D)
(To be administered by a health care professional)

Patient Name _____ Today's Date _____

The HAM-D is designed to rate the severity of depression in patients. Although it contains 21 items, calculate the patient's score on the first 17 items.

<input type="checkbox"/> 1. DEPRESSED MOOD (Gloomy attitude, pessimism about the future, feelings of worthlessness, tendency to weep) 0 = Absent 1 = Slight, etc. 2 = Moderate, weeping 3 = Frequent weeping 4 = Excessive weeping	<input type="checkbox"/> 6. INSOMNIA - Delayed (Having trouble getting up in the morning and feeling tired during the day) 0 = Absent 1 = Occasional 2 = Frequent
<input type="checkbox"/> 2. FEELINGS OF GUILT 0 = Absent 1 = Self-reproach, feels beside has let people down, etc. 2 = Ideas of guilt 3 = Preoccupation with a past event; delusions and fears 4 = Hallucinations of guilt	<input type="checkbox"/> 7. WORK AND INTERESTS 0 = Absent 1 = Poor appetite, fatigue, indecision and loss of interest in hobbies, decreased social activities 2 = Productivity decreased 3 = Unable to work. Stopped working because of depression 4 = Had to take time off after treatment or memory loss due to a lower score

HAMILTON DEPRESSION RATING SCALE (HAM-D)

(To be administered by a health care professional)

Patient Name _____ Today's Date _____

The HAM-D is designed to rate the severity of depression in patients. Although it contains 21 areas, calculate the patient's score on the first 17 answers.

1. DEPRESSED MOOD

(Gloomy attitude, pessimism about the future, feeling of sadness, tendency to weep)

0 = Absent

1 = Sadness, etc.

2 = Occasional weeping

3 = Frequent weeping

4 = Extreme symptoms

6. INSOMNIA - Delayed

(Waking in early hours of the morning and unable to fall asleep again)

0 = Absent

1 = Occasional

2 = Frequent

2. FEELINGS OF GUILT

0 = Absent

1 = Self-reproach, feels he/she has let people down

2 = Ideas of guilt

3 = Present illness is a punishment; delusions of guilt

4 = Hallucinations of guilt

7. WORK AND INTERESTS

0 = No difficulty

1 = Feelings of incapacity, listlessness, indecision and vacillation

2 = Loss of interest in hobbies, decreased social activities

3 = Productivity decreased

4 = Unable to work. Stopped working because of present illness only. (Absence from work after treatment or recovery may rate a lower score).



consultation records



semantic-based approach
extracts depressive **symptoms**
(depressed mood, suicide
ideas, anxiety, ...)



concept hierarchies, Hamilton Depression Rating Scale (HDRS)
KBs (HowNet), domain ontology



Experiments done with **PsychPark**,
a virtual psychiatric clinic maintained
by a group of volunteer professionals

Using Semantic Dependencies to Mine Depressive Symptoms from Consultation Records

Chung-Hsien Wu and Liang-Chih Yu, National Cheng Kung University

Fong-Lin Jang, Chi-Mei Medical Center

HAMILTON DEPRESSION RATING SCALE (HAM-D)
(To be administered by a health care professional)

Patient Name _____ Today's Date _____

The HAM-D is designed to rate the severity of depression in patients. Although it contains 21 items, calculate the patient's score over the first 17 items.

<input type="checkbox"/> 1. DEPRESSED MOOD (Gloomy attitude, pessimism about the future, feelings of worthlessness, tendency to weep) 0 = Absent 1 = Slight, etc. 2 = Moderate, weeping 3 = Frequent weeping 4 = Excessive weeping	<input type="checkbox"/> 6. INSOMNIA - Delayed (Having trouble getting up in the morning and feeling tired during the day) 0 = Absent 1 = Occasional 2 = Frequent
<input type="checkbox"/> 2. FEELINGS OF GUILT 0 = Absent 1 = Self-reproach, feels beside has let people down, etc. 2 = Ideas of guilt 3 = Preoccupation with a past event; delusions and fears 4 = Hallucinations of guilt	<input type="checkbox"/> 7. WORK AND INTERESTS 0 = Absent 1 = Poor appetite, fatigue, indecision and loss of interest in hobbies, decreased social activities 2 = Productivity decreased 3 = Unable to work. Stopped working because of depression 4 = Had to take time off after treatment or memory loss due to a lower score



search technology to assist individuals to locate docs related to their depressive problems



consultation docs
(long) query

(depressive problems & symptoms)

recommendations (suggestions & advice written by experts)



high-level **discourse** analysis
3 main discourse units: **events, symptoms & relations**



online **discussion boards** (webmd), **SA-UK** (www.social-anxiety-community.org/db), **John Tung Foundation**, www.jtf.org.tw), **email databases** (www.psychpark.org), **HDRS**



Psychiatric document retrieval using a discourse-aware model

Liang-Chih Yu^a, Chung-Hsien Wu^{b,*}, Fong-Lin Jang^c

^a Department of Information Management, Yuan-Ze University, Chung-Li, Taiwan, ROC

^b Department of Computer Science and Information Engineering, National Cheng Kung University, Tainan, Taiwan, ROC

^c Department of Psychiatry, Chi-Mei Medical Center, Tainan, Taiwan, ROC



tweet classification

strongly concerning possibly concerning safe to ignore

text classification:
SVM/Logistic Regression
unigrams + freq-based features

training data: extracted tweets using **pre-defined phrases**
and the retrieved tweets were **coded by humans**

classifier performance: **80%**

some individuals broadcast their suicidality on SM
suicide prevention tool?



Detecting suicidality on Twitter

Bridianne O'Dea ^{a,*}, Stephen Wan ^b, Philip J. Batterham ^c, Alison L. Calear ^c, Cecile Paris ^b, Helen Christensen ^a

^a Black Dog Institute, The University of New South Wales, Hospital Road, Randwick, NSW 2031, Australia

^b Commonwealth Scientific and Industrial Research Organisation (CSIRO) Information and Communication Technology Centre, Corner of Vittoria and Pembroke Roads, Marsfield, NSW 2122, Australia

^c National Institute for Mental Health Research, Building 63, The Australian National University, Canberra ACT 2601, Australia





publicly available
profile updates



seeking for
traces of depression



manual coders review histories of status updates
according to established clinical criteria
Diagnostic and Statistical Manual (DSM)



users categorized according to DSM

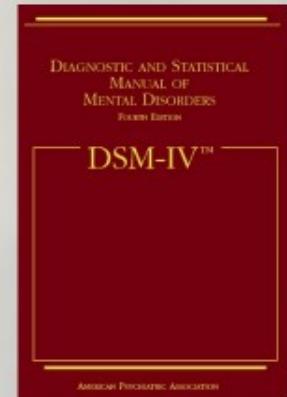


relationship between **depression on profile**
and **age, graduation year, gender, relationship status,**
facebook activity, ...

Research Article

FEELING BAD ON FACEBOOK: DEPRESSION DISCLOSURES BY COLLEGE STUDENTS ON A SOCIAL NETWORKING SITE

Megan A. Moreno, M.D. M.S.Ed. M.P.H.,^{1*} Lauren A. Jelenchick, B.S.,¹ Katie G. Egan,¹
Elizabeth Cox, M.D. Ph.D.,¹ Henry Young, Ph.D.,² Kerry E. Gannon, B.S.,¹ and Tara Becker, Ph.D.¹



DIAGNOSTIC AND STATISTICAL
MANUAL OF
MENTAL DISORDERS
FOURTH EDITION

DSM-IV™



publicly available
profile updates



seeking for
traces of depression



manual coders review histories of status updates
according to established clinical criteria
Diagnostic and Statistical Manual (DSM)



users categorized according to DSM

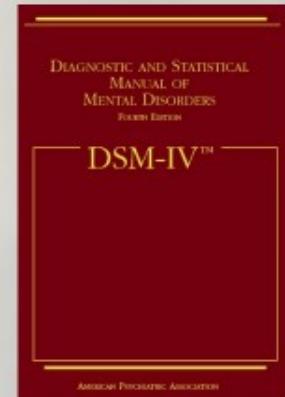


relationship between **depression on profile**
and **age, graduation year, gender, relationship status,**
facebook activity, ...

Research Article

FEELING BAD ON FACEBOOK: DEPRESSION DISCLOSURES BY COLLEGE STUDENTS ON A SOCIAL NETWORKING SITE

Megan A. Moreno, M.D. M.S.Ed. M.P.H.,^{1*} Lauren A. Jelenchick, B.S.,¹ Katie G. Egan,¹
Elizabeth Cox, M.D. Ph.D.,¹ Henry Young, Ph.D.,² Kerry E. Gannon, B.S.,¹ and Tara Becker, Ph.D.¹





publicly available profile updates



seeking for traces of depression



manual coders review according to established

Diagnostic and Statistical Manual (DSM)



users categorized according to DSM



relationship between **depression on profile** and **age, graduation year, gender, relationship status, facebook activity, ...**

Major Depression Episodes (MDE): symptoms

depressed mood, loss of interest/pleasure in activities, appetite changes, sleep problems, psychomotor agitation/retardation, energy loss, feeling worthless or guilty, decreased concentration or suicidal ideation.

5 or more of these symptoms during the same 2 week period

at least one must be depressed mood or lost of interest/pleasure

ON SOCIAL

Egan,¹
cker, Ph.D.¹





publicly available
profile updates



seeking for
traces of depression



manual coders review histories of status updates
according to established clinical criteria
Diagnostic and Statistical Manual (DSM)



users categorized according to DSM

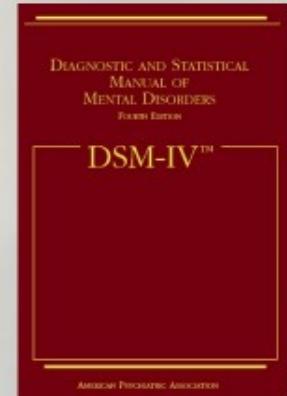


relationship between **depression on profile**
and **age, graduation year, gender, relationship status,**
facebook activity, ...

Research Article

FEELING BAD ON FACEBOOK: DEPRESSION DISCLOSURES BY COLLEGE STUDENTS ON A SOCIAL NETWORKING SITE

Megan A. Moreno, M.D. M.S.Ed. M.P.H.,^{1*} Lauren A. Jelenchick, B.S.,¹ Katie G. Egan,¹
Elizabeth Cox, M.D. Ph.D.,¹ Henry Young, Ph.D.,² Kerry E. Gannon, B.S.,¹ and Tara Becker, Ph.D.¹



depression bipolar disorder

seasonal affective disorder (SAD)

post-traumatic stress disorder (PTSD)

automatically identifying
 **self-expressions of mental illness diagnoses**
e.g. "I was diagnosed with X."

 statistical **classifiers** to distinguish each group from a control group

 different types of **features** (LIWC, n-grams, ...)

 open-vocabulary analysis: **language use** relevant to **mental health**

Computational Linguistics and Clinical Psychology

Workshop at ACL 2014, 27 June 2014

Quantifying Mental Health Signals in Twitter

Glen Coppersmith Mark Dredze Craig Harman

Human Language Technology Center of Excellence

Johns Hopkins University

Baltimore, MD, USA



crowdsourcing

- AMT turkers: asked to take a standard **clinical depression survey**
- Beck Depression Inventory (BDI)

? followed by **self-reported info** and got the turkers' Twitter usernames!

measures of depressive behaviour (engagement, emotion, linguistic style, depression language, activity, ...)

classification powered by different types of features (emotion from LIWC, time, linguistic style, n-grams, user engagement and ego-network)



Predicting Depression via Social Media

Munmun De Choudhury

Michael Gamon

Scott Counts

Eric Horvitz

Microsoft Research, Redmond WA 98052

{mumnumd, mgamon, counts, horvitz}@microsoft.com



Beck's Depression Inventory

This depression inventory can be self-scored. The scoring scale is at the end of the questionnaire.

1.

- 0 I do not feel sad.
- 1 I feel sad
- 2 I am sad all the time and I can't snap out of it.
- 3 I am so sad and unhappy that I can't stand it.

2.

- 0 I am not particularly discouraged about the future.
- 1 I feel discouraged about the future.
- 2 I feel I have nothing to look forward to.
- 3 I feel the future is hopeless and that things cannot improve.

3.

- 0 I do not feel like a failure.
- 1 I feel I have failed more than the average person.
- 2 As I look back on my life, all I can see is a lot of failures.
- 3 I feel I am a complete failure as a person.

4.

- 0 I get as much satisfaction out of things as I used to.
- 1 I don't enjoy things the way I used to.
- 2 I don't get real satisfaction out of anything anymore.
- 3 I am dissatisfied or bored with everything.

5.

- 0 I don't feel particularly guilty
- 1 I feel guilty a good part of the time.
- 2 I feel quite guilty most of the time.
- 3 I feel guilty all of the time.

6.

- 0 I don't feel I am being punished.
- 1 I feel I may be punished.
- 2 I expect to be punished.
- 3 I feel I am being punished.

7.

- 0 I don't feel disappointed in myself

ty, ...)



crowdsourcing

- AMT turkers: asked to take a standard **clinical depression survey**
- Beck Depression Inventory (BDI)

? followed by **self-reported info** and got the turkers' Twitter usernames!

measures of depressive behaviour (engagement, emotion, linguistic style, depression language, activity, ...)

classification powered by different types of features (emotion from LIWC, time, linguistic style, n-grams, user engagement and ego-network)



Predicting Depression via Social Media

Munmun De Choudhury

Michael Gamon

Scott Counts

Eric Horvitz

Microsoft Research, Redmond WA 98052

{mummund, mgamon, counts, horvitz}@microsoft.com





crowdsourcing

- AMT turkers: asked standard **clinical** Beck Depression

*Whether or not they had been diagnosed with clinical depression in the past. If so, when.
If they were clinically depressed, what was the estimated time of its onset.
If they are currently depressed, or using any anti-depression medications.*



ion via Social Media

Munmun De Choudhury

Michael Gamon

Scott Counts

Eric Horvitz

Microsoft Research, Redmond WA 98052

{mumnumd, mgamon, counts, horvitz}@microsoft.com

? followed by **self-reported info** and got the turkers' Twitter usernames!

measures of depressive behaviour (engagement, emotion, linguistic style, depression language, activity, ...)

classification powered by different types of features (emotion from LIWC, time, linguistic style, n-grams, user engagement and ego-network)





crowdsourcing

- AMT turkers: asked to take a standard **clinical depression survey**
- Beck Depression Inventory (BDI)

? followed by **self-reported info** and got the turkers' Twitter usernames!

measures of depressive behaviour (engagement, emotion, linguistic style, depression language, activity, ...)

classification powered by different types of features (emotion from LIWC, time, linguistic style, n-grams, user engagement and ego-network)



Predicting Depression via Social Media

Munmun De Choudhury

Michael Gamon

Scott Counts

Eric Horvitz

Microsoft Research, Redmond WA 98052

{mumnumd, mgamon, counts, horvitz}@microsoft.com

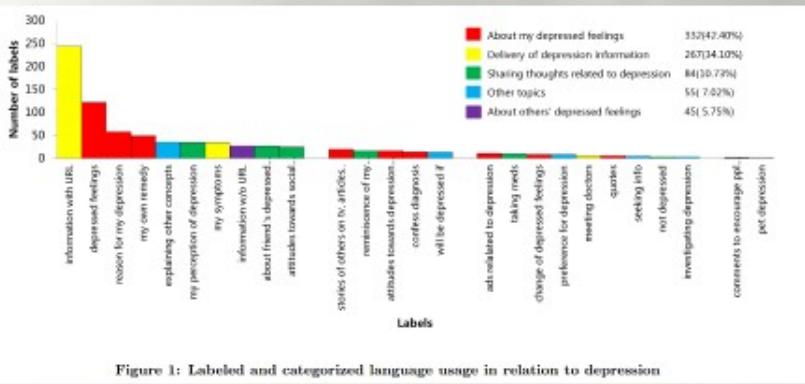


ACM SIGKDD Workshop on Health Informatics (HI-KDD 2012) - August 12, 2012



sample of tweets
about depression

categorization of tweets:



Depressive Moods of Users Portrayed in Twitter

Minsu Park
KAIST
373-1 Guseondong
Deajeon, Korea
mansumansu@kaist.ac.kr

Chiyoung Cha
Ewha Womans University
82-2 Daehyeon-dong
Seoul, Korea
chiyoung@ewha.ac.kr

Meeyoung Cha
KAIST
373-1 Guseondong
Deajeon, Korea
meeyoungcha@kaist.ac.kr



also performed a **screening test**
(69 young adults):

- surveying users (self-judged depression level, CES-D test)
- collecting tweets of the same users
- comparing depression levels vs sentiments & language

