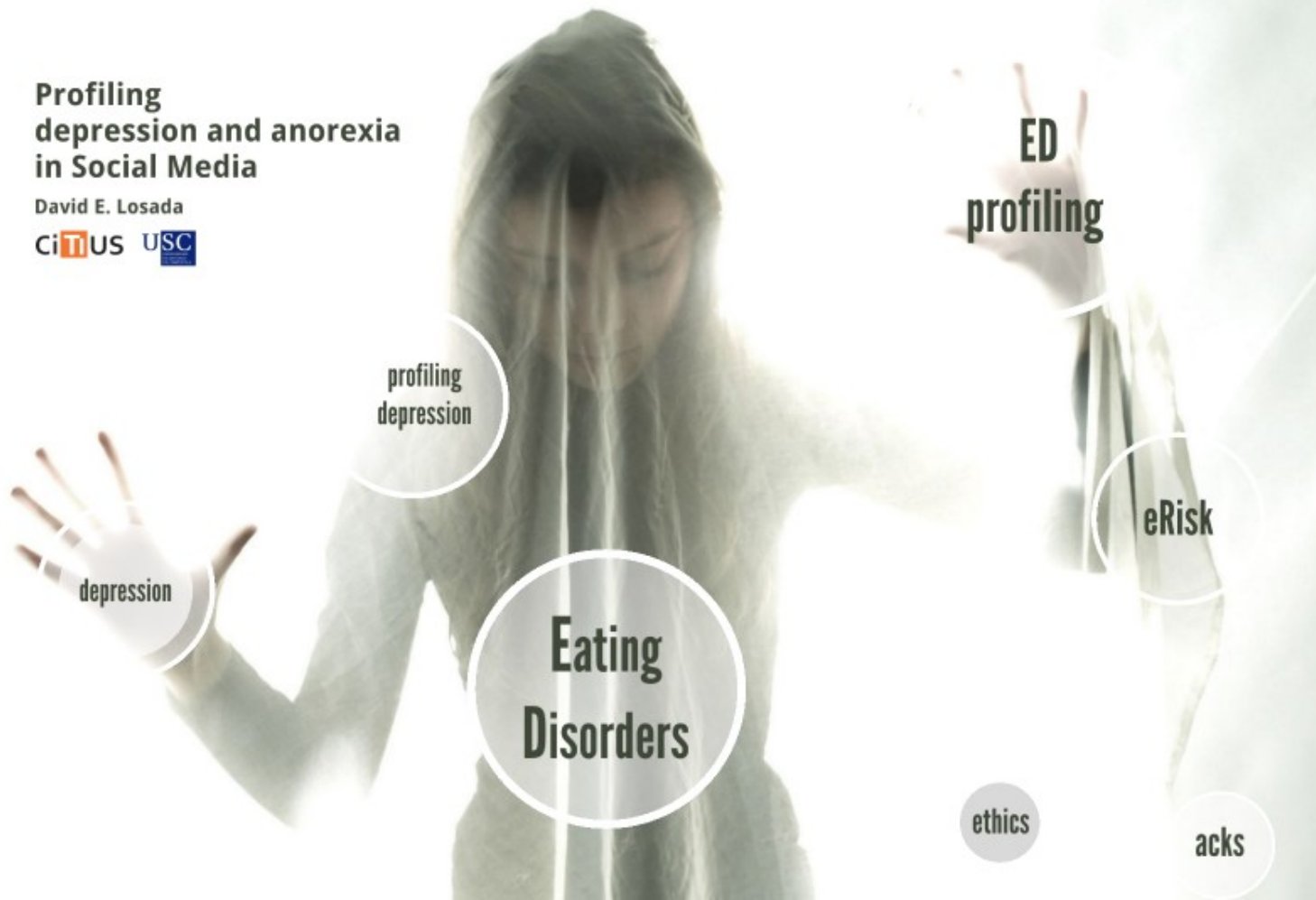


Profiling depression and anorexia in Social Media

David E. Losada

CiMUS USC



depression

profiling
depression

Eating
Disorders

ED
profiling

eRisk

ethics

acks

depression

common mental disorder

persistent sadness
hopelessness
loss of interest
sleeping problems
inability to carry out daily activities
reduced concentration
guilt
self-harm
loss of energy
restlessness
change of appetite
worthlessness
anxiety
indecisiveness
suicide



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**



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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





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

Data Mining in Bioinformatics

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 last 17 items.