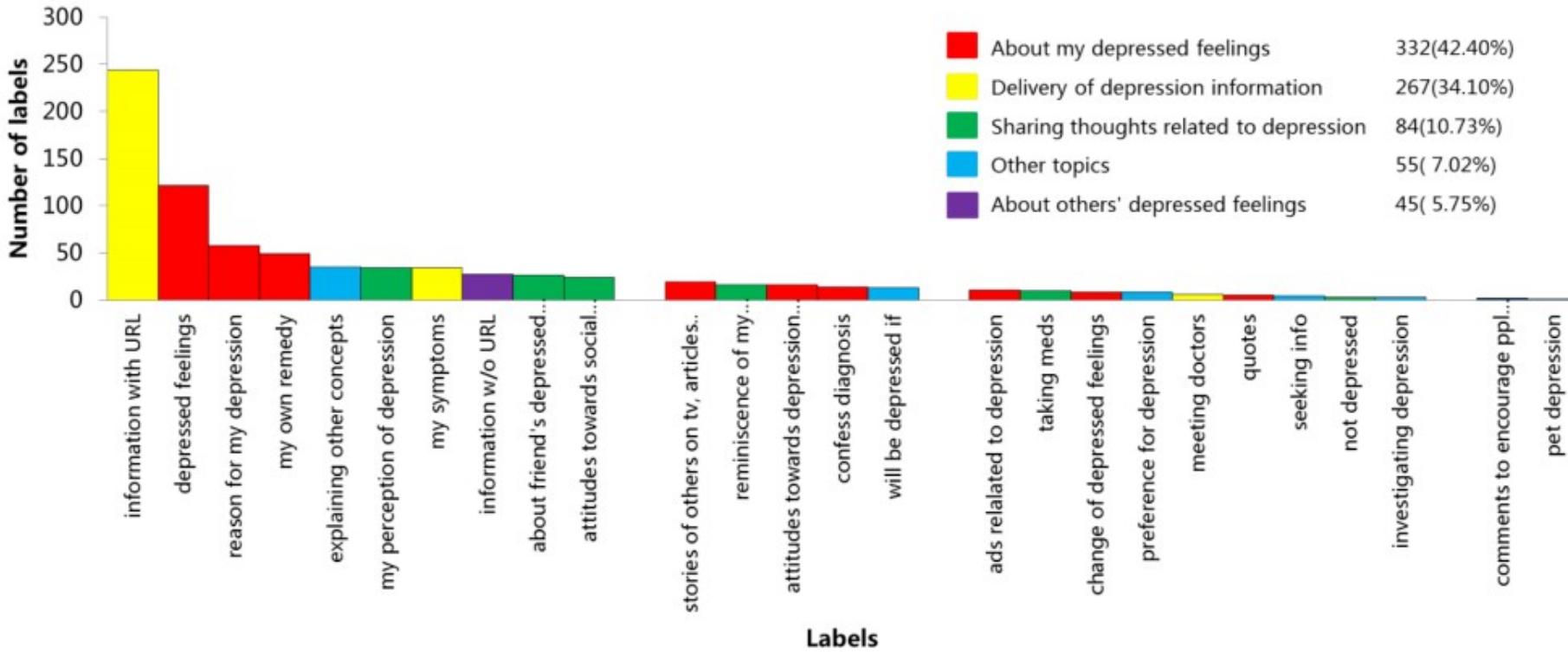
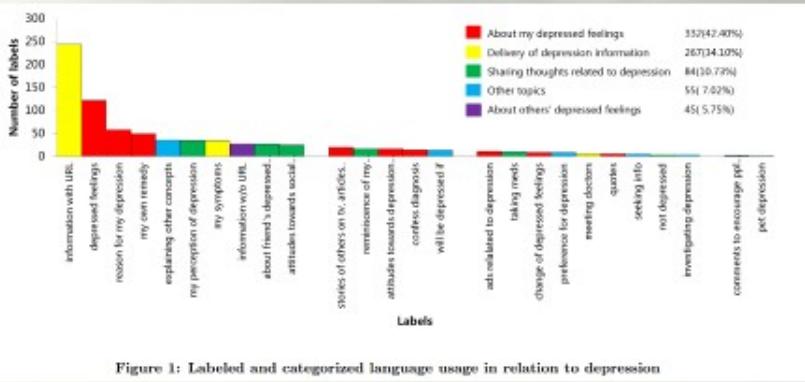


Figure 1: Labeled and categorized language usage in relation to depression



sample of tweets about depression

categorization of tweets:



ACM SIGKDD Workshop on Health Informatics (HI-KDD 2012) - August 12, 2012

Depressive Moods of Users Portrayed in Twitter

Minsu Park
KAIST
373-1 Guseondong
Deajeon, Korea
mansumansu@kaist.ac.kr

Chiyoung Cha
Ewha Womans University
82-2 Daehyeon-dong
Seoul, Korea
chiyoung@ewha.ac.kr

Meeyoung Cha
KAIST
373-1 Guseondong
Deajeon, Korea
meeyoungcha@kaist.ac.kr



also performed a **screening test**
(69 young adults):

- ✓ surveying users (self-judged depression level, CES-D test)
- 🐦 collecting tweets of the same users
- ⌚ comparing depression levels vs sentiments & language



sample of tweets about depression

categorization of tweets:

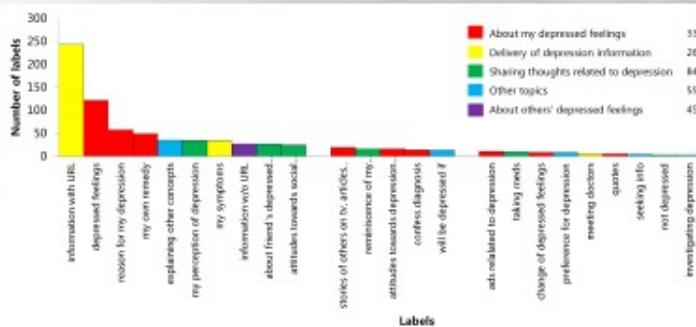


Figure 1: Labeled and categorized language usage in relation to depression

CESD-R

The Center for Epidemiologic Studies Depression Scale Revised

Welcome to the CESD-R

The CESD-R is a screening test for depression and depressive disorder. The CESD-R measures symptoms defined by the American Psychiatric Association's Diagnostic and Statistical Manual (DSM-V) for a major depressive episode.

At the top of each of the following screens, you will see a statement. For each statement, please indicate how often you have felt this way recently by selecting the option you most agree with.



Start the CESD-R

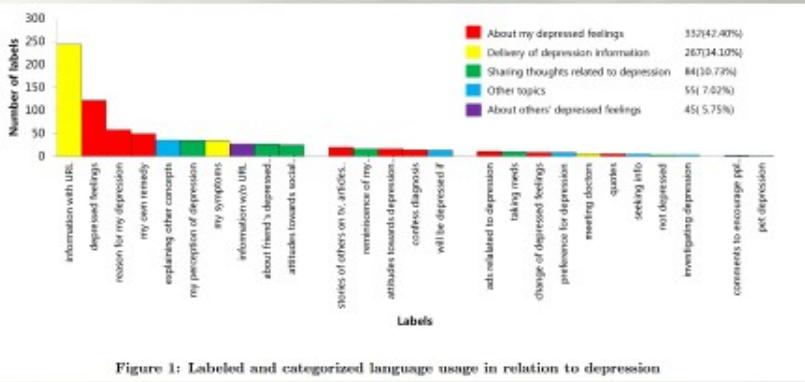


collecting tweets of the same users
comparing depression levels vs sentiments & language



sample of tweets about depression

categorization of tweets:



ACM SIGKDD Workshop on Health Informatics (HI-KDD 2012) - August 12, 2012

Depressive Moods of Users Portrayed in Twitter

Minsu Park
KAIST
373-1 Guseondong
Deajeon, Korea
mansumansu@kaist.ac.kr

Chiyoung Cha
Ewha Womans University
82-2 Daehyeon-dong
Seoul, Korea
chiyoung@ewha.ac.kr

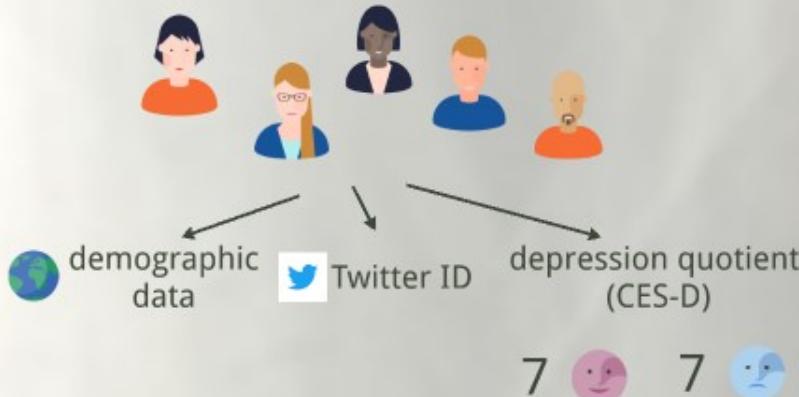
Meeyoung Cha
KAIST
373-1 Guseondong
Deajeon, Korea
meeyoungcha@kaist.ac.kr



also performed a **screening test**
(69 young adults):

- surveying users (self-judged depression level, CES-D test)
- collecting tweets of the same users
- comparing depression levels vs sentiments & language

recruited participants (**screening survey**)



Perception Differences between the Depressed and Non-Depressed Users in Twitter

demographic data

Twitter ID

depression quotient
(CES-D)

personal **interviews** (e.g. at cafe's)
participants' experiences with SM
experience with depression

Minsu Park
KAIST
mansumansu@kaist.ac.kr

David W. McDonald
University of Washington
dwmc@uw.edu

Meeyoung Cha
KAIST
meeyoungcha@kaist.ac.kr

- coded the (recorded) interviews according to different **themes**
- also got and analysed tweets from the participants' **friends**



216 **college** students



CES-D questionnaires



30% met min. criteria
for **depression**



network data (campus)
usage statistics
contents not recorded!



studied increment of internet usage, avg packets per user,
p2p statistics, and compares them among groups

Associating Internet Usage with Depressive Behavior Among College Students

RAGHAVENDRA KOTIKALAPUDI, SRIRAM CHELLAPPAN,
FRANCES MONTGOMERY, DONALD WUNSCH, AND KARL LUTZEN

Digital Object Identifier 10.1109/MTS.2012.2225462

Date of publication: 19 December 2012

IEEE TECHNOLOGY AND SOCIETY MAGAZINE | WINTER 2012

1932-4529/12/\$31.00 ©2012 IEEE

| 73





216 college students



CES-D questionnaire

flows, packets,
octets, durations,
protocols (chats, p2p, email,...)



30% met min.
for depression



network data (on campus)
usage statistics
contents not recorded!



studied increment of internet usage, avg packets per user,
p2p statistics, and compares them among groups

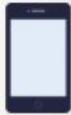
Rating Usagepressive for Among College Students

RAGHAVENDRA KOTIKALAPUDI, SRIRAM CHELLAPPAN,
FRANCES MONTGOMERY, DONALD WUNSCH, AND KARL LUTZEN

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

IEEE TECHNOLOGY AND SOCIETY MAGAZINE | WINTER 2012

1932-4529/12/\$31.00 ©2012 IEEE



user's phone data



Patient Health
Questionnaire-9



Original Paper

Mobile Phone Sensor Correlates of Depressive Symptom Severity in Daily-Life Behavior: An Exploratory Study

Sohrab Saeb^{1,2}, PhD; Mi Zhang³, PhD; Christopher J Karr¹, MA; Stephen M Schueller¹, PhD; Marya E Corden¹, MPH; Konrad P Kording², PhD; David C Mohr¹, PhD

¹Center for Behavioral Intervention Technologies, Department of Preventive Medicine, Northwestern University, Chicago, IL, United States

²Rehabilitation Institute of Chicago, Department of Physical Medicine and Rehabilitation, Northwestern University, Chicago, IL, United States

³Department of Electrical and Computer Engineering, Michigan State University, East Lansing, MI, United States



physical context-motion, variability of **location**, variability of **time**, home **stay**, social **settings**, phone **usage** (e.g. screen state)



depressed users

visited **fewer locations**, spent **more time at home**, **moved less** through geographic space, had **greater phone usage** duration and frequency

PATIENT HEALTH QUESTIONNAIRE-9 (PHQ-9)

Over the last 2 weeks, how often have you been bothered
by any of the following problems?
(Use "✓" to indicate your answer)

	Not at all	Several days	More than half the days	Nearly every day
1. Little interest or pleasure in doing things	0	1	2	3
2. Feeling down, depressed, or hopeless	0	1	2	3
3. Trouble falling or staying asleep, or sleeping too much	0	1	2	3
4. Feeling tired or having little energy	0	1	2	3
5. Poor appetite or overeating	0	1	2	3
6. Feeling bad about yourself — or that you are a failure or have let yourself or your family down	0	1	2	3
7. Trouble concentrating on things, such as reading the newspaper or watching television	0	1	2	3
8. Moving or speaking so slowly that other people could have noticed? Or the opposite — being so fidgety or restless that you have been moving around a lot more than usual	0	1	2	3
9. Thoughts that you would be better off dead or of hurting yourself in some way	0	1	2	3

For office coding 0 + + +
=Total Score: _____

If you checked off any problems, how difficult have these problems made it for you to do your
work, take care of things at home, or get along with other people?

Not difficult
at all

Somewhat
difficult

Very
difficult

Extremely
difficult

Sohrab Saeed
Konrad P K

¹Center for Be

²Rehabilitation

³Department o



user's phone data



Patient Health
Questionnaire-9



Original Paper

Mobile Phone Sensor Correlates of Depressive Symptom Severity in Daily-Life Behavior: An Exploratory Study

Sohrab Saeb^{1,2}, PhD; Mi Zhang³, PhD; Christopher J Karr¹, MA; Stephen M Schueller¹, PhD; Marya E Corden¹, MPH; Konrad P Kording², PhD; David C Mohr¹, PhD

¹Center for Behavioral Intervention Technologies, Department of Preventive Medicine, Northwestern University, Chicago, IL, United States

²Rehabilitation Institute of Chicago, Department of Physical Medicine and Rehabilitation, Northwestern University, Chicago, IL, United States

³Department of Electrical and Computer Engineering, Michigan State University, East Lansing, MI, United States



physical context-motion, variability of **location**, variability of **time**, home **stay**, social **settings**, phone **usage** (e.g. screen state)



depressed users

visited **fewer locations**, spent **more time at home**, **moved less** through geographic space, had **greater phone usage** duration and frequency



essays by college students

-  currently-depressed
 -  formerly-depressed
 -  never-depressed

Linguistic Inquiry and Word Count (LIWC)

depressed participants:

- ▲ negatively valenced words, **neg emotions**
 - ▲ 1st person singular (I,me,my)
(think a great deal about **themselves**)
 - slightly more positive emotions than never-depressed

Language use of depressed and depression-vulnerable college students

Stephanie S. Rude, Eva-Maria Gortner, and James W. Pennebaker

University of Texas at Austin, USA

Journal of Business Ethics

Each of the default LIWC2015 categories is composed of a list of dictionary words that define that scale. Table 1 provides a comprehensive list of the default LIWC2015 dictionary categories, scales, sample scale words, and relevant scale word counts.

Table 1. LIWC2015 Output Variable Information

Category	Abbrev	Examples	Words in category	Internal Consistency (Uncorrected α)	Internal Consistency (Corrected α)
Word count	WC	-	-	-	-
Summary Language Variables					
Analytical thinking	Analytic	-	-	-	-
Cloud	Cloud	-	-	-	-
Authentic	Authentic	-	-	-	-
Emotional tone	Tone	-	-	-	-
Words/sentence	WPS	-	-	-	-
Words > 6 letters	Sixltr	-	-	-	-
Dictionary words	Die	-	-	-	-
Linguistic Dimensions					
Total function words	funct	it, to, no, very	491	.85	.24
Total pronouns	pronoun	I, them, itself	153	.25	.67
Personal pronouns	ppron	I, them, her	93	.20	.61
1st pers singular	i	I, me, mine	24	.41	.81
1st pers plural	we	we, us, our	12	.43	.82
2nd person	you	you, your, thou	30	.28	.70
3rd pers singular	she/he	she, her, him	17	.49	.85
3rd pers plural	they	they, their, they'd	11	.37	.78
Impersonal pronouns	ipron	it, it's, those	59	.28	.71
Articles	article	a, an, the	3	.05	.23
Prepositions	prep	to, with, above	74	.04	.18
Auxiliary verbs	auxverb	am, will, have	141	.16	.54
Common Adverbs	adverb	very, really	140	.43	.82
Conjunctions	conj	and, but, whereas	43	.14	.50
Negations	negate	no, not, never	62	.29	.71
Other Grammar					
Common verbs	verb	eat, come, carry	1000	.05	.23
Common adjectives	adj	free, happy, long	764	.04	.19
Comparisons	compare	greater, best, after	317	.08	.35
Interrogatives	interrog	how, when, what	48	.18	.57
Numbers	number	second, thousand	36	.45	.83
Quantifiers	quant	few, many, much	77	.23	.64
Psychological Processes					
Affective processes	affect	happy, cried	1393	.18	.57
Positive emotion	posemo	love, nice, sweet	620	.23	.64
Negative emotion	negemo	hurt, ugly, nasty	744	.17	.55
Anxiety	anx	worried, fearful	116	.31	.73
Anger	anger	hate, kill, annoyed	230	.16	.53
Sadness	sad	crying, grief, sad	136	.28	.70
Social processes	social	mite, talk, they	756	.51	.86
Family	family	daughter, dad, aunt	118	.55	.88

Category	Abbrev	Examples	Words in category	Internal Consistency (Uncorrected α)	Internal Consistency (Corrected α)
Friends	friend	buddy, neighbor	95	.20	.60
Female references	female	girl, her, mom	124	.53	.87
Male references	male	boy, his, dad	116	.52	.87
Cognitive processes	cogproc	cause, know, ought	797	.65	.92
Insight	insight	think, know	259	.47	.84
Causation	cause	because, effect	125	.26	.67
Discrepancy	discrep	should, would	83	.34	.76
Tentative	tentat	maybe, perhaps	178	.44	.83
Certainty	certain	always, never	113	.31	.73
Differentiation	differ	haven't, but, else	81	.38	.78
Perceptual processes	percept	look, heard, feeling	436	.17	.55
See	see	view, saw, seen	126	.46	.84
Hear	hear	listen, hearing	93	.27	.69
Feel	feel	feels, touch	128	.24	.65
Biological processes	bio	eat, blood, pain	748	.29	.71
Body	body	cheek, hands, spit	215	.52	.87
Health	health	clinic, flu, pill	294	.09	.37
Sexual	sexual	horny, love, incest	131	.37	.78
Ingestion	ingest	dish, eat, pizza	184	.67	.92
Drives	drives	drives	1103	.39	.80
Affiliation	affiliation	ally, friend, social	248	.40	.80
Achievement	achieve	win, success, better	213	.41	.81
Power	power	superior, bully	518	.35	.76
Reward	reward	take, prize, benefit	120	.27	.69
Risk	risk	danger, doubt	103	.26	.68
Time orientations	TimeOrient				
Past focus	pastfocus	ago, did, talked	341	.23	.64
Present focus	presentfocus	today, is, now	424	.24	.66
Future focus	futurefocus	may, will, soon	97	.26	.68
Relativity	relative	area, bend, exit	974	.50	.86
Motion	motion	arrive, car, go	325	.36	.77
Space	space	down, in, thin	360	.45	.83
Time	time	end, until, season	310	.39	.79
Personal concerns					
Work	work	job, majors, xerox	444	.69	.93
Leisure	leisure	cook, chat, movie	296	.50	.86
Home	home	kitchen, landlord	100	.46	.83
Money	money	audit, cash, owe	226	.60	.90
Religion	relig	altar, church	174	.64	.91
Death	death	bury, coffin, kill	74	.39	.79
Informal language	informal		380	.46	.84
Swear words	swear	fuck, damn, shit	131	.45	.83
Netspeak	netspeak	btw, lol, thx	209	.42	.82
Assent	assent	agree, OK, yes	36	.10	.39
Nonfluencies	nonflu	er, hm, umm	19	.27	.69
Fillers	filler	Imean, youknow	14	.06	.27



essays by college students

-  currently-depressed
 -  formerly-depressed
 -  never-depressed

Linguistic Inquiry and Word Count (LIWC)

depressed participants:

- ▲ negatively valenced words, **neg emotions**
 - ▲ 1st person singular (I,me,my)
(think a great deal about **themselves**)
 - slightly more positive emotions than never-depressed

Language use of depressed and depression-vulnerable college students

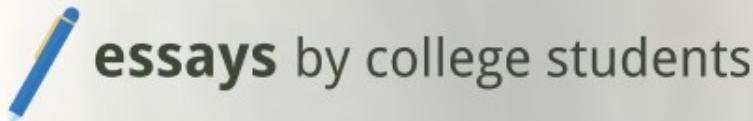
Stephanie S. Rude, Eva-Maria Gortner, and James W. Pennebaker

University of Texas at Austin, USA

Journal of Knowledge Management

Table 1. LAMP-PCR Assay for <i>Salmonella</i> Enterica				
Category	Method	Target	Sample	Sample Size (μL)
Sample Preparation				
	Homogenization			
	Sample dilution			
	Sample extraction			
	Sample concentration			
	Sample storage			
	Sample transport			
	Sample processing			
	Sample preparation			
Primer Design				
	Primer design			
	Primer synthesis			
	Primer storage			
	Primer concentration			
	Primer dilution			
	Primer storage			
Reagent Preparation				
	Master mix			
	Master mix storage			
	Master mix dilution			
	Master mix storage			
Instrumentation				
	Thermal cycler			
	Thermal cycler storage			
	Thermal cycler dilution			
	Thermal cycler storage			
Assay				
	Assay setup			
	Assay storage			
	Assay dilution			
	Assay storage			
Postassay				
	Postassay storage			
	Postassay dilution			
	Postassay storage			

Page 4



essays by college students



BDI score



Linguistic Inquiry and Word Count (**LIWC**)
and Latent Dirichlet Allocation (**LDA**) features

Qualitative analysis: LDA extracts **topics**
whose associated **words** are themes
related to **depression**

Using Topic Modeling to Improve Prediction of Neuroticism and Depression in College Students

Philip Resnik

University of Maryland
College Park, MD 20742
resnik@umd.edu

Anderson Garron

University of Maryland
College Park, MD 20742
agarron@cs.umd.edu

Rebecca Resnik

Mindwell Psychology Bethesda
5602 Shields Drive
Bethesda, MD 20817
drrebeccaresnik@gmail.com

Detecting depression and mental illness on social media: an integrative review

Sharath Chandra Guntuku¹, David B Yaden¹, Margaret L Kern²,
Lyle H Ungar¹ and Johannes C Eichstaedt¹



¹University of Pennsylvania, Philadelphia, PA, United States

²The University of Melbourne, Melbourne, Australia

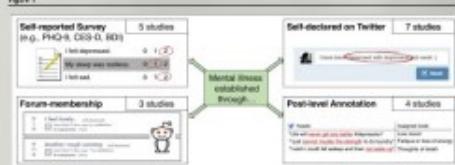
Current Opinion in Behavioral Sciences 2017, 18:43–49

104 • JUNE 2006 • THE DOCTOR'S OFFICE BUSINESS

Predictive distributions induced by different model linear models examined in this study. The largest dataset, $n = 100$, is used.

ACU uses the Reuse-on-Operating Characteristics (ROC) Curve, Precision-Recall (Precision vs. Recall) Plot for the positive. Accuracy of class prediction is based on ROC-AUC metric. Sustained Vector Machine (SVM) Process Component Analysis (PCA) - RECALL Rate Function:
• RECALL with 95% True Positives
• Within example (not cross-validation)
• Using true features as input of the classifier are harder measures by the inter-related Persons by Term Pair (SPT) entry in the SGD-W-R Personnel

100



Rate survey used in studies on measurement of health or individual income. These studies "The number of enclaves selected for analysis in the present site is 1000 sites. The mean community size, self-reported according to sampling strategy for depression measure the PHQ-4 (Patient Health Questionnaire) 1000 (1000 x 1000 = 100 000). 100 000 / 1000 = 100 sites. EXPRESSION: NUMBER OF SITES, BEZ / 1000. SOURCE: INSTITUT MÉTROPOLE 2013.

Journal of Health Politics, Policy and Law, Vol. 34, No. 4, December 2009
DOI 10.1215/03616878-34-4 © 2009 by The University of Chicago

World Health Organization | Geneva, Switzerland

principle, for saturated I_{EL} and more sharply than through the polarization of surfaces (see Fig. 1). For example, tensile strength increased by about 10% at generally provided a higher degree of yielding I_{EL}. We find complete studies that compare the elongations of I_{EL} from monolithic materials. Figures 2 and 3 (Table 1) summarize the mechanical characteristics of the samples.

Prediction based on response

Prognostic self-report outcome measures often reflect a high degree of validity and reliability (eg. see [11]). In psychological and epidemiological research, self-report scores are second most in clinical usefulness, which is said to make it a useful tool in decision making [12]. However, few studies that predict subsequent depression rates find significant participants' responses to depression surveys in comparison with their actual medical data.

However, some scholars have argued that depression may be a chronic condition [13]. For example, high levels under the HADS (Home and Hospital Depression and Anxiety Scale) of depression at baseline were associated with a significant increase in self-reported symptoms of depression over time [14].

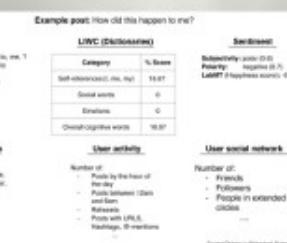
The most cited study used Takiue unitary to examine network and language data preceding a recent episode of depression [67]. The presence of depression was established through participants reporting the occurrence and

scale, combined with water strategy. Studies Depression Inventory of Beck's Depression Inventory revealed several dimensions of depression, including distorted cognitions, low self-esteem, and cognitive-related losses during depression course.

over depressive and post-ESRD status from year and model a repeated first episode of depression with sufficiently long lagging. Characteristics of depression and 290 ESRD subjects, which were similar on all variables, and modeled as logistic patterns that differentiated

d depression from Twitter using the CED II as their source from the most recent instantiation of the CED II using Aggression, aggression

10



Digitized by srujanika@gmail.com

Table 1

Prediction performances achieved by different mental illness studies reviewed in this paper. The relevant dataset, features, and prediction settings are provided.

Ref.	Year	Dataset			Section	Mental Illness Criteria	Features (predictors)					Outcome Type	Model	Metric	Performance	
		Platform	N (users)	Cases (conditions; base rate [BR])			Programs	LINWC	Sentiment	Topics	Metadata	Others				
[8]	2013	Twitter	476	Depression = 171 (BR = 36%)	A	survey (CESD + BDI)		Y	Y		Y	Social Network	Binary	PCA, SVM w/ RBF Kernel	Accuracy	.72
[13]	2014	Facebook	165	Post-partum Depression = 28 (BR = 17%)	A	survey (PHQ-9)		Y	Y		Y	User Activity, Social Capital	Binary	Logistic Regression	pseudo-R2 ^b	.36
[14]	2014	Facebook	28,749	(continuous Depression score)	A	survey (Personality)	Y	Y		Y			Continuous	Ridge Regression	Correlation	.38
[12]	2015	Twitter	209	Depression = 81 (BR = 39%)	A	survey (CESD)	Y	Y	Y	Y	Y	User Activity	Binary	SVM	Accuracy	.69
[11]	2016	Twitter	378	Depression = 105 (BR = 28%) PTSD = 63 (BR = 17%)	A	survey (CESD)		Y	Y		Y	Time-Series, LaBMT	Binary	Random Forests	AUC	Depression = .87 PTSD = .89
[40]	2014	Twitter	5,972	PTSD = 244 (BR = 4%)	B	self-declared	Y	Y					Binary	(not reported)	ROC	(AUC not reported)
[42]	2014	Twitter	21,866	11,866 (across 4 Conditions, BR = 54%)	B	self-declared	Y	Y	Y		Y	User Activity	Binary	Log linear classifier	Precision ^a	Depression = .48 Bipolar = .64 PTSD = .67 SAD = .42
[17]	2015	Twitter	1,957	Depression = 483 (BR = 25%) PTSD = 370 (BR = 19%)	B	self-declared	Y	Y	Y	Y		Age, Gender, Personality	Binary	Logistic Regression	AUC	Depression = .85 PTSD = .91
[21]	2015	Twitter	4,026	2,013 (across 10 Conditions, BR = 50%)	B	self-declared	Y	Y					Binary	(not reported)	Precision ^a	Depression = .48 Bipolar = .63 Anxiety = .85 Eating Dis. = .76
[41]	2016	Twitter	250	Suicide Attempt = 125 (BR = 50%)	B	self-declared	Y		Y		Y	User Activity	Binary	(not reported)	Precision ^a	.70
[43]	2016	Twitter	900	Depression = 326 (BR = 36%)	B	self-declared	Y						Binary	Naïve Bayes	AUC	.70
[19]	2017	Twitter	9,611	4820 (across 8 Conditions, BR = 50%)	B	self-declared	Y					Gender	Multi-Task	Neural Network	AUC	Depression = .76 Bipolar = .75 Depression = .76 Suicide Attempt = .83

AUC: Area Under the Receiver Operating Characteristic (ROC) Curve; Precision: fraction of cases ruled positive that are truly positive; Accuracy: fraction of cases that are correctly labeled by the model; SVM: Support Vector Machines; PCA: Principal Component Analysis; RBF – Radial Basis Function.

^aPrecision with 10% False Alarms.

^bWithin-sample (not cross-validated).

^cUsing the Depression facet of the Neuroticism factor measured by the International Personality Item Pool (IPIP) proxy to the NEO-PI-R Personality Inventory [38].

Studies highlighted in green report AUCs; AUCs are not base rate dependent and can be compared across studies.

Detecting depression and mental illness on social media: an integrative review

Sharath Chandra Guntuku¹, David B Yaden¹, Margaret L Kern²,
Lyle H Ungar¹ and Johannes C Eichstaedt¹



¹University of Pennsylvania, Philadelphia, PA, United States

²The University of Melbourne, Melbourne, Australia

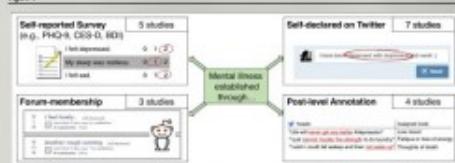
Current Opinion in Behavioral Sciences 2017, 18:43–49

104 • JUNE 2006 • THE DOCTOR'S OFFICE BUSINESS

Predictive distributions induced by different model linear models examined in this study. The largest dataset, $n = 100$, is used.

Using the [Journals](#) or [List of the Periodicals](#) you can find resources by the title indicated. Periodicals by Term [List](#) ([SPSSyntax](#)) in the [M&D-W-R Periodicals](#).

100



Rate survey used in studies on measurement of health or individual income. These studies "The number of enclaves selected for analysis in the present site is 1000 sites. The mean community size, self-reported according to sampling strategy for depression measure the PHQ-4 (Patient Health Questionnaire) 1000 (1000 x 1000 = 100 000). 100 000 / 1000 = 100 sites. EXPRESSION: NUMBER OF SITES, BEZ / 1000. SOURCE: INSTITUT MÉTROPOLE 2013.

Journal of Health Politics, Policy and Law, Vol. 34, No. 4, December 2009
DOI 10.1215/03616878-34-4 © 2009 by The University of Chicago

World Health Organization on behalf of the Global Health Sector

principle, for saturated I_{EL} and more sharply than through the polarization of surfaces (see Fig. 1). For example, tensile strength increased by about 10% at generally provided a higher degree of yielding I_{EL}. We find complete studies that compare the elongations of I_{EL} from monolithic materials. Figures 2 and 3 (Table 1) summarize the mechanical characteristics

Prediction based on response

Prognostic self-report outcome measures often reflect a high degree of validity and reliability (eg. see [11]). In psychological and epidemiological research, self-report scores are second most in clinical usefulness, which is said to make it a useful tool in decision making [12]. However, few studies that predict subsequent depression rates find significant participants' responses to depression surveys in comparison with their actual medical data.

However, some scholars have argued that depression may be a chronic condition [13]. For example, high levels under the BDI-II (Beck Depression Inventory-II) of depression have been suggested to be performed independently of clinical symptoms of actual health by long periods of time.

The most cited study used Takiue unitary to examine network and language data preceding a recent episode of depression [67]. The presence of depression was established through participants reporting the occurrence and

wide, combined with severe single, Subacute Depression and Beck's Depression Inventory revealed several distinctions and areas, including: distorted self, lack social interaction, and depression-influenced living depression cases.

over depressive and post-TMD states from 1991 and model a repeated first episode of musculoskeletal pain. Using the Diagnostic Classification of Mental Disorders and 29 ICD-10 codes, which were selected by us, and modeled as logistic processes that differentiated

of depression from Twitter using the CED II as their source from the most recent iteration of the CED II using Aggression, glorification

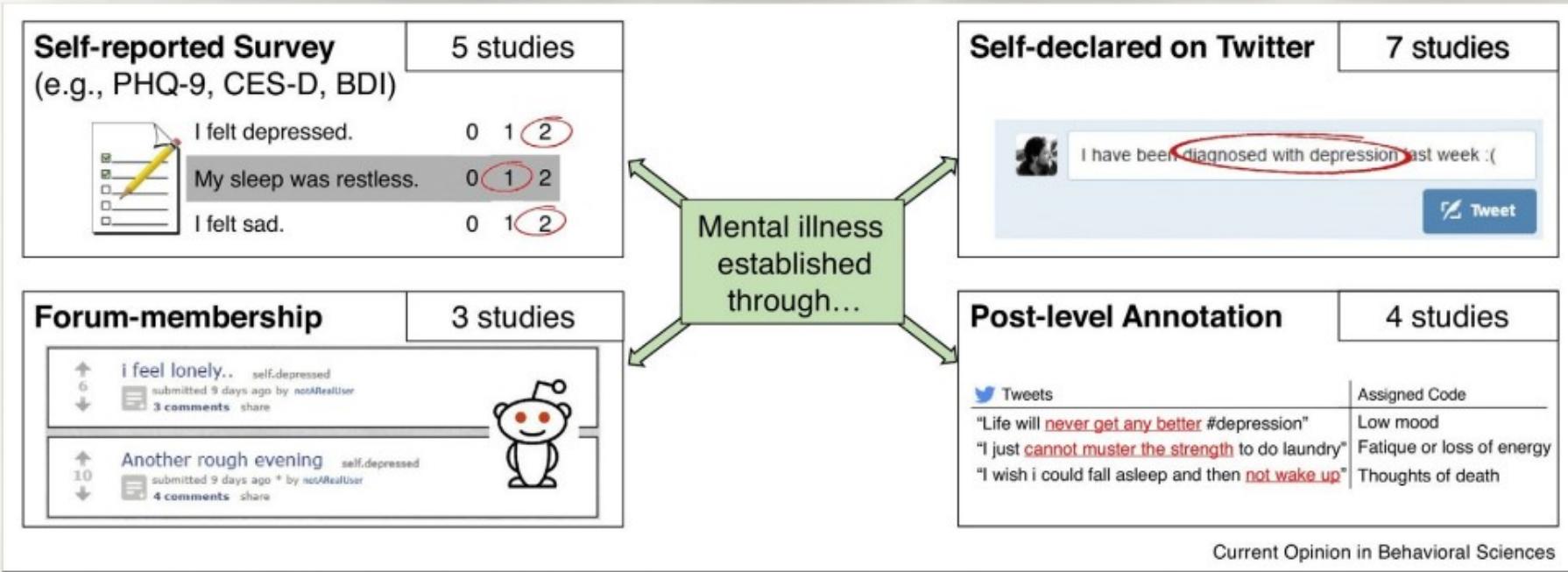
10



strengths of children included in the different studies are summarized in Table 3. Levels of risk factors and preventive health care, as well as the

Digitized by srujanika@gmail.com

Figure 1



Data sources used in studies as assessment criteria to establish mental illness status. The number of studies selected for review in the present article is provided. The most commonly used self-reported screening surveys for depression include the PHQ-9 = Patient Health Questionnaire [7], CES-D = Centers for Epidemiological Studies Depression Scale Revised [9], BDI = Beck Depression Inventory [10].