<p><input type="checkbox"/> 1. DEPRESSED MOOD (Downy 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</p>	<p><input type="checkbox"/> 6. INSOMNIA - Disturbed (Waking in early hours of the morning and unable to fall asleep again) 0 = Absent 1 = Occasional 2 = Frequent</p>
<p><input type="checkbox"/> 2. FEELINGS OF GUILT 0 = Absent 1 = Self-accusations, feels he/she has let people down 2 = Ideas of guilt 3 = Frequent ideas in a paralytic, delusions of guilt 4 = Hallucinations of guilt</p>	<p><input type="checkbox"/> 8. MOOD AND INTERESTS 0 = No difficulty 1 = Feelings of incapacity, listlessness, reduction and no pleasure 2 = Loss of interest in hobbies, decreased social activities 3 = Productivity decreased 4 = Unable to work, stopped working because of present illness only. (Distance from work after treatment or recovery may rate a lower score)</p>

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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
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 **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 Vinnia 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

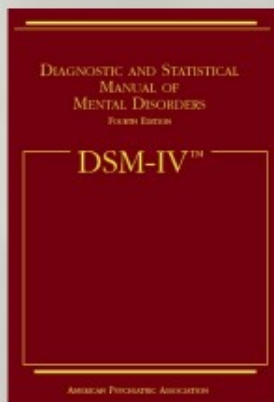


relationship between **depression on profile**
and **age, graduation year, gender, relationship status,**
facebook activity, ...

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-IVTM



publicly available
profile updates



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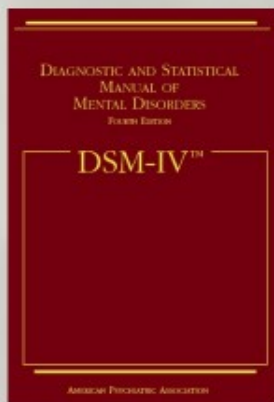


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relationship between **depression on profile**
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facebook activity, ...

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

Journal of Clinical Psychiatry 28:447-455 (2011)

ON
SOCIAL

Egan,¹
Becker, Ph.D.¹

PSYCHIATRY
JOURNAL

DSM-IV™

AMERICAN PSYCHIATRIC ASSOCIATION



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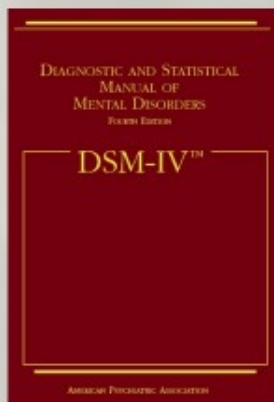


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depression bipolar disorder

seasonal affective disorder (SAD)


post-traumatic stress disorder (PTSD)


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

 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**



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!

Predicting Depression via Social Media

Munmun De Choudhury

Michael Gamon

Scott Counts

Eric Horvitz

Microsoft Research, Redmond WA 98052

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

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)

Beck Depression Inventory
This questionnaire measures how you feel. The questionnaire is of the self-report type.
1. I am no longer interested in my life.
2. I feel sad.
3. I have lost interest in my life.
4. I feel lonely.
5. I feel like I am alone.
6. I feel like I am not wanted.
7. I feel like I am not needed.
8. I feel like I am not important.
9. I feel like I am not useful.
10. I feel like I am not a person.
11. I feel like I am not a human being.
12. I feel like I am not a part of the world.
13. I feel like I am not a part of the future.
14. I feel like I am not a part of the past.
15. I feel like I am not a part of the present.
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18. I feel like I am not a part of the past.
19. I feel like I am not a part of the present.
20. I feel like I am not a part of the world.

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, ...