Detecting depression and mental illness on social media: an integrative review

Sharath Chandra Guntuku¹, David B Yaden¹, Margaret L Kern²,
Lyle H Ungar¹ and Johannes C Eichstaedt¹



¹University of Pennsylvania, Philadelphia, PA, United States

²The University of Melbourne, Melbourne, Australia

Current Opinion in Behavioral Sciences 2017, 18:43–49

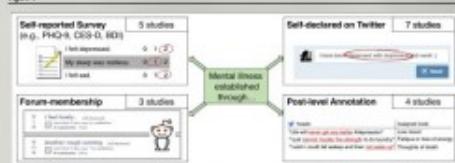
104 • JUNE 2006 • THE DOCTOR'S OFFICE BUSINESS

Predictive performance attributed to different model terms studies examined in this paper. The second column contains the

Ref	Var	Series	Status	One-time/Recurrent	Start Date	End Date	Performance			Release Date	Total	Units	Performance
							Actual	Target	Variance				
10-100	Phase	Phase A	Completed	One-time	2023-01-01	2023-01-31	100	100	0	2023-01-31	100	100	100%
10-101	Phase	Phase B	Completed	One-time	2023-02-01	2023-02-28	100	100	0	2023-02-28	100	100	100%
10-102	Phase	Phase C	Completed	One-time	2023-03-01	2023-03-31	100	100	0	2023-03-31	100	100	100%
10-103	Phase	Phase D	Completed	One-time	2023-04-01	2023-04-30	100	100	0	2023-04-30	100	100	100%
10-104	Phase	Phase E	Completed	One-time	2023-05-01	2023-05-31	100	100	0	2023-05-31	100	100	100%
10-105	Phase	Phase F	Completed	One-time	2023-06-01	2023-06-30	100	100	0	2023-06-30	100	100	100%
10-106	Phase	Phase G	Completed	One-time	2023-07-01	2023-07-31	100	100	0	2023-07-31	100	100	100%
10-107	Phase	Phase H	Completed	One-time	2023-08-01	2023-08-31	100	100	0	2023-08-31	100	100	100%
10-108	Phase	Phase I	Completed	One-time	2023-09-01	2023-09-30	100	100	0	2023-09-30	100	100	100%
10-109	Phase	Phase J	Completed	One-time	2023-10-01	2023-10-31	100	100	0	2023-10-31	100	100	100%
10-110	Phase	Phase K	Completed	One-time	2023-11-01	2023-11-30	100	100	0	2023-11-30	100	100	100%
10-111	Phase	Phase L	Completed	One-time	2023-12-01	2023-12-31	100	100	0	2023-12-31	100	100	100%
10-112	Phase	Phase M	Completed	One-time	2024-01-01	2024-01-31	100	100	0	2024-01-31	100	100	100%
10-113	Phase	Phase N	Completed	One-time	2024-02-01	2024-02-29	100	100	0	2024-02-29	100	100	100%
10-114	Phase	Phase O	Completed	One-time	2024-03-01	2024-03-31	100	100	0	2024-03-31	100	100	100%
10-115	Phase	Phase P	Completed	One-time	2024-04-01	2024-04-30	100	100	0	2024-04-30	100	100	100%
10-116	Phase	Phase Q	Completed	One-time	2024-05-01	2024-05-31	100	100	0	2024-05-31	100	100	100%
10-117	Phase	Phase R	Completed	One-time	2024-06-01	2024-06-30	100	100	0	2024-06-30	100	100	100%
10-118	Phase	Phase S	Completed	One-time	2024-07-01	2024-07-31	100	100	0	2024-07-31	100	100	100%
10-119	Phase	Phase T	Completed	One-time	2024-08-01	2024-08-31	100	100	0	2024-08-31	100	100	100%
10-120	Phase	Phase U	Completed	One-time	2024-09-01	2024-09-30	100	100	0	2024-09-30	100	100	100%
10-121	Phase	Phase V	Completed	One-time	2024-10-01	2024-10-31	100	100	0	2024-10-31	100	100	100%
10-122	Phase	Phase W	Completed	One-time	2024-11-01	2024-11-30	100	100	0	2024-11-30	100	100	100%
10-123	Phase	Phase X	Completed	One-time	2024-12-01	2024-12-31	100	100	0	2024-12-31	100	100	100%
10-124	Phase	Phase Y	Completed	One-time	2025-01-01	2025-01-31	100	100	0	2025-01-31	100	100	100%
10-125	Phase	Phase Z	Completed	One-time	2025-02-01	2025-02-28	100	100	0	2025-02-28	100	100	100%
10-126	Phase	Phase AA	Completed	One-time	2025-03-01	2025-03-31	100	100	0	2025-03-31	100	100	100%
10-127	Phase	Phase BB	Completed	One-time	2025-04-01	2025-04-30	100	100	0	2025-04-30	100	100	100%
10-128	Phase	Phase CC	Completed	One-time	2025-05-01	2025-05-31	100	100	0	2025-05-31	100	100	100%
10-129	Phase	Phase DD	Completed	One-time	2025-06-01	2025-06-30	100	100	0	2025-06-30	100	100	100%
10-130	Phase	Phase EE	Completed	One-time	2025-07-01	2025-07-31	100	100	0	2025-07-31	100	100	100%
10-131	Phase	Phase FF	Completed	One-time	2025-08-01	2025-08-31	100	100	0	2025-08-31	100	100	100%
10-132	Phase	Phase GG	Completed	One-time	2025-09-01	2025-09-30	100	100	0	2025-09-30	100	100	100%
10-133	Phase	Phase HH	Completed	One-time	2025-10-01	2025-10-31	100	100	0	2025-10-31	100	100	100%
10-134	Phase	Phase II	Completed	One-time	2025-11-01	2025-11-30	100	100	0	2025-11-30	100	100	100%
10-135	Phase	Phase JJ	Completed	One-time	2025-12-01	2025-12-31	100	100	0	2025-12-31	100	100	100%
10-136	Phase	Phase KK	Completed	One-time	2026-01-01	2026-01-31	100	100	0	2026-01-31	100	100	100%
10-137	Phase	Phase LL	Completed	One-time	2026-02-01	2026-02-28	100	100	0	2026-02-28	100	100	100%
10-138	Phase	Phase MM	Completed	One-time	2026-03-01	2026-03-31	100	100	0	2026-03-31	100	100	100%
10-139	Phase	Phase NN	Completed	One-time	2026-04-01	2026-04-30	100	100	0	2026-04-30	100	100	100%
10-140	Phase	Phase OO	Completed	One-time	2026-05-01	2026-05-31	100	100	0	2026-05-31	100	100	100%
10-141	Phase	Phase PP	Completed	One-time	2026-06-01	2026-06-30	100	100	0	2026-06-30	100	100	100%
10-142	Phase	Phase QQ	Completed	One-time	2026-07-01	2026-07-31	100	100	0	2026-07-31	100	100	100%
10-143	Phase	Phase RR	Completed	One-time	2026-08-01	2026-08-31	100	100	0	2026-08-31	100	100	100%
10-144	Phase	Phase SS	Completed	One-time	2026-09-01	2026-09-30	100	100	0	2026-09-30	100	100	100%
10-145	Phase	Phase TT	Completed	One-time	2026-10-01	2026-10-31	100	100	0	2026-10-31	100	100	100%
10-146	Phase	Phase UU	Completed	One-time	2026-11-01	2026-11-30	100	100	0	2026-11-30	100	100	100%
10-147	Phase	Phase VV	Completed	One-time	2026-12-01	2026-12-31	100	100	0	2026-12-31	100	100	100%
10-148	Phase	Phase WW	Completed	One-time	2027-01-01	2027-01-31	100	100	0	2027-01-31	100	100	100%
10-149	Phase	Phase XX	Completed	One-time	2027-02-01	2027-02-28	100	100	0	2027-02-28	100	100	100%
10-150	Phase	Phase YY	Completed	One-time	2027-03-01	2027-03-31	100	100	0	2027-03-31	100	100	100%
10-151	Phase	Phase ZZ	Completed	One-time	2027-04-01	2027-04-30	100	100	0	2027-04-30	100	100	100%
10-152	Phase	Phase AAA	Completed	One-time	2027-05-01	2027-05-31	100	100	0	2027-05-31	100	100	100%
10-153	Phase	Phase BBB	Completed	One-time	2027-06-01	2027-06-30	100	100	0	2027-06-30	100	100	100%
10-154	Phase	Phase CCC	Completed	One-time	2027-07-01	2027-07-31	100	100	0	2027-07-31	100	100	100%
10-155	Phase	Phase DDD	Completed	One-time	2027-08-01	2027-08-31	100	100	0	2027-08-31	100	100	100%
10-156	Phase	Phase EEE	Completed	One-time	2027-09-01	2027-09-30	100	100	0	2027-09-30	100	100	100%
10-157	Phase	Phase FFF	Completed	One-time	2027-10-01	2027-10-31	100	100	0	2027-10-31	100	100	100%
10-158	Phase	Phase GGG	Completed	One-time	2027-11-01	2027-11-30	100	100	0	2027-11-30	100	100	100%
10-159	Phase	Phase HHH	Completed	One-time	2027-12-01	2027-12-31	100	100	0	2027-12-31	100	100	100%
10-160	Phase	Phase III	Completed	One-time	2028-01-01	2028-01-31	100	100	0	2028-01-31	100	100	100%
10-161	Phase	Phase JJJ	Completed	One-time	2028-02-01	2028-02-28	100	100	0	2028-02-28	100	100	100%
10-162	Phase	Phase KKK	Completed	One-time	2028-03-01	2028-03-31	100	100	0	2028-03-31	100	100	100%
10-163	Phase	Phase LLL	Completed	One-time	2028-04-01	2028-04-30	100	100	0	2028-04-30	100	100	100%
10-164	Phase	Phase MMM	Completed	One-time	2028-05-01	2028-05-31	100	100	0	2028-05-31	100	100	100%
10-165	Phase	Phase NNN	Completed	One-time	2028-06-01	2028-06-30	100	100	0	2028-06-30	100	100	100%
10-166	Phase	Phase OOO	Completed	One-time	2028-07-01	2028-07-31	100	100	0	2028-07-31	100	100	100%
10-167	Phase	Phase PPP	Completed	One-time	2028-08-01	2028-08-31	100	100	0	2028-08-31	100	100	100%
10-168	Phase	Phase QQQ	Completed	One-time	2028-09-01	2028-09-30	100	100	0	2028-09-30	100	100	100%
10-169	Phase	Phase RRR	Completed	One-time	2028-10-01	2028-10-31	100	100	0	2028-10-31	100	100	100%
10-170	Phase	Phase SSS	Completed	One-time	2028-11-01	2028-11-30	100	100	0	2028-11-30	100	100	100%
10-171	Phase	Phase TTT	Completed	One-time	2028-12-01	2028-12-31	100	100	0	2028-12-31	100	100	100%
10-172	Phase	Phase UUU	Completed	One-time	2029-01-01	2029-01-31	100	100	0	2029-01-31	100	100	100%
10-173	Phase	Phase VVV	Completed	One-time	2029-02-01	2029-02-28	100	100	0	2029-02-28	100	100	100%
10-174	Phase	Phase WWW	Completed	One-time	2029-03-01	2029-03-31	100	100	0	2029-03-31	100	100	100%
10-175	Phase	Phase XXX	Completed	One-time	2029-04-01	2029-04-30	100	100	0	2029-04-30	100	100	100%
10-176	Phase	Phase YYY	Completed	One-time	2029-05-01	2029-05-31	100	100	0	2029-05-31	100	100	100%
10-177	Phase	Phase ZZZ	Completed	One-time	2029-06-01	2029-06-30	100	100	0	2029-06-30	100	100	100%
10-178	Phase	Phase AAAA	Completed	One-time	2029-07-01	2029-07-31	100	100	0	2029-07-31	100	100	100%
10-179	Phase	Phase BBBB	Completed	One-time	2029-08-01	2029-08-31	100	100	0	2029-08-31	100	100	100%
10-180	Phase	Phase CCCC	Completed	One-time	2029-09-01	2029-09-30	100	100	0	2029-09-30	100	100	100%
10-181	Phase	Phase DDDD	Completed	One-time	2029-10-01	2029-10-31	100	100	0	2029-10-31	100	100	100%
10-182	Phase	Phase EEEE	Completed	One-time	2029-11-01	2029-11-30	100	100	0	2029-11-30	100	100	100%
10-183	Phase	Phase FFFF	Completed	One-time	2029-12-01	2029-12-31	100	100	0	2029-12-31	100	100	100%
10-184	Phase	Phase GGGG	Completed	One-time	2030-01-01	2030-01-31	100	100	0	2030-01-31	100	100	100%
10-185	Phase	Phase HHHH	Completed	One-time	2030-02-01	2030-02-28	100	100	0	2030-02-28	100	100	100%
10-186	Phase	Phase IIII	Completed	One-time	2030-03-01	2030-03-31	100	100	0	2030-03-31	100	100	100%
10-187	Phase	Phase JJJJ	Completed	One-time	2030-04-01	2030-04-30	100	100	0	2030-04-30	100	100	100%
10-188	Phase	Phase KKKK	Completed</td										

AUC: Area Under the Receiver Operating Characteristic (ROC) Curve; Prevalence: Proportion of cases to total positive; True Positive: Proportion of cases to total positive. Assessed at 10% case prevalence (corresponding to the mean). Sens: Sensitivity; Spec: Specificity; ROC: Receiver Operating Characteristic Analysis; HR: Hazard Ratio.

100



Rate survey used in studies on measurement of health or individual income. These studies "The number of enclaves selected for analysis in the present site is 1000 sites. The mean community size, self-reported according to sampling strategy for depression measure the PHQ-4 (Patient Health Questionnaire) 1000 (1000 x 1000 = 100 000). 100 000 / 1000 = 100 sites. EXPRESSION: NUMBER OF SITES, BEZ / 1000. SOURCE: INSTITUT MÉTROPOLE 2013.

Journal of Health Politics, Policy and Law, Vol. 34, No. 4, December 2009
DOI 10.1215/03616878-34-4 © 2009 by the Southern Political Science Association

World Health Organization, Geneva, Switzerland

principles, by enhanced tissue and muscle shear through the administration of steroids (see Table 1). At a single tissue, though increased movement between articular providers provides a higher degree of stability (Fig. 1).

Prediction based on survey responses
 Psychotherapy self-report measures the mental illness having a high degree of validity and sensitivity (e.g., see EIT). In psychological and epidemiological research, self-report surveys are second choice in clinical outcomes, which are usually mostly study to date have used as an outcome measure. My findings from studies that predict survey-assessed depression status by collecting participants' responses to depression surveys in comparison with their medical records.

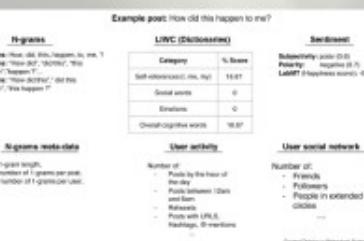
The main aim of this study was to examine network and language data preceding a recent episode of depression [67]. The presence of depression was evaluated through participants reporting the occurrence and

data of a depressive episode, combined with scores on Center for Epidemiologic Studies Depression Index (CES-D) and Beck's Depression Inventory (BDI-II). This study revealed several distressing activities by depressed wives, including: desired more negative emotions, low social interaction, self-care, and watching television-related items about the year preceding depressive events.

et al. [11] predicted mean degeneration and progressive dementia (PDD) rates from 2002 and 2006 data that generated a reported first episode rate [3] for the Example Operating Characteristic curve (EOC) of 97 degenerations and 90 PDDs, were aggregated to weeks, which consider one week aggregation of days, and modeled as logistic functions of activity patterns that differentiated 4 from manually driven.

one of [11] predicted depression from Trinitrophenol in Japanese sample, using the CERH II as their main criterion. Using scores from the more recent criteria preceding the administration of the CERH-II, it appears that recognizing depression, particularly

10



Examples of studies included in the different body's core reference in FIGURE 1, LNUC (2015), EEA (2015), EEA and WHO (2015), EEA, WHO, and

Digitized by srujanika@gmail.com

Figure 2

Example post: How did this happen to me?		
N-grams	LIWC (Dictionaries)	Sentiment
1-grams: How, did, this, happen, to, me, ?		
2-grams: "How did", "did this", "this happen", "happen ?"...		
3-grams: "How did this", "did this happen", "this happen ?"		
...		
N-grams meta-data		
Avg. 1-gram length,	Number of:	
Avg. number of 1-grams per post,	- Posts by the hour of	
Total number of 1-grams per user,	the day	
...	- Posts between 12am	
	and 6am	
	- Retweets	
	- Posts with URLs,	
	Hashtags, @-mentions	
	...	
User activity		
		Number of:
		- Friends
		- Followers
		- People in extended
		circles
	
		Current Opinion in Behavioral Sciences

Examples of features included in the different feature sets referenced in Table 1. LIWC: Linguistic Inquiry and Word Count [20], LabMT: Language Assessment by Mechanical Turk [39].

Detecting depression and mental illness on social media: an integrative review

Sharath Chandra Guntuku¹, David B Yaden¹, Margaret L Kern²,
Lyle H Ungar¹ and Johannes C Eichstaedt¹



¹University of Pennsylvania, Philadelphia, PA, United States

²The University of Melbourne, Melbourne, Australia

Current Opinion in Behavioral Sciences 2017, 18:43–49

104 • JUNE 2006 • THE DOCTOR'S OFFICE BUSINESS

Predictive distributions induced by different model linear models examined in this study. The largest dataset, $n = 100$, is used.

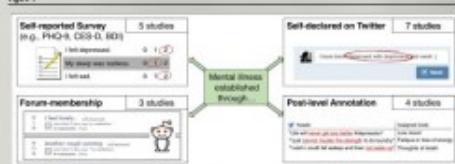
AICD Area Under the Receiver Operating Characteristic (ROC) Curve; Predictor fraction of cases tested positive that are truly positive. Assessor's test of case-control (100% vs 40%) ROC model fit. Support vector machine (SVM); Support Vector Machine (SVM); Complement Analysis (CA) – ROC area test statistic.

*Prediction with 100% Rule of Adj-Hat

**Using 100% ROC curve test statistic

***Using 100% ROC curve test statistic

10



Rate survey used in studies on measurement of health or individual income. These studies "The number of enclaves selected for analysis in the present site is 1000 sites. The mean community size, self-reported according to sampling strategy for depression measure the PHQ-4 (Patient Health Questionnaire) 1000 (1000 x 1000 = 100 000). 100 000 / 1000 = 100 sites. EXPRESSION: NUMBER OF SITES, BEZ / 1000. SOURCE: INSTITUT MÉTROPOLE 2013.

Journal of Health Politics, Policy and Law, Vol. 34, No. 4, December 2009
DOI 10.1215/03616878-34-4 © 2009 by the Southern Political Science Association

World Health Organization | Geneva, Switzerland | 2010

principle, for saturated I_{EL} and more sharply than through the polarization of surfaces (see Fig. 1). For example, tensile strength increased by about 10% at generally provided a higher degree of yielding I_{EL}. We find complete studies that compare the elongations of I_{EL} from monolithic materials. Figures 2 and 3 (Table 1) summarize the mechanical characteristics

Prediction based on response

Prognostic self-report outcome measures often reflect a high degree of validity and reliability (eg. see [11]). In psychological and epidemiological research, self-report scores are second most in clinical usefulness, which is said to make it a useful tool in decision making [12]. However, few studies that predict subsequent depression rates find significant participants' responses to depression surveys in comparison with their actual medical data.

However, some scholars have argued that depression may be a chronic condition [13]. For example, high levels under the BDI-II (Beck Depression Inventory-II) of depression have been suggested to be performed independently of clinical symptoms of actual health by some scholars.