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AMT turkers: asked to rate 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



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

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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)

Beck Depression Inventory
This questionnaire asks how often you have experienced the following symptoms in the past 2 weeks.
1. I am sad most of the time.
2. I have lost interest in my usual activities.
3. I have lost weight or gained weight without trying to.
4. I have trouble sleeping.
5. I have trouble concentrating.
6. I feel tired or exhausted most of the time.
7. I feel worthless or guilty.
8. I have thoughts of harming myself or others.
9. I have thoughts of death or suicide.
10. I have lost my appetite.
11. I have lost my energy.
12. I have lost my interest in sex.
13. I have lost my interest in my usual activities.
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Beck Depression Inventory
This questionnaire measures how you feel. The questionnaire is of the self-report type.
1. I am as cheerful as I usually am.
2. I have lost interest in my usual activities.
3. I have lost weight without trying to lose weight.
4. I have trouble sleeping.
5. I have lost interest in sex.
6. I have trouble concentrating.
7. I have trouble making decisions.
8. I have trouble getting going in the morning.
9. I have trouble remembering things.
10. I have trouble thinking clearly.
11. I have trouble feeling motivated.
12. I have trouble feeling interested in things.
13. I have trouble feeling like I have a future.
14. I have trouble feeling like I have a purpose.
15. I have trouble feeling like I have a place in the world.
16. I have trouble feeling like I have a role to play.
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30. I have trouble feeling like I have a place in the world.



sample of **tweets**
about depression

categorization of tweets:

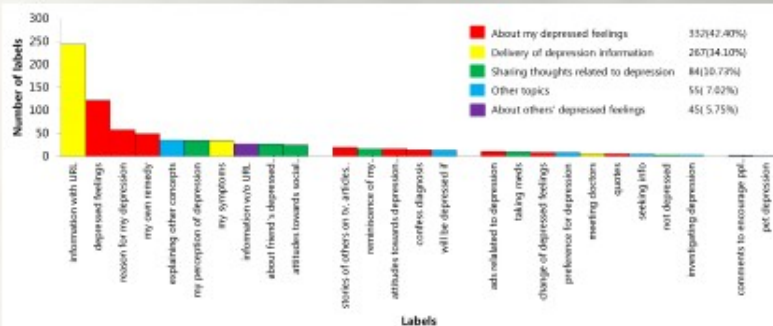


Figure 1: Labeled and categorized language usage in relation to depression

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

Depressive Moods of Users Portrayed in Twitter

Minsu Park
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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

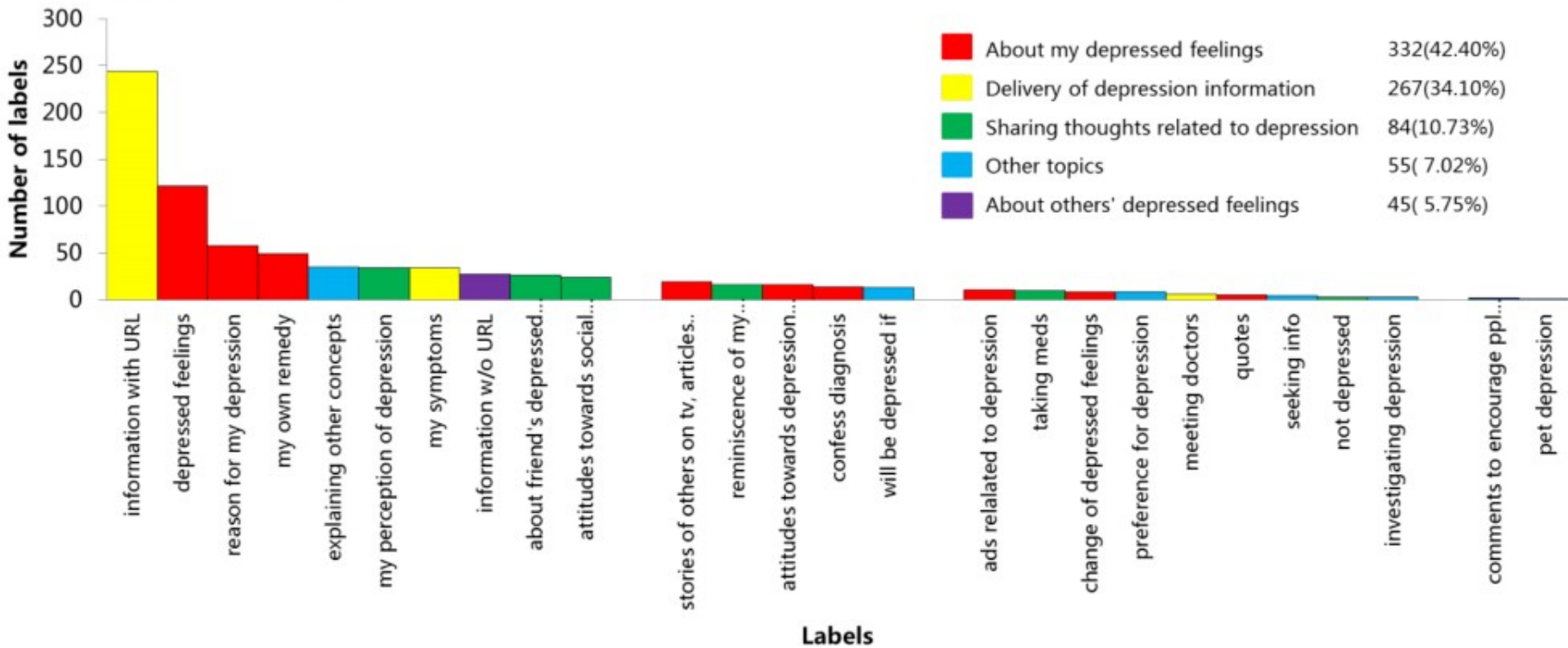


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sample of **tweets**
about depression

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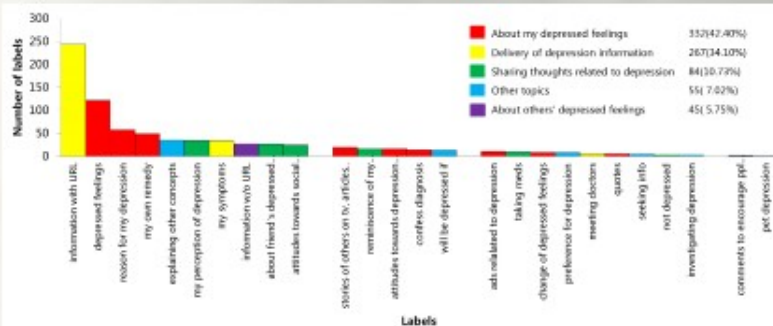


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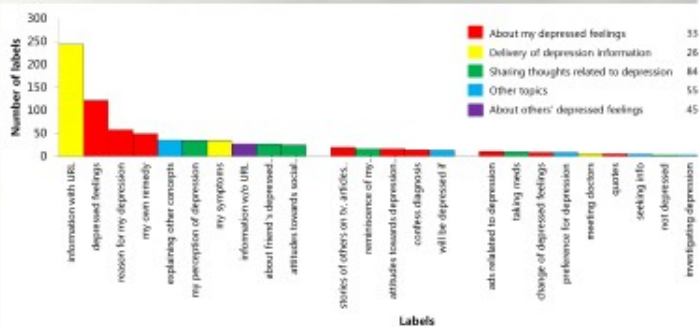


Figure 1: Labeled and categorized language usage in relation to depression

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:

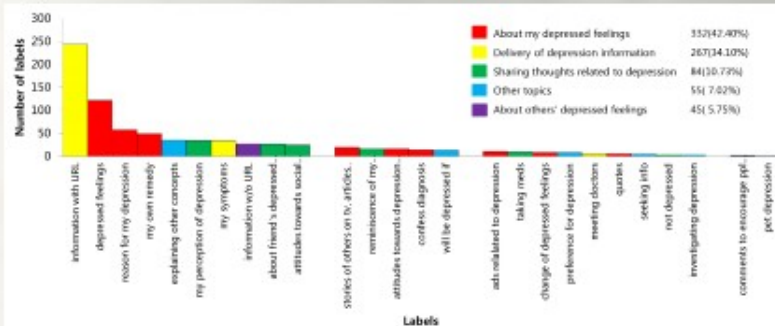


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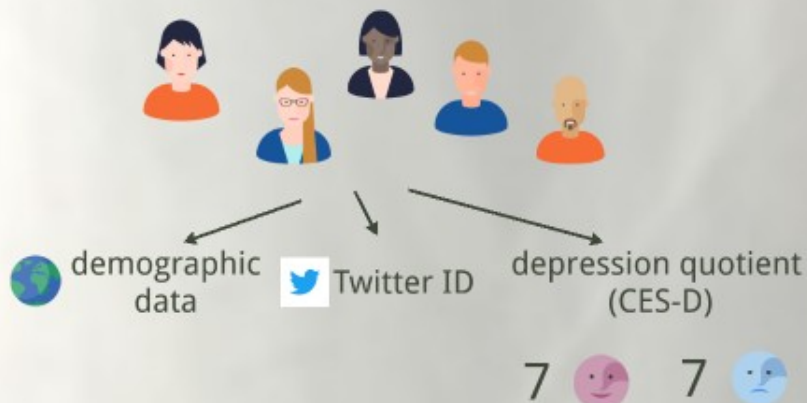
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(69 young adults):

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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**

Minsu Park
KAIST
mansumansu@kaist.ac.kr

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

Meeyoung Cha
KAIST
meeyoungcha@kaist.ac.kr

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

 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/\$31.0002012IEEE

| 73





216 **college** students



CES-D question



30% met min.
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

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

Measuring Usage Patterns 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/\$31.0002012IEEE



user's phone data



Patient Health
Questionnaire-9

Item	Response	Score
1. Little or no interest in doing things	1 = Not at all, 2 = A little, 3 = Quite a bit	1-3
2. Feeling down, depressed, or hopeless	1 = Not at all, 2 = A little, 3 = Quite a bit	1-3
3. Trouble sleeping	1 = Not at all, 2 = A little, 3 = Quite a bit	1-3
4. Feeling tired or having little energy	1 = Not at all, 2 = A little, 3 = Quite a bit	1-3
5. Thinking about death or suicide	1 = Not at all, 2 = A little, 3 = Quite a bit	1-3
6. Trouble concentrating	1 = Not at all, 2 = A little, 3 = Quite a bit	1-3
7. Moving or talking so slowly that others notice	1 = Not at all, 2 = A little, 3 = Quite a bit	1-3
8. Feeling nervous, anxious, or on edge	1 = Not at all, 2 = A little, 3 = Quite a bit	1-3
9. Becoming so tired that you need more sleep	1 = Not at all, 2 = A little, 3 = Quite a bit	1-3

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

h aire-9

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 <input type="checkbox"/>	Somewhat difficult <input type="checkbox"/>	Very difficult <input type="checkbox"/>	Extremely difficult <input type="checkbox"/>
---	---	---	--

Sohrab Sael

Konrad P K

¹Center for Bel

²Rehabilitation

³Department of



user's phone data



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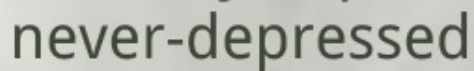
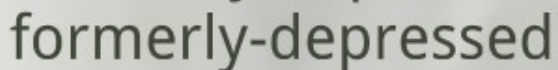
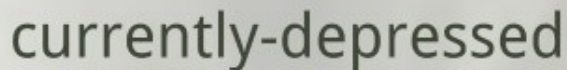


physical context-motion, variability of **location**, variability of **time**, home **stay**, social **settings**, phone **usage** (e.g. screen state)



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depressed participants:

- ▲ negatively valenced words, **neg emotions**
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(think a great deal about **themselves**)
- ▲ slightly more positive emotions than never-depressed

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

University of Texas at Austin, USA

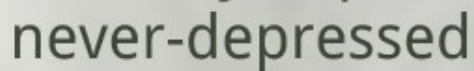
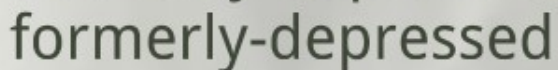
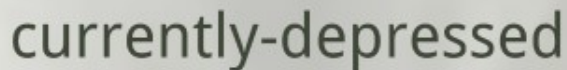
[illegible][illegible]