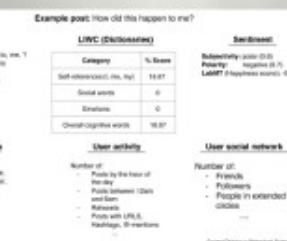
The most cited study used Takiue unitary to examine network and language data preceding a recent episode of depression [67]. The presence of depression was established through participants reporting the occurrence and

scale, combined with water strategy. Studies Depression Inventory of Beck's Depression Inventory revealed several dimensions of depression, including distorted cognitions, low self-esteem, and cognitive-related losses during depression course.

over depressive and post-ESRD status from year and model a repeated first episode of depression with sufficiently long lagging. Characteristics of depression and 290 ESRD subjects, which were similar on all variables, and modeled as logistic patterns that differentiated

d depression from Twitter using the CED II as their source from the most recent instantiation of the CED II using Aggression, aggression

10



Digitized by srujanika@gmail.com



Profiling depression and anorexia in Social Media

David E. Losada

CiTUS USC

profiling
depression

depression

Eating
Disorders

ED
profiling

eRisk

ethics

acks

eating disorders (ED)

complex mental disorders

responsible for the **highest mortality rate** among mental illnesses

"Pro-ana"

refers to individuals with an ED disorder
who focus on having an ED as a **lifestyle choice**
as opposed to a psychiatric disorder

"Thinspiration"

desire to be thin

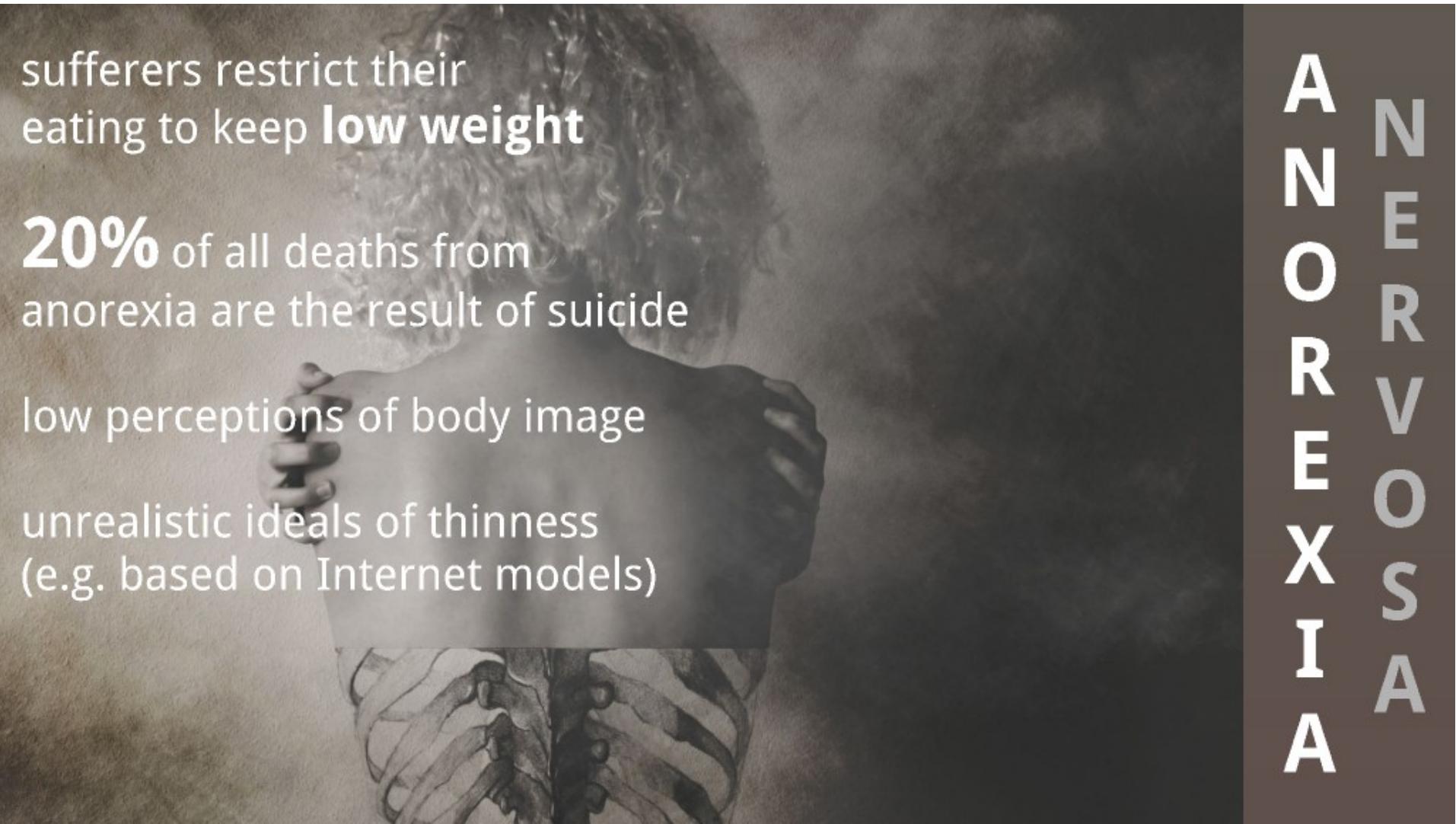
anorexia
nervosa

bulimia
nervosa

symptoms &
prevalence

clinical
studies

ANOREXIA



sufferers restrict their eating to keep **low weight**

20% of all deaths from anorexia are the result of suicide

low perceptions of body image

unrealistic ideals of thinness
(e.g. based on Internet models)

Bulimia nervosa

repeated
cycles of
binge
eating
and
purgung



eating disorders symptoms

extreme behavioural/emotional
responses to eating food & gaining weight

self-starvation

laxative abuse

anxiety

depression

prevalence of ED has significantly grown

The costs of eating disorders

Social, health and
economic impacts

Assessing the impact of
eating disorders across the
UK on behalf of BEAT.

February 2015



*Assessing the impact of
eating disorders across the
UK on behalf of BEAT.*

February 2015



prevalence of ED has significantly grown

The costs of eating disorders

Social, health and
economic impacts

Assessing the impact of
eating disorders across the
UK on behalf of BEAT.

February 2015



prevalence of ED has significantly grown

The costs of eating disorders

Social, health and economic impacts

Assessing the impact of eating disorders across the UK on behalf of BEAT.

February 2015



There are increasing numbers of reported cases of eating disorders in the UK

Separately from prevalence data research involving GP data in the UK indicates an increase in the age-standardised annual incidence of all diagnosed eating disorders (ages 10-49) from 32.2 to 37.2 per 100,000 between 2000 and 2008. This increase appears to be the result of an increase in the unspecified eating disorders category, an AN and BN quarters combined (see table).

Separately, as outlined in Table 2.3, time series analysis of data on the total number of cases of eating disorders being diagnosed in England illustrates a further steady increasing prevalence over time with a 34% increase in admissions since 2009/10 – approximately 7% per annum.

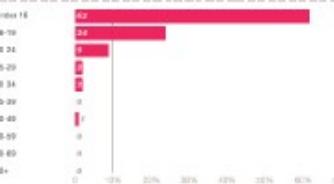
This recorded change may reflect increases in the understanding of eating disorders especially the lesser known disorders and particularly binge eating disorder which has only recently been acknowledged in statistical recording¹¹.

Our survey indicates that eating disorders most commonly initially present amongst the young, and national data indicates that they can also start later in life and can be life-long conditions

Table 2.3
Count of PHEs and primary care agency cases of eating disorders in England, 2009-2014

Count of Primary care agencies (PCAs) where the primary diagnosis was an eating disorder (England)	
2009-2010	1,952
2010-2011	1,804
2011-2012	1,812
2012-2013	2,004
2013-2014	2,177
2014-2015	2,334

Figure 3.1
Age when symptoms of an eating disorder first出现



¹⁰Wiles, M., Hughes, A.M., Pearson, L. and Tressler, J.L. (2013). The incidence of eating disorders in the UK: 2008-2009. Report from the General Practice Research Database. BMJ Open, 3, e003496 [Epub ahead of print]. Available at: <http://bmjopen.bmjjournals.com/content/3/6/e003496.full.html>

¹¹American Psychiatric Association. (2013). Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition. Washington, DC: American Psychiatric Publishing.

There are increasing numbers of reported cases of eating disorders in the UK

Separately from prevalence data research involving GP data in the UK indicates an increase in the age-standardised annual incidence of all diagnosed eating disorders (for ages 10-49) from 32.3 to 37.2 per 100,000 between 2000 and 2009. This increase appears to be due to an increase in the unspecified eating disorder category as AN and BN numbers remained fairly stable³³.

Separately, as outlined in Table 3.3, time series analysis of data on the total number of cases of eating disorders being diagnosed in England illustrates a similar trend in increasing prevalence over time with a 34% increase in admissions since 2005-06 – approximately 7% per annum.

These recorded changes may reflect increases in the understanding of eating disorders especially the lesser known disorders and particularly binge eating disorder which has only recently been acknowledged in statistical recording³⁴.

Table 3.3

Count of FAEs with primary diagnosis of eating disorder in England, 2005-2014

	Count of Finished Admissions Episodes (FAEs) where the primary diagnosis was of eating disorders (England)
2005-2006	1,882
2006-2007	1,924
2007-2008	1,872
2008-2009	1,868
2009-2010	2,067
2010-2011	[missing data]
2011-2012	2,285
2012-2013	2,380
2013-2014	2,855

prevalence of ED has significantly grown

The costs of eating disorders

Social, health and economic impacts

Assessing the impact of eating disorders across the UK on behalf of BEAT.

February 2015



There are increasing numbers of reported cases of eating disorders in the UK

Separately from prevalence data research involving GP data in the UK indicates an increase in the age-standardised annual incidence of all diagnosed eating disorders (ages 10-49) from 32.2 to 37.2 per 100,000 between 2000 and 2008. This increase appears to be the result of an increase in the unspecified eating disorders category, an AN and BN quarters combined (see table).

Separately, as outlined in Table 2.3, time series analysis of data on the total number of cases of eating disorders being diagnosed in England illustrates a similar trend in increasing prevalence over time with a 34% increase in admissions since 2009/10 – approximately 7% per annum.

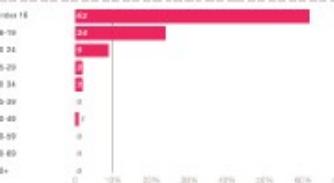
This recorded change may reflect increases in the understanding of eating disorders especially the lesser known disorders and particularly binge eating disorder which has only recently been acknowledged in statistical recording¹¹.

Our survey indicates that eating disorders most commonly initially present amongst the young, and national data indicates that they can also start later in life and can be life-long conditions

Table 2.3
Count of PHEs and primary care agency cases of eating disorders in England, 2009-2014

Count of Primary care agencies (PCAs) where the primary diagnosis was an eating disorder (England)	
2009-2010	1,952
2010-2011	1,804
2011-2012	1,812
2012-2013	2,004
2013-2014	2,127
2014-2015	2,134

Figure 3.1
Age when symptoms of an eating disorder first出现



¹⁰Wiles, M., Hughes, A.M., Pearson, L. and Tressler, J.L. (2013). The incidence of eating disorders in the UK: 2008-2009. Report from the General Practice Research Database. BMJ Open, 3, e003496 [Epub ahead of print]. Available at: <http://bmjopen.bmjjournals.org/content/3/6/e003496.full.pdf>

¹¹American Psychiatric Association. (2013). Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition. Washington, DC: American Psychiatric Publishing.

prevalence of ED has significantly grown

The costs of eating disorders

Social, health and
economic impacts

Assessing the impact of
eating disorders across the
UK on behalf of BEAT.

February 2015



prevalence of ED has significantly grown

The costs of eating disorders

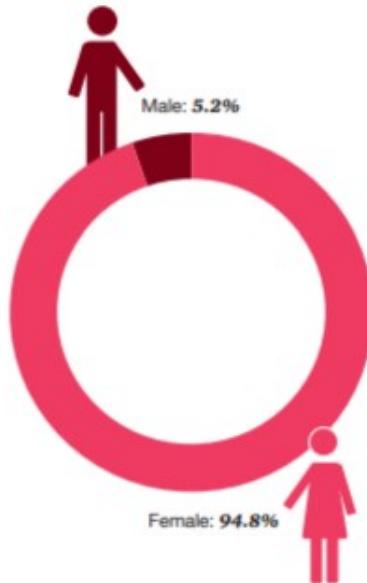
Social, health and
economic impacts

Assessing the impact of
eating disorders across the
UK on behalf of BEAT.

February 2015



Figure 3.3
Gender breakdown of survey respondents



prevalence of ED has significantly grown

The costs of eating disorders

Social, health and
economic impacts

Assessing the impact of
eating disorders across the
UK on behalf of BEAT.

February 2015



prevalence of ED has significantly grown

The costs of eating disorders

Social, health and economic impacts

Assessing the impact of eating disorders across the UK on behalf of BEAT.

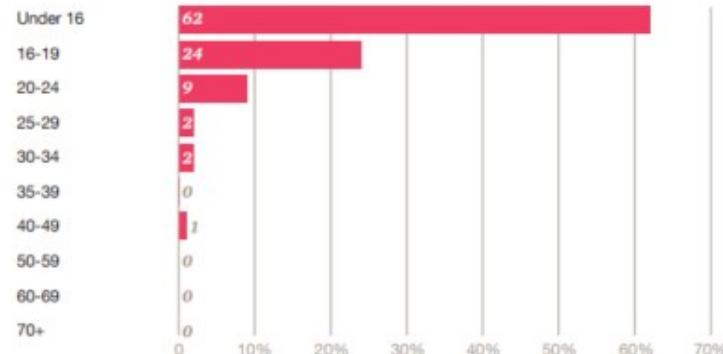
February 2015



Our survey indicates that eating disorders most commonly initially present amongst the young, and national data indicates that they can also start later in life and can be life-long conditions

Figure 3.1

Age when symptoms of an eating disorder first appeared



Base: 517

prevalence of ED has significantly grown

The costs of eating disorders

Social, health and
economic impacts

Assessing the impact of
eating disorders across the
UK on behalf of BEAT.

February 2015



prevalence of ED has significantly grown

The costs of eating disorders

Social, health and economic impacts

Assessing the impact of eating disorders across the UK on behalf of BEAT.

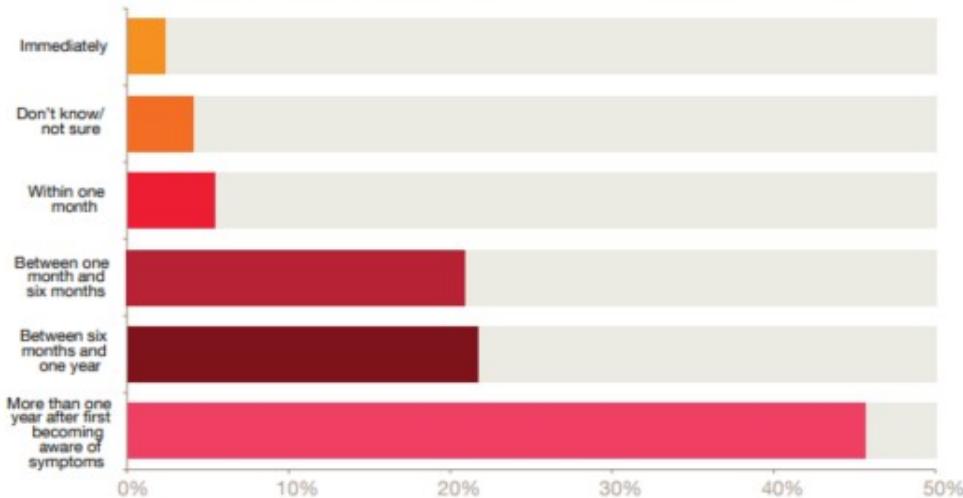
February 2015



Almost half of sufferers wait longer than a year after recognising symptoms of an eating disorder before seeking help

Figure 4.1

Time between recognising symptoms and seeking help



Base:
517

clinical studies



surveys & interviews

limitations:

- **small** groups of individuals
- **denial** of illness
- participants **conceal** their condition or its extent
- **ambivalence** towards treatment
- high **drop-out** rates
- predefined **questionnaires** alone may be **insufficient** to reveal the physical/psychological states



Profiling depression and anorexia in Social Media

David E. Losada

CiTUS USC

profiling
depression

depression

Eating
Disorders

ED
profiling

eRisk

ethics

acks

ED profiling

natural language can be **indicative** of personality, social status, emotions, mental health, disorders, ...



and interactions/communities in SM can also provide useful signals ...

people's **behaviour** + **content** generated
on SM → infer their mental health states



Social Media

(semi-)anonymous & open nature of SM:
encourages people to **socialize** and **self-disclose**



naturally occurring data in a non-reactive
way.



SM data complements **conventional data**

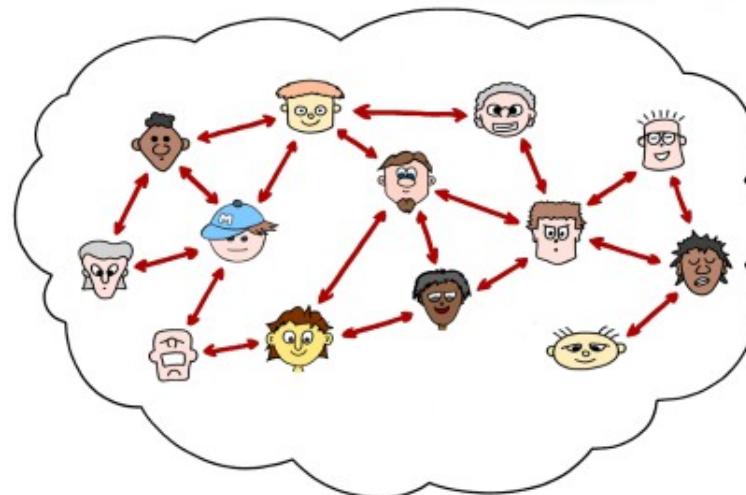


harmful content

vs

useful recommendations & advice

pro-ED communities
(support engagement
with ED lifestyles)



**Social
Media**

recovery and
support
communities



people affected by anorexia:
age group in which **SM**
are used **heavily**

contagion effects on those exposed to
dangerous content

pro-ED websites **negatively affect**
females' **perceptions of their body image**



pro-ED communities:
often "**hidden in plain sight**"
use of **atypical language or tags**
(seek to avoid outsiders encountering and reporting them)



pro-anorexia communities:

claim to provide support

promote disordered eating

discourage people from seeking help or trying to recover

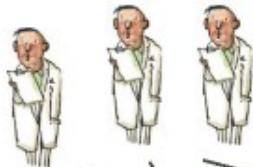


ED & SM: relevant refs

140 videos 

11 h 

3 doctors



informative pro-anorexia others

[J Med Internet Res.](#) 2013 Feb 13;15(2):e30. doi: 10.2196/jmir.2237.