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	-	-	-	-
Clout	Clout	-	-	-	-
Authentic	Authentic	-	-	-	-
Emotional tone	Tone	-	-	-	-
Words/sentence	WPS	-	-	-	-
Words > 6 letters	Sixtr	-	-	-	-
Dictionary words	Die	-	-	-	-
Linguistic Dimensions					
Total function words	funcf	it, to, no, very	491	.05	.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	shehe	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	more, 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	135	.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	hasn'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		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					
Past focus	focuspast	ago, did, talked	341	.23	.64
Present focus	focuspresent	today, is, now	424	.24	.66
Future focus	focusfuture	may, will, soon	97	.26	.68
Relativity	relativ	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
Netpeak	netpeak	btw, lol, tho	209	.42	.82
Assent	assent	agree, OK, yes	36	.10	.39
Nonfluencies	nonflu	er, hm, umm	19	.27	.69
Fillers	filler	I mean, yunknow	14	.06	.27



depressed participants:

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(think a great deal about **themselves**)
- ▲ slightly more positive emotions than never-depressed

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

University of Texas at Austin, USA

TABLE 1. SWPCC (Swedish Work Environment Survey) by gender and age group

Table 1. SWPCC (Swedish Work Environment Survey) by gender and age group

Age group	Gender	Sample size	Mean SWPCC score	Standard deviation (SD)	Median SWPCC score
18-24 years	Male	100	4.2	1.2	4.0
25-34 years	Male	100	4.5	1.1	4.3
35-44 years	Male	100	4.8	1.0	4.6
45-54 years	Male	100	5.0	0.9	4.8
55-64 years	Male	100	5.2	0.8	5.0
65-74 years	Male	100	5.4	0.7	5.2
75-84 years	Male	100	5.6	0.6	5.4
85-94 years	Male	100	5.8	0.5	5.6
95-104 years	Male	100	6.0	0.4	5.8
105-114 years	Male	100	6.2	0.3	6.0
115-124 years	Male	100	6.4	0.2	6.2
125-134 years	Male	100	6.6	0.1	6.4
135-144 years	Male	100	6.8	0.1	6.6
145-154 years	Male	100	7.0	0.1	6.8
155-164 years	Male	100	7.2	0.1	7.0
165-174 years	Male	100	7.4	0.1	7.2
175-184 years	Male	100	7.6	0.1	7.4
185-194 years	Male	100	7.8	0.1	7.6
195-204 years	Male	100	8.0	0.1	7.8
205-214 years	Male	100	8.2	0.1	8.0
215-224 years	Male	100	8.4	0.1	8.2
225-234 years	Male	100	8.6	0.1	8.4
235-244 years	Male	100	8.8	0.1	8.6
245-254 years	Male	100	9.0	0.1	8.8
255-264 years	Male	100	9.2	0.1	9.0
265-274 years	Male	100	9.4	0.1	9.2
275-284 years	Male	100	9.6	0.1	9.4
285-294 years	Male	100	9.8	0.1	9.6
295-304 years	Male	100	10.0	0.1	9.8
305-314 years	Male	100	10.2	0.1	10.0
315-324 years	Male	100	10.4	0.1	10.2
325-334 years	Male	100	10.6	0.1	10.4
335-344 years	Male	100	10.8	0.1	10.6
345-354 years	Male	100	11.0	0.1	10.8
355-364 years	Male	100	11.2	0.1	11.0
365-374 years	Male	100	11.4	0.1	11.2
375-384 years	Male	100	11.6	0.1	11.4
385-394 years	Male	100	11.8	0.1	11.6
395-404 years	Male	100	12.0	0.1	11.8
405-414 years	Male	100	12.2	0.1	12.0
415-424 years	Male	100	12.4	0.1	12.2
425-434 years	Male	100	12.6	0.1	12.4
435-444 years	Male	100	12.8	0.1	12.6
445-454 years	Male	100	13.0	0.1	12.8
455-464 years	Male	100	13.2	0.1	13.0
465-474 years	Male	100	13.4	0.1	13.2
475-484 years	Male	100	13.6	0.1	13.4
485-494 years	Male	100	13.8	0.1	13.6
495-504 years	Male	100	14.0	0.1	13.8
505-514 years	Male	100	14.2	0.1	14.0
515-524 years	Male	100	14.4	0.1	14.2
525-534 years	Male	100	14.6	0.1	14.4
535-544 years	Male	100	14.8	0.1	14.6
545-554 years	Male	100	15.0	0.1	14.8
555-564 years	Male	100	15.2	0.1	15.0
565-574 years	Male	100	15.4	0.1	15.2
575-584 years	Male	100	15.6	0.1	15.4
585-594 years	Male	100	15.8	0.1	15.6
595-604 years	Male	100	16.0	0.1	15.8
605-614 years	Male	100	16.2	0.1	16.0
615-624 years	Male	100	16.4	0.1	16.2