Misleading health-related information promoted through video-based social media: anorexia on YouTube.

Syed-Abdul S¹, Fernandez-Luque L, Jian WS, Li YC, Crain S, Hsu MH, Wang YC, Khandregzen D, Chuluunbaatar E, Nguyen PA, Liou DM.

✉ Author information

¹ Graduate Institute of Medical Informatics, College of Medical Science and Technology, Taipei Medical University, Taipei, Taiwan.

pro-anorexia info found in **29.3%** of anorexia-related videos

pro-anorexia content: more **highly favored & rated**

82.6% of pro-anorexia video raters  **liked the misleading info**

top viewers



need to raise awareness about the **trustworthiness of online information**

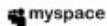
health authorities: study the content dissemination strategies used by the pro-anorexics & design their own **dissemination strategies for informative content**



robust **search** engines: find trustworthy content & filter out misleading information



ED & SM: relevant refs



made personal contacts with several **pro-ED groups** on Facebook and MySpace to get access to, observe and analyze the groups' content

large presence of pro-ana/pro-bulimia groups

- harmful** for the viewers/participants....
- but also found positive social interactions
(social support, help with isolation, ...)



Linguistic Inquiry and Word Count (LIWC)

to compare the psychological processes and personal concerns of pro-ED users amongst the two SM sites

Content analysis

revealed some differences between the two social networking sites

Eating Disorders, 18:393–407, 2010
Copyright © Taylor & Francis Group, LLC
ISSN: 1064-0266 print/1532-530X online
DOI: 10.1080/10640266.2010.511918



Pro-Eating Disorder Communities on Social Networking Sites: A Content Analysis

ADRIENNE S. JUARASCIO

Department of Psychology, Drexel University, Philadelphia, Pennsylvania, USA

AMBER SHOAIB

Department of Psychology, Towson University, Towson, Maryland, USA

C. ALIX TIMKO

Department of Behavioral and Social Sciences, University of the Sciences, Philadelphia, Pennsylvania, USA

ED & SM: relevant refs



personal **weblogs**, a popular form of text-based, diary-like, online journals.

31 **pro-ED** blogs, 29 **recovery** blogs,
and 27 **control** blogs



language of pro-ED blogs: **lower cognitive processing**,
a more closed-minded writing style, **less emotionally expressive**,
contained fewer social references, and focused more
on eating-related contents than recovery blogs.



12 **language indicators** correctly classified the blogs in 84% of the cases.

language patterns reflect the psychological conditions of the blog authors
and provide insight into their various **stages of coping**

Journal of Language and Social Psychology
32(2) 212–226
© 2013 SAGE Publications
DOI: 10.1177/0261927X12474278
jls.sagepub.com


**Language Use in
Eating Disorder Blogs:
Psychological Implications
of Social Online Activity**

Markus Wolf¹, Florian Theis¹, and Hans Kordy¹

ED & SM: relevant refs

pro-ED Twitter profiles' refs to EDs

45 Pro-ED profiles



how the **followers** reference EDs



profile info + all tweets +
random sample of followers

Journal of Adolescent Health 58 (2016) 659–664



Original article

#Proana: Pro-Eating Disorder Socialization on Twitter

Alina Arseniev-Koehler ^{a,b,*}, Hedwig Lee, Ph.D. ^a, Tyler McCormick, Ph.D. ^{a,c}, and Megan A. Moreno, M.D., M.S.Ed, M.P.H. ^{b,d}

^aDepartment of Sociology, University of Washington, Seattle, Washington

^bCenter for Child Health, Behavior and Development, Seattle Children's Research Institute, Seattle, Washington

^cDepartment of Statistics, University of Washington, Seattle, Washington

^dDepartment of Pediatrics, University of Washington, Seattle, Washington

JOURNAL OF
ADOLESCENT
HEALTH
www.jahonline.org



expressions of disordered eating patterns & notable audience of followers

might provide **social support** but **reinforce an ED identity**

ED & SM: relevant refs

⚠ Instagram banned searches on several proED tags and issued content advisories on others

investigated pro-ED communities in the aftermath of moderation

despite moderation strategies, pro-ED communities are active and thriving

pro-ED community adopted nonstandard lexical variations of moderated tags to circumvent restrictions

increasingly complex lexical variants emerged over time

more toxic, self-harm, and vulnerable content



The 19th ACM conference on Computer-Supported Cooperative Work and Social Computing
February 27–March 2, 2016

#thyghgapp: Instagram Content Moderation and Lexical Variation in Pro-Eating Disorder Communities

Stevie Chancellor Jessica Pater Trustin Clear Eric Gilbert Munmun De Choudhury
School of Interactive Computing, Georgia Institute of Technology, Atlanta GA 30332
{schancellor3, pater, trustin}@gatech.edu, {gilbert, mchoudhu}@cc.gatech.edu



ED & SM: relevant refs



analyzed photo sharing on Flickr

is **posting of ED content** discouraged by
posting of recovery-oriented content?



pro-anorexia and pro-recovery
communities **interact to a high degree**

pro-recovery community takes steps to ensure
that their content is **visible to the pro-anorexia
community**:

pro-recovery users:

employ similar words to those used by pro-anorexia users to describe their photographs
comment to pro-anorexia content (counterproductive, entrenches pro-anorexia users
in their stance)

J Med Internet Res. 2012 Nov-Dec; 14(6): e151.
Published online 2012 Nov 7. doi: [10.2196/jmir.2239](https://doi.org/10.2196/jmir.2239)

PMCID: PMC3510717

Pro-Anorexia and Pro-Recovery Photo Sharing: A Tale of Two Warring Tribes

Monitoring Editor: Gunther Eysenbach

Reviewed by Stephen Lewis

[Elad Yom-Tov, PhD](#),¹ [Luis Fernandez-Luque, MSc](#),^{2,3} [Ingmar Weber, PhD](#),⁴ and [Steven P Crain, PhD](#)⁵

¹Microsoft Research, Herzliya, Israel

²Northern Research Institute, Tromsø, Norway

³Computer Science Department, University of Tromsø, Tromsø, Norway

⁴Yahoo Research, Barcelona, Spain

⁵Department of Computer Science, Oberlin College, Oberlin, OH, United States



491 users

ED & SM: relevant refs



explored **community structures** and **interactions** among individuals who suffer from ED

snowball sampling: individuals who self-identify as ED (profile) + their connections (followers/followees)



predictive models: ED vs non-EDs (SVM, **97%** accuracy)



Tao Wang
ESRC DTC, IILS

Markus Brede
Department of ECS

Antonella Ianni
Department of Economics
University of Southampton, UK
{t.wang, Markus.Brede, A.Ianni, E.Mentzakis}@soton.ac.uk

Emmanouil Mentzakis
Department of Economics



Detecting and Characterizing Eating-Disorder Communities on Social Media

Analyzed **social status**, **behavioural patterns** and **psychometric properties**

💡 **key characteristics of ED:** young ages, prevailing urges to **lose weight** even if being clinically underweight, high social **anxiety**, intensive **self-focused** attention, deep **negative emotion**, increased mental **instability**, and excessive concerns of **body image** and **ingestion**



patterns of **homophily** (tendency of individuals to connect with others who share similar characteristics)

ED & SM: relevant refs



Instagram posted content on pro-ED tags

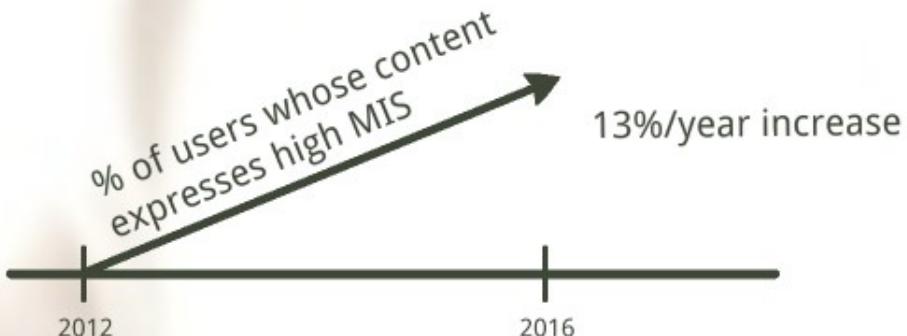
LDA topic modelling + novice/clinical annotations



mental illness severity (MIS) in user's content

MIS rating prediction with **regression models**

forecast MIS levels up to 8 months in the future



The 19th ACM conference on
Computer-Supported Cooperative
Work and Social Computing
February 27–March 2, 2016

Quantifying and Predicting Mental Illness Severity in Online Pro-Eating Disorder Communities

Stevie Chancellor
College of Computing
Georgia Tech
Atlanta, GA 30332
schancellor3@gatech.edu

Zhiyuan (Jerry) Lin
College of Computing
Georgia Tech
Atlanta, GA 30332
zlin48@gatech.edu

Erica L. Goodman
Department of Psychology
University of North Dakota
Grand Forks, ND 58202
erica.goodman@my.und.edu

Stephanie Zerwas
Department of Psychiatry
University of North Carolina
Chapel Hill, NC 27599
zerwas@med.unc.edu

Munmun De Choudhury
College of Computing
Georgia Tech
Atlanta, GA 30332
munmund@gatech.edu



26M posts



100k users

ED & SM: relevant refs

tumblr: pro-anorexia and pro-recovery communities

pro-anorexia:

- 💧 enacting anorexia as a **lifestyle** choice
- 📌 common **pro-anorexia tags**

pro-recovery:

- 👉 try to **educate** pro-anorexia individuals of the **health risks** of anorexia

distinctive affective, social, cognitive and linguistic style **markers**

- 📍 pro-anorexics: greater negative affect, higher cognitive impairment, greater feelings of social isolation and self-harm
- ▣ **predictive technology**: detect anorexia content (80% accuracy)



5th International Conference on Digital Health (Florence, Italy, 18th – 20th May 2015)

Anorexia on Tumblr: A Characterization Study

Munmun De Choudhury
School of Interactive Computing
Georgia Institute of Technology
Atlanta, GA 30308
munmund@gatech.edu

ED & SM: relevant refs



content removed

(against community guidelines)

30K pro-ED posts that were public
on Instagram but have since been **removed**



distinctive signals in deleted content:

more **dangerous actions, self-harm** tendencies,
and **vulnerability** (wrt posts that remain public)



classifier: public pro-ED posts vs removed posts (69% acc)

possible applications:



identify moments for **just-in-time intervention**

(e.g. contact a friend or reach out to a specialists)



facilitate **better content moderation**

San Jose, CA, USA



May 7-12

The 34th Annual CHI Conference on Human Factors in Computing Systems

San Jose Convention Center

<https://chi2016.acm.org>

"This Post Will Just Get Taken Down": Characterizing Removed Pro-Eating Disorder Social Media Content

Stevie Chancellor
Georgia Tech
Atlanta GA 30332
schancellor3@gatech.edu

Zhiyuan (Jerry) Lin
Georgia Tech
Atlanta GA 30332
zlin48@gatech.edu

Munmun De Choudhury
Georgia Tech
Atlanta GA 30332
munmund@gatech.edu

ED & SM: relevant refs

CHI'17

Proceedings of the 2017 ACM SIGCHI Conference on
Human Factors in Computing Systems



dataset of 1M **photo posts** associated with EDs

tumblr: **prohibits the glorification of self-harm, and promoting EDs** their accompanying lifestyles



multimodal: textual + visual features
of pro-ED content



deep learning classifier to detect content that **violates community guidelines**
(state-of-the-art Deep Neural Network)
performed comparably to ground truth that included actually moderated Tumblr data

Possible application:



pruning the search space of posts that need intervention.

Multimodal Classification of Moderated Online Pro-Eating Disorder Content

Stevie Chancellor*

Georgia Tech

Atlanta, GA USA

schancellor3@gatech.edu

Yannis Kalantidis

Yahoo Research

San Francisco, CA USA

ykalant@image.ntua.gr

Jessica A. Pater

Georgia Tech

Atlanta, GA USA

pater@gatech.edu

Munmun De Choudhury

Georgia Tech

Atlanta, GA USA

munmund@gatech.edu

David A. Shamma

Centrum Wiskunde &

Informatica (CWI)

Amsterdam, Netherlands

aymans@acm.org

| annotated data for training

ED & SM: main research themes

impact/prevalence of ED-related contents in SM

analysis of **communities & interactions**

content analysis, psychometrics

content moderation/ violation of SM guidelines

misleading health-related info

effect of moderation

learning technology (classification/regression)

Body Mass Index
purge
proana lbs
lowest weight
Ultimate Goal Weight
legspo
Current Weight binge



Profiling depression and anorexia in Social Media

David E. Losada

CiTUS USC

profiling
depression

depression

Eating
Disorders

ED
profiling

eRisk

ethics

acks



ethics

honor the privacy of the affected individuals

abide by appropriate ethical guidelines

data

use cases

**freedom of speech
vs
security**

data



sensitive/private data

/ informed **consent**

ensure security/privacy (storage, access, firewalls)

🚫 **no disclosure** of personally identifiable info

vs



public data

⚠️ ✖️ **no interaction** with subjects

no need of institutional review **approval**

avoids the need of contacting subjects, which can be coercive and may change user behaviour

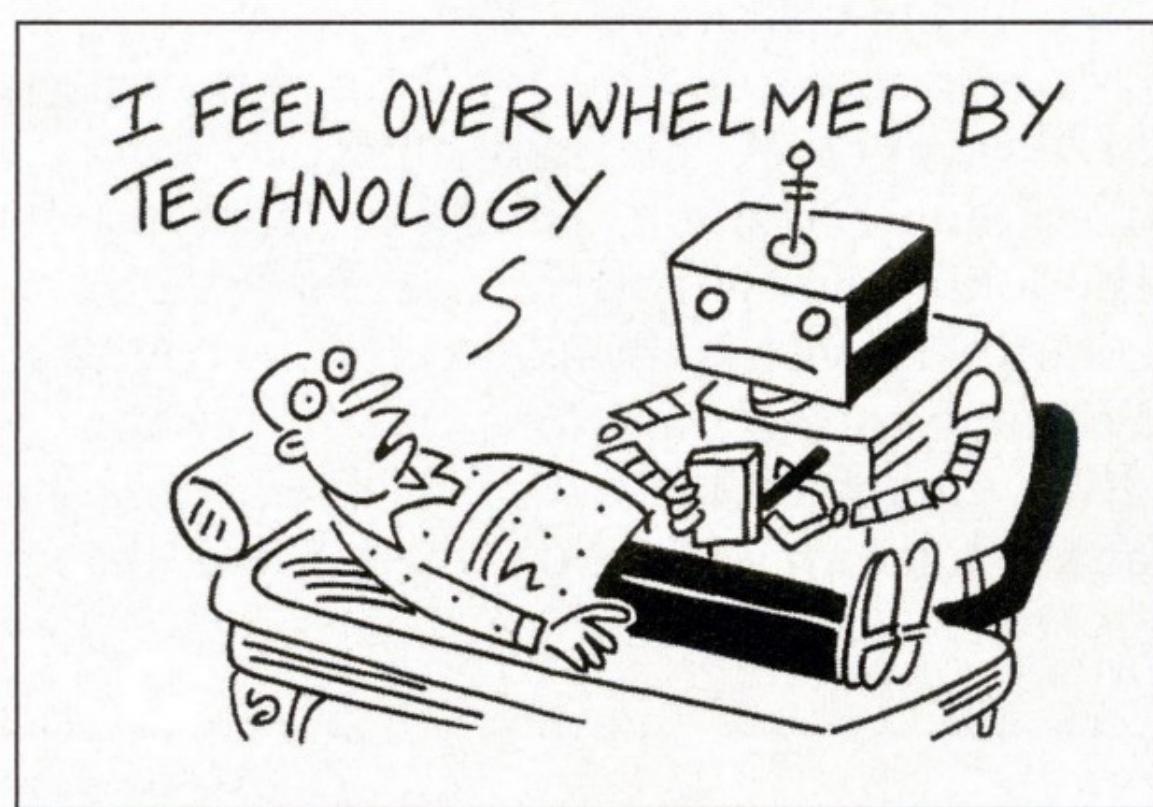
use cases

automatic assessments?



use cases

automatic assessments?



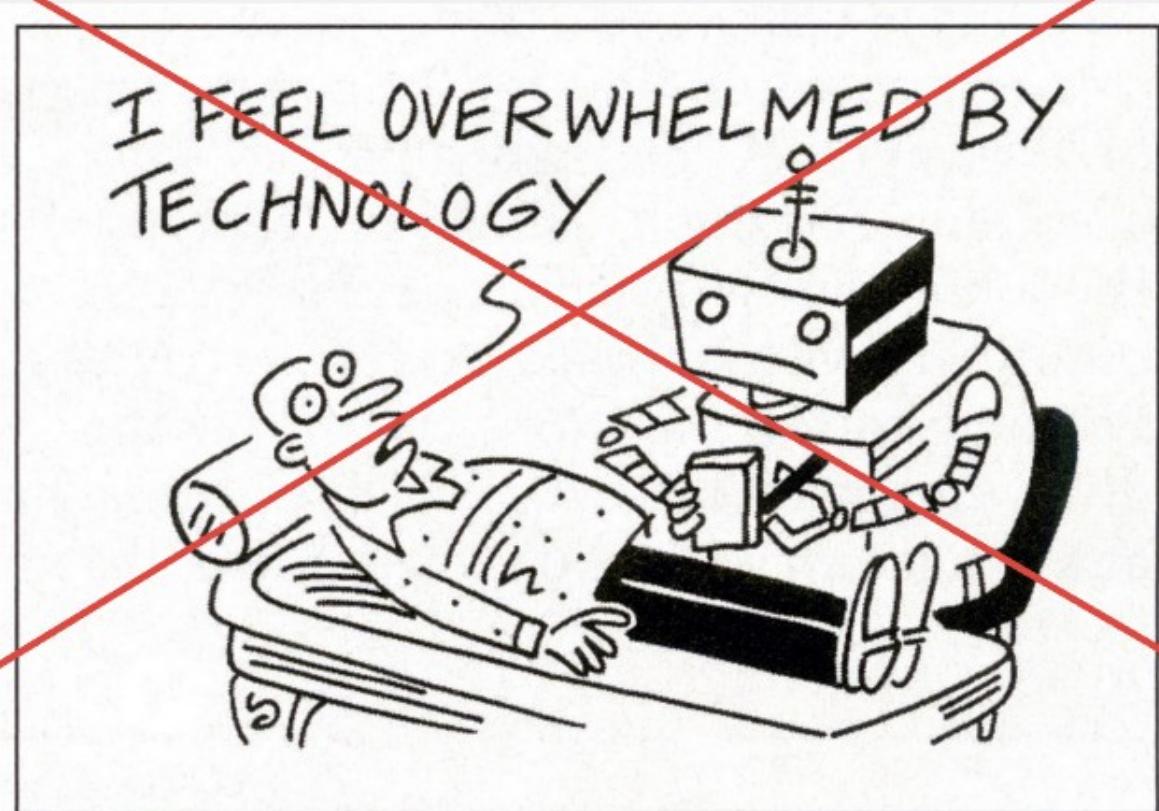
© HALDANE/THE TIMES/NEWS SYNDICATION

use cases

automatic assessments?



NO WAY!!!



© HALDANE/THE TIMES/NEWS SYNDICATION

use cases

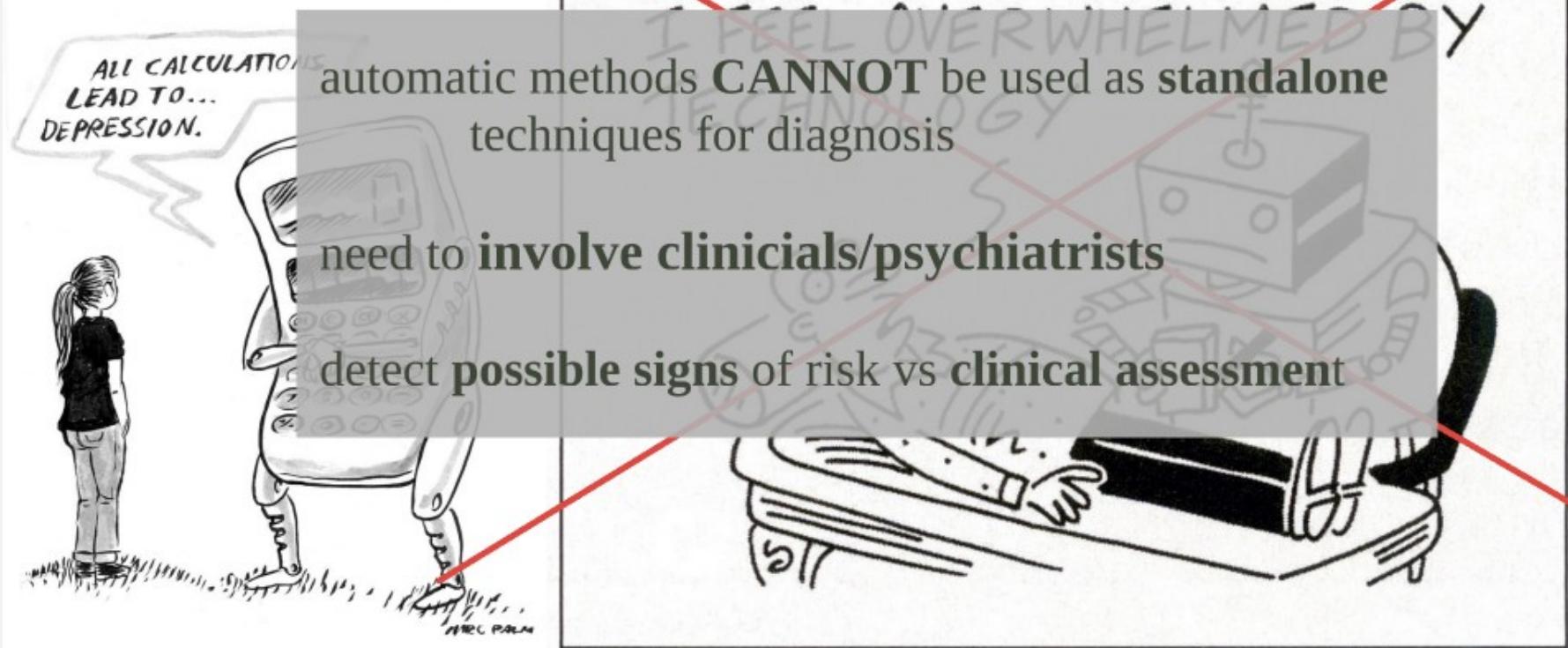
automatic assessments?

NO WAY!!!

automatic methods **CANNOT** be used as **standalone** techniques for diagnosis

need to **involve** **clinicians/psychiatrists**

detect **possible signs** of risk vs **clinical assessment**



interventions?



👍 ensure that the intended **benefits** of these interventions outweigh
👎 the **risks**

⚠ reveal SM detected **risk** to...
the individual himself or
an identified trusted social
contact or clinician

some SM sites have **basic
intervention systems**

interventions?



Help Center

Q Hi David, how can we help?

Return to Facebook

Home

Using Facebook

Managing Your Account

Privacy and Safety

Policies and Reporting

Support Inbox

Creating an Account

Friending

Your Home Page

Messaging

Photos

Videos

Pages

Groups

Events

Payments

Apps

Facebook Mobile and Desktop Apps

Accessibility

Suicide Prevention

If you've encountered a direct threat of suicide on Facebook, please contact law enforcement or a [suicide hotline](#) immediately.

I'm having thoughts about suicide or self-injury.

I need to find a suicide helpline for myself or a friend.

What should I do if someone posts something about suicide or self-injury?

How do I help a member of the US military community (example: active soldier, veteran or family member) who has posted suicidal content?

How do I help an LGBT person who has posted suicidal content on Facebook?

How do I help a law enforcement officer who has posted suicidal content?

Visit our Family Safety Center for more safety information, tools, and resources.

By Frits Ahlefeldt

use cases: example

suggests possible uses
of this technology:

The screenshot shows the header of a journal article. At the top right is the journal title "Internet Interventions 2 (2015) 183–188". Below it is the Elsevier logo, which includes a tree illustration and the word "ELSEVIER". To the right of the logo is the journal title "Internet Interventions" and the journal homepage URL "journal homepage: www.invent-journal.com/". Further to the right is a small thumbnail image of the journal cover, which features a globe and the journal title.

Detecting suicidality on Twitter

Bridianne O'Dea ^{a,*}, Stephen Wan ^b, Philip J. Batterham ^c, Alison L. Calear ^c, Cecile Paris ^b, Helen Christensen ^a

^a Black Dog Institute, The University of New South Wales, Hospital Road, Randwick, NSW 2031, Australia
^b Commonwealth Scientific and Industrial Research Organisation (CSIRO) Information and Communication Technology Centre, Corner of Victoria and Pembroke Roads, Marsfield, NSW 2122, Australia
^c National Institute for Mental Health Research, Building 63, The Australian National University, Canberra ACT 2601, Australia

CrossMark



users must **consent to**:

their tweets being **monitored** by an organisation or an individual
permission to be contacted if ‘strongly concerning’ tweet detected

use cases: example

suggests possible uses of this technology:



mental health agencies



tool for automatic screening for depression



given the subject's permission, the system may **proactively** and **automatically screen for signs of depression**
(e.g. within the subject's online posts)

Artificial Intelligence in Medicine 56 (2012) 19–25

Contents lists available at SciVerse ScienceDirect

Artificial Intelligence in Medicine

journal homepage: www.elsevier.com/locate/aim





Proactive screening for depression through metaphorical and automatic text analysis

Yair Neuman^{a,*}, Yohai Cohen^{b,1}, Dan Assaf^a, Gabbi Kedma^a

^a Department of Education, Ben-Gurion University of the Negev, Beer-Sheva 84105, Israel

^b Gilasio Coding, Tel-Aviv, Israel

use cases: example

suggests possible uses of
this technology:



mental health



tool for automating
the detection of depression



given the subject's
and **automated**
(e.g. within the

Artificial Intelligence in Medicine 56 (2012) 19–25



Contents lists available at SciVerse ScienceDirect

Artificial Intelligence in Medicine



the subject is informed and offered the opportunity
to complete a short **online questionnaire**



signs of depression?

the questionnaire also identifies
symptoms of depression ?



the subject is advised to consult a **mental health expert**



omatic text



freedom of speech vs security



what contents should be **banned by Social Media?**



is social media content a lethal **threat to vulnerable people?**



how **effective** would the **interventions** be, in terms of supressing risk content?

freedom of speech vs security



Advantages of "moderation" policies

🚫 moderating **deviant content** can constrain sentiments that might **harm** individuals/communities

🚫 avoids **contagion**-like effects

🤝 **favours user engagement** (negative content causes people to leave)



Advantages of "no moderation" policies

📢 it is better for vulnerable people to **identify** and **express themselves**

👥 discussing dangerous ideas might help people **disinhibit themselves from self-harm**

🔥 after **banning** certain contents, some communities became more **insular** and focused on more **dangerous** ideas

Advantages of "moderation" policies

- ⚠️ moderating **deviant content** can constrain sentiments that might **harm** individuals/communities
- 🔴 avoids **contagion**-like effects
- 🤝 favours user **engagement** (negative content causes people to leave)

freedom of speech vs security



Advantages of "moderation" policies

🚫 moderating **deviant content** can constrain sentiments that might **harm** individuals/communities

🚫 avoids **contagion**-like effects

🤝 **favours user engagement** (negative content causes people to leave)



Advantages of "no moderation" policies

📢 it is better for vulnerable people to **identify** and **express themselves**

👥 discussing dangerous ideas might help people **disinhibit themselves from self-harm**

🔥 after **banning** certain contents, some communities became more **insular** and focused on more **dangerous** ideas

Advantages of "no moderation" policies

- ➡ it is better for vulnerable people to **identify and express themselves**
- 🌱 discussing dangerous ideas might help people **disinhibit themselves from self-harm**
- 🔥 **after banning** certain contents, some communities became more **insular** and focused on more **dangerous** ideas

freedom of speech vs security



Advantages of "moderation" policies

🚫 moderating **deviant content** can constrain sentiments that might **harm** individuals/communities

🚫 avoids **contagion**-like effects

🤝 **favours user engagement** (negative content causes people to leave)



Advantages of "no moderation" policies

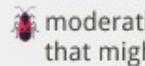
📢 it is better for vulnerable people to **identify** and **express themselves**

👥 discussing dangerous ideas might help people **disinhibit themselves from self-harm**

🔥 after **banning** certain contents, some communities became more **insular** and focused on more **dangerous** ideas

freedom of speech vs security

Advantages



need of collaborations from **industry professionals, researchers, designers, psychologists, and other stakeholders** to make decisions in this area....

avoids contagion-like effects

favours user engagement (negative content causes people to leave)



discussing dangerous ideas might help people disinhibit themselves from self-harm



after banning certain contents, some communities became more **insular** and focused on more **dangerous** ideas



Profiling depression and anorexia in Social Media

David E. Losada

CiTUS USC

profiling
depression

depression

Eating
Disorders

ED
profiling

eRisk

ethics

acks



organizers



eRisk

early **Risk** prediction on the Internet



explores the **evaluation** methodology,
effectiveness **metrics** and
practical **applications** (particularly
those related to **health** and **safety**) of
early risk detection on the Internet



eRisk @
clef 2017



eRisk @
clef 2018

data

<http://early.irlab.org/>

positive
vs
control

task
format

organizers

David E. Losada



Centro Singular de Investigación
en Tecnoloxías da
Información

Fabio Crestani



Javier Parapar



UNIVERSIDADE DA CORUÑA



eRisk @ clef 2017



- ① **workshop** open to the submission of papers describing **test collections** or **data sets** suitable for early risk prediction, early risk prediction challenges, tasks and evaluation **metrics** or specific early risk detection **solutions**
- ② **pilot task on early risk detection of depression**
exploratory task on early risk detection of depression
sequentially processing pieces of evidence and detect early traces of depression as soon as possible

eRisk @ clef 2018



- ① Task1. Early Detection of Signs of Depression**
(continuation of the eRisk 2017 pilot task)
sequentially processing pieces of evidence and detect early traces of depression as soon as possible.

- ② Task2. Early Detection of Signs of Anorexia**
(new in 2018)
sequentially processing pieces of evidence and detect early traces of anorexia as soon as possible.

data



**early
intervention is
crucial**



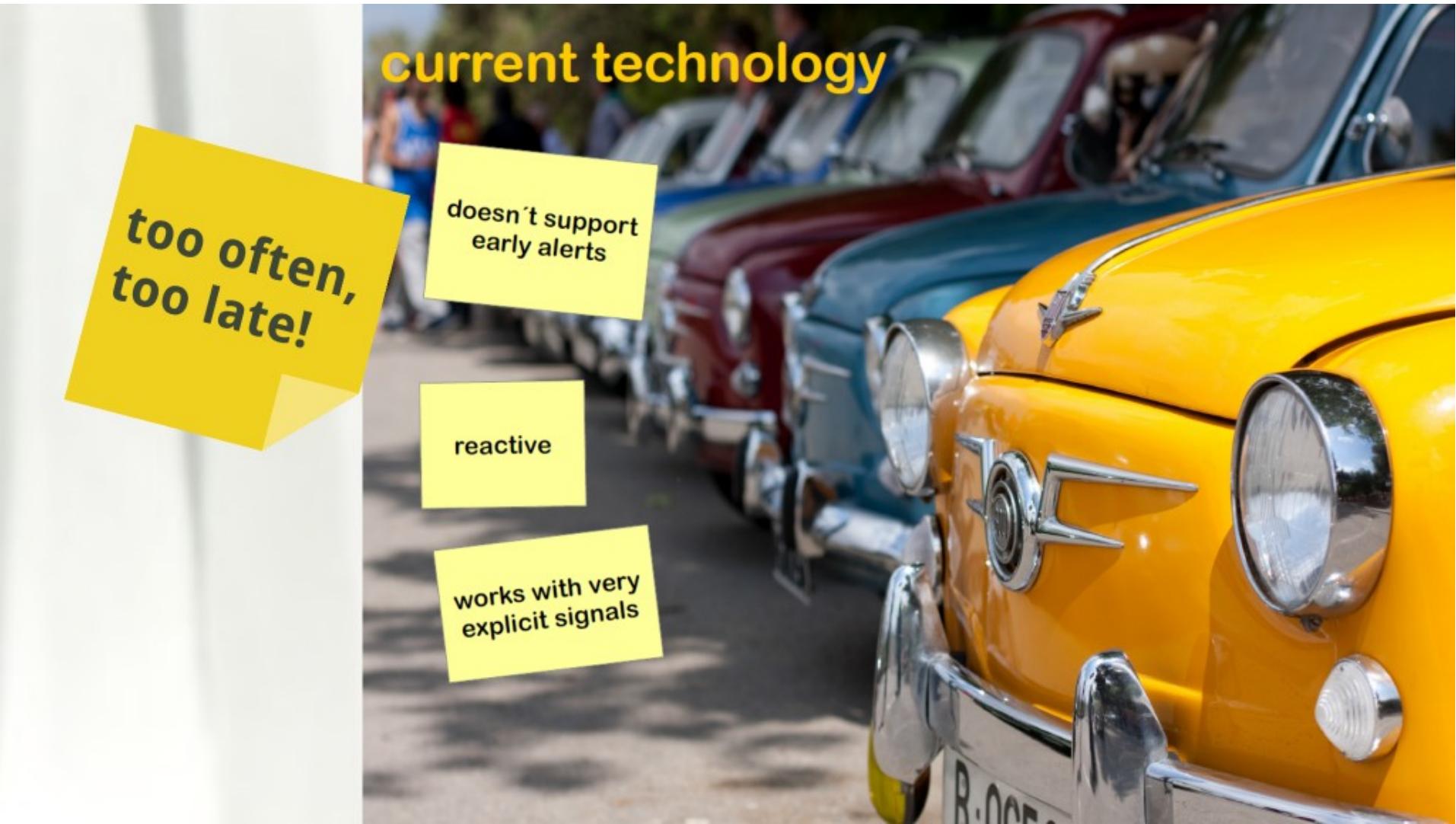
current technology

doesn't support
early alerts

reactive

works with very
explicit signals



A photograph of a row of classic cars parked outdoors. In the foreground, a bright yellow classic car is visible, showing its front grille with a chrome hood ornament and round headlights. Several yellow sticky notes are overlaid on the image, containing text related to "current technology".

**too often,
too late!**

doesn't support
early alerts

reactive

works with very
explicit signals

current technology

current technology

doesn't support
early alerts

reactive

works with very
explicit signals

data

key aims

instigate research on the **onset** of depression

proactive technologies

early alerts

track **temporal** evolution

Lack of data on depression & language

few collections available

focus on 2-class categorisation

no temporal dimension, no early risk analysis

A ed a ac d b e a f f a g f f ef a e a
hippi fi a di a e c a h i a en amb ad i ae t ea
sf s i a n m a n t d a v o l a g h a e d s e r e c r o a t o u T e
t n d ff r i a a co a d o q e p h g r g r m g n w a k e m h a p a e
w h d n t b w e r e v y q l l t o p m s i e s v l t r d o a s t a n o e a
i c m w h w e b s h e v g n p d e o m i w d e p i m p i t e e n
t i s n r t r n t l r i o n , v o p m u u z d r p m d i t i n
v ? r s t r t s w t w u s x y ts u s , r t , r o p t o p r n n m n o n o



little context about the tweet writer



difficult to assess whether a mention of
depression is **genuine**

no way to extract a **long history** of
tweets (e.g. several years)



A Thin Line

get the facts / take control / your stories / draw your line / blog



A Thin Line

no way to extract any history

short messages, little context



MIS SUBREDDITS ▾ PORTADA · TODOS · ALEATORIO | ASKREDDIT · FUNNY · PICS · VIDEOS · TODAYILEARNED · GAMING · GIFS · WORLDNEWS · MOVIES · NEWS

reddit DEPRESSION activo nuevo subiendo polémico popular con gold patrocinados

↑ 1 from the bottom of your heart you can see the love in me. I'm bleeding, you know? Cathartis
384 enviado hace 2 meses por self.depression (self.depression)
[Aa] + 38 comentarios compartir

↑ /r/depression Weekly Blend - Come with me, we're gonna have a good time (self.depression)
27 enviado hace 7 días por self.depression (self.depression)
[Aa] + 297 comentarios compartir

↑ I you up just now (self.depression)
1 124 enviado hace 8 horas por self.depression (self.depression)
[Aa] + 25 comentarios compartir

↑ ... I think I need to go to the hospital. I'm gonna die... anyone who has the same problem
2 37 enviado hace 6 horas por self.depression (self.depression)
[Aa] + 5 comentarios compartir

↑ Today, I'm gonna be a better person. I'm gonna be happy (self.depression)
3 43 enviado hace 8 horas por self.depression (self.depression)
[Aa] + 21 comentarios compartir





large history for each redditor (several years)

many subreddits (**communities**) about different
medical conditions (e.g. depression or
anorexia)

long messages

terms & conditions allow use
for **research** purposes





depression group vs control group

Adopted **extraction method** from

Coppersmith et al. 2014:

pattern matching search

search for **explicit** mentions of **diagnosis**

(e.g. “I was diagnosed with depression”)

“I am depressed”

“I think I have depression”

manual inspection of the results



depression group vs control group

large set of **random** redditors

from a **wide range of subreddits**
(news, media, ...)

also included some **false positives**
from the depression subreddit
(e.g. “My wife has depression”, “I am a
student interested in depression”)

redditor profile



retrieved **all history**

from any subreddit
his/her posts +
his/her comments to other posts

often several years of text

removed the post/comment with
the **explicit** mention of the
diagnosis (depression group)

redditor profile



pre- & post-diagnosis text

organised the writings in
chronological order

XML archives

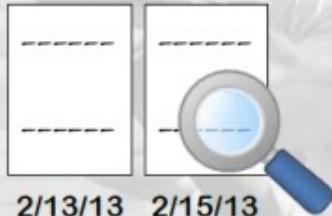


task format

detect **early traces** of depression

for each subject, **sequentially process** pieces of evidence...

John Doe's writings
(post or comments)



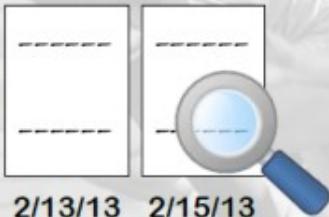
- possible case of depression
- no depression
- no decision yet

task format

anorexia
detect **early traces** of depression

for each subject, **sequentially process**
pieces of evidence...

John Doe's writings
(post or comments)



chunk 1 (oldest writings)
10% of writings

anorexia

possible case of depression

no depression

anorexia

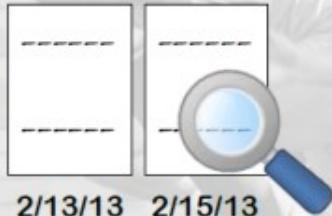
no decision yet

task format

detect **early traces** of depression

for each subject, **sequentially process** pieces of evidence...

John Doe's writings
(post or comments)



chunk 1 (oldest writings)
10% of writings

- possible case of depression
- no depression
- no decision yet

task format

detect **early traces** of depression

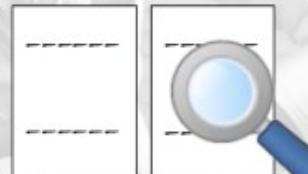
for each subject, **sequentially process** pieces of evidence...

John Doe's writings
(post or comments)



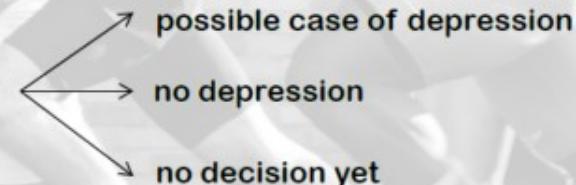
2/13/13 2/15/13

chunk 1 (oldest writings)
10% of writings



3/3/13 3/15/13

chunk 2
10% of writings



task format

detect **early traces** of depression

for each subject, **sequentially process** pieces of evidence...

John Doe's writings
(post or comments)



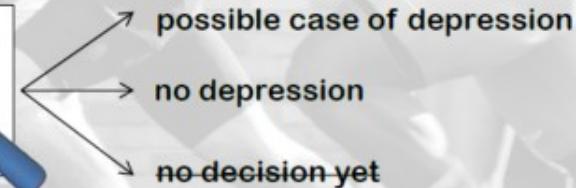
2/13/13 2/15/13

chunk 1 (oldest writings) ...
10% of writings



1/12/15 3/12/15

chunk 10 (newest writings)
10% of writings



performance metric

Early Risk Detection Error:

$$ERDE_O(d, k) = \begin{cases} c_{fp} & \text{(false positive)} \\ c_{fn} & \text{(false negative)} \\ c_{tp} * Ic_o(k) & \text{(true positive)} \\ 0 & \text{(true negative)} \end{cases}$$

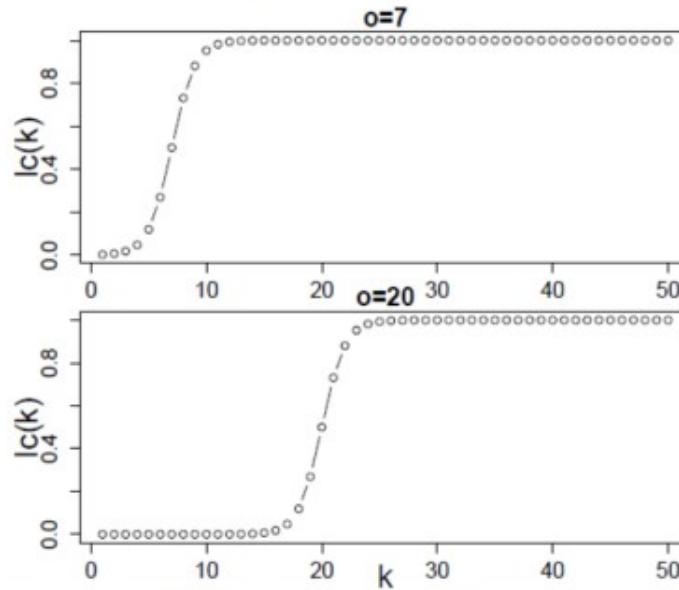


performance metric

True Positive cost



Latency cost function



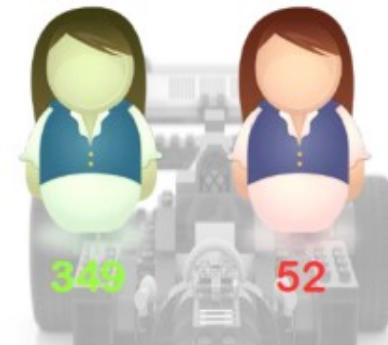
penalty to late detections

splits

Training



Test

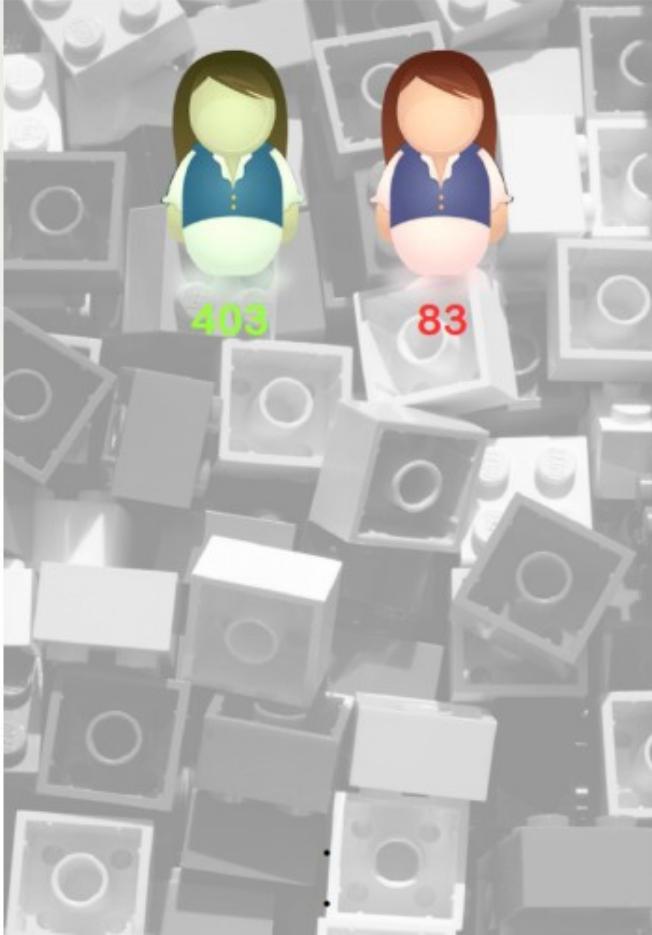


	Train		Test	
	<i>Depressed</i>	<i>Control</i>	<i>Depressed</i>	<i>Control</i>
Num. subjects	83	403	52	349
Num. submissions (posts & comments)	30,851	264,172	18,706	217,665
Avg num. of submissions per subject	371.7	655.5	359.7	623.7
Avg num. of days from first to last submission	572.7	626.6	608.31	623.2
Avg num. words per submission	27.6	21.3	26.9	22.5

Table 1. Main statistics of the train and test collections



Training

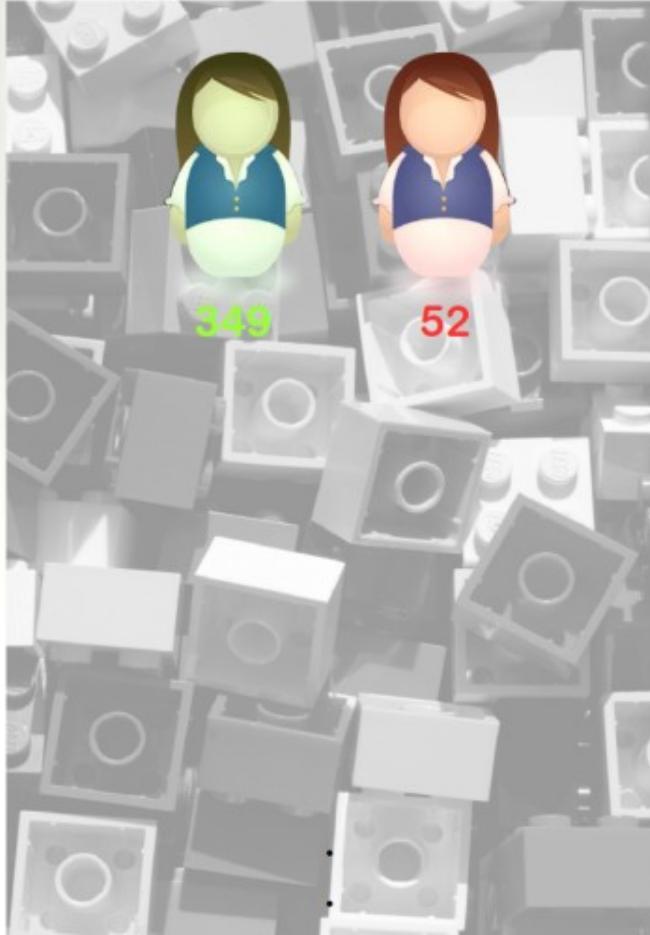


Nov 30th, 2016

**all history of all training users
provided to the participants
(all chunks)**



Test



Feb 6th, 2017

chunk1 of all test users provided

Feb 13th, 2017

decisions on chunk1

chunk2 of all test users provided

Feb 20th, 2017

decisions on chunks 1-2

chunk3 of all test users provided

Apr 10th, 2017

decisions on chunks 1-10



teams

Institution	Submitted files
ENSEEIHT, France	GPLA GPLB GPLC GPLD
FH Dortmund, Germany	FHDOA FHDOB FHDOC FHDOD FHDOE
U. Arizona, USA	UArizonaA UArizonaB UArizonaC UArizonaD UArizonaE
U. Autónoma Metropolitana, Mexico	LyRA LyRB LyRC LyRD LyRE
U. Nacional de San Luis, Argentina	UNSLA
U. of Quebec in Montreal, Canada	UQAMA UQAMB UQAMC UQAMD UQAME
UACH-INAOE, Mexico-USA	CHEPEA CHEPEB CHEPEC CHEPED
ISA FRCCSC RAS, Russia	NLPISA



results

	<i>ERDE</i> ₅	<i>ERDE</i> ₅₀	F1	P	R
GPLA	17.33%	15.83%	0.35	0.22	0.75
GPLB	19.14%	17.15%	0.30	0.18	0.83
GPLC	14.06%	12.14%	0.46	0.42	0.50
GPLD	14.52%	12.78%	0.47	0.39	0.60
FHDOA	12.82%	9.69%	0.64	0.61	0.67
FHDOB	12.70%	10.39%	0.55	0.69	0.46
FHDOC	13.24%	10.56%	0.56	0.57	0.56
FHDOD	13.04%	10.53%	0.57	0.63	0.52
FHDOE	14.16%	12.42%	0.60	0.51	0.73
UArizonaA	14.62%	12.68%	0.40	0.31	0.58
UArizonaB	13.07%	11.63%	0.30	0.33	0.27
UArizonaC	17.93%	12.74%	0.34	0.21	0.92
UArizonaD	14.73%	10.23%	0.45	0.32	0.79
UArizonaE	14.93%	12.01%	0.45	0.34	0.63
LyRA	15.65%	15.15%	0.14	0.11	0.19
LyRB	16.75%	15.76%	0.16	0.11	0.29
LyRC	16.14%	15.51%	0.16	0.12	0.25
LyRD	14.97%	14.47%	0.15	0.13	0.17
LyRE	13.74%	13.74%	0.08	0.11	0.06
UNSLA	13.66%	9.68%	0.59	0.48	0.79
UQAMA	14.03%	12.29%	0.53	0.48	0.60
UQAMB	13.78%	12.78%	0.48	0.49	0.46
UQAMC	13.58%	12.83%	0.42	0.50	0.37
UQAMD	13.23%	11.98%	0.38	0.64	0.27
UQAME	13.68%	12.68%	0.39	0.45	0.35
CHEPEA	14.75%	12.26%	0.48	0.38	0.65
CHEPEB	14.78%	12.29%	0.47	0.37	0.63
CHEPEC	14.81%	12.57%	0.46	0.37	0.63
CHEPED	14.81%	12.57%	0.45	0.36	0.62
NLPISA	15.59%	15.59%	0.15	0.12	0.21



Profiling depression and anorexia in Social Media

David E. Losada

CiTUS USC

profiling
depression

depression

Eating
Disorders

ED
profiling

eRisk

ethics

acks

THANKS!

funding

resources

funding

This work was supported by the
“Ministerio de Economía y Competitividad”
of the Government of Spain and
FEDER Funds under
research projects
TIN2012-33867 and TIN2015-64282-R.



GOBIERNO
DE ESPAÑA

MINISTERIO
DE ECONOMÍA
Y COMPETITIVIDAD



Unión Europea

Fondo Europeo
de Desarrollo Regional
“Una manera de hacer Europa”

This research was funded by the Swiss
National Science Foundation
(project “Early risk prediction on the Internet:
an evaluation corpus”, 2015)



SWISS NATIONAL SCIENCE FOUNDATION



resources

CC BY 2.0: <https://creativecommons.org/licenses/by/2.0/>

Mark Ingle. (markingleukc at flickr). Trapped. <https://goo.gl/PX8hMv>

brett jordan. Tell me about your mother board. <https://goo.gl/eTKjt5>

Matti Mattila. Dotted world map. <https://goo.gl/hcfdrN>

Simon Cockell. Random, scale-free network. <https://goo.gl/BtfW3t>

USFWS Mountain-Prairie. Hiding in Plain Sight. <https://goo.gl/a4qgDM>

Jurgen Appelo. Network. <https://goo.gl/wxVa5p>

ankxt. Are you ok?. <https://goo.gl/gKQRu3>

Gerald Gabernig. winter.depression. <https://goo.gl/xb8ooK>

Joel Olives. Clusters. <https://goo.gl/JeRXnN>

Tim Morgan. database. <https://goo.gl/Cy1Ncu>

Oscar Rethwill. AH&DY 100m. <https://goo.gl/9NK8kF>

woodleywonderworks. Pablo's cubism period began at three. <https://goo.gl/zhKHF4>



resources

CC BY-NC-ND 2.0. <https://creativecommons.org/licenses/by-nc-nd/2.0/>

Frits Ahlefeldt Founder Hiking.org. hospital-volunteer. <https://goo.gl/ebLf6j>

Marc Palm. Figuring Out Life. <https://goo.gl/q9FTR6>
collective nouns. <https://goo.gl/jWjLCr>

Andy Cull. Downward Spiral. <https://goo.gl/UE2u8v>

Mary Lock. Anorexia. <https://goo.gl/3XHp8u>

jordi Borràs i Vivó. Seat 600. <https://goo.gl/utq2eo>

grace mcdunnough. Are we ready for our predicted future? <https://goo.gl/rr3Bfg>



resources

CC BY-ND 2.0. <https://creativecommons.org/licenses/by-nd/2.0/>

Susana Fernandez. Friendship. <https://goo.gl/N3Co1W>

CC BY-SA 2.0. <https://creativecommons.org/licenses/by-sa/2.0/>

justin lincoln. 120913_113852_417. <https://goo.gl/UPLfoL>

Helen Harrop. trapped in the shadows. <https://goo.gl/odnQp2>



resources

CC BY-NC 2.0. <https://creativecommons.org/licenses/by-nc/2.0/>

WRme2. Grangemouth. <https://goo.gl/gibn4w>

Timothy Takemoto. The Mirror of the Japanese is not the Gaze of the others.
<https://goo.gl/1xHdGA>

Daryl-RhysT. Cutey Doodles Jan 2014 - tween girl. <https://goo.gl/s7mPSe>

Frits Ahlefeldt Founder Hiking.org. you got hikers illustration.
<https://goo.gl/cRgPNC>

Mark Smiciklas. Social Media ROI. <https://goo.gl/qUt4NR>

Nilufer Gadgieva. Writing Forever. <https://goo.gl/ow2F8S>

Kathleen Donovan. Chat Bubble. <https://goo.gl/mAsBjQ>

Fotero. Consulta. <https://goo.gl/J5W6FT>

Andy Kennelly. grouping. <https://goo.gl/t8Y1Mh>

Emily. The Right Tool. <https://goo.gl/EYxtYr>



Profiling depression and anorexia in Social Media

David E. Losada

CiTUS USC

profiling
depression

depression

Eating
Disorders

ED
profiling

eRisk

ethics

acks