[illegible]



essays by college students



BDI score



linear **regression**



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**

2013 Conference on Empirical Methods in
Natural Language Processing

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

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

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Lyle H Ungar¹ and Johannes C Eichstaedt¹

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²The University of Melbourne, Melbourne, Australia

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



TABLE 4

Proportion of patients with different mental illness diagnoses reviewed in this paper. The relevant dataset, features, and statistical analyses are available.

[illegible]

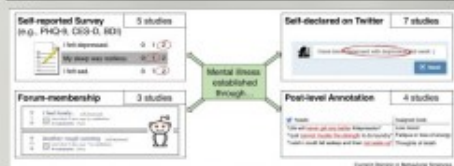
NJC Area Under the Receiver Operating Characteristic (ROC) Curve: Fraction of cases used and positive that are in y positive. No overlap between cases that are correctly classified and the model. Some Support Vector Machine (SVM) ROC Analysis: 100% - 100% (100%)

*We teamed with 700 Public Affairs Ltd.

*Using the *Journal* as based on the Toronto and London manuscripts by the late national President Dr. John F. Fox (FNU) given to the M.D.W. & Research Society [10].

Stylus high lifted in green sector (B,C). B,Cs are not high only decreased and not big compared across electric

Figure 3



Each source used is listed as a paragraph entry to establish exactly whose study. The number of studies selected to review is the present size of the meta-analysis. The next summary text will report summary statistics for depression, anxiety, PTSD, and Post-Traumatic Stress Disorder (PTSD) in children and the next summary text will report summary statistics for depression, anxiety, PTSD, and Post-Traumatic Stress Disorder (PTSD) in adults.

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principle, he collected fewer and more strongly than through the utilization of vectors (see Table 1 for sample used, though vector-based movement is common). At generally provides a higher degree of reliability [4].

We first compare studies that attempt to distinguish causality of events from psychological methods (Section A and B). Table 1 summarizes the methodological details of these studies.

Prediction based on survey responses

Psychometric self-report sources for mental illness have a high degree of validity and reliability (e.g., see [11]). In psychological and epidemiological research, self-report surveys are second only to clinical interviews, which are used in clinical trials to date but have not been used as an outcome measure. We discuss how studies that predict survey-based diagnosis status by reflecting participants' responses to depression surveys in conjunction with their social media data.

The most cited study used Twitter activity to examine network and language data preceding a recent episode of depression [87]. The presence of depression was established through participants receiving the questionnaire, as

review data of a depressive episode, combined with work on the Centre for Epidemiologic Studies Depression Scale Revised (CES-D) and Beck's Depression Inventory (BDI-II). This study revealed several distinctions in power among the depressed men, including: domestic violence, more negative emotion, less social interaction, more self-blame, and maintaining depression-related beliefs throughout the year since their depressive onset.

Rever et al. [11] predicted near-degenerate and pseudo-degenerate states (PTSDs) using four sets of *Twelve monomers* that provided a repeated data set (see Figure 7) for examples of molecules with identical high levels under the Boolean Operating Characteristic (BOC) score (M.T. of 8) (depression and 80 PTSDs). Data were aggregated to nodes, which concerns on performed aggregation to days, and modeled as logistic class indicators of activity patterns (see differences in high-level data matrix, 40 days).

Tropea *et al.* [12] predicted depression from Twitter data in a Japanese sample, using the CBR II as the measurement collection. Using tweets from the most recent 6–18 weeks preceding the administration of the CBR-I was sufficient for measuring depressive symptoms.

Figure 1

Example post: How did this happen to me?			
#grains	LWFC (dislikes)		Seedbank
1-grain: How did this happen to me, I	Category	% Score	Subjectivity: 0.00-0.01
1-grain: "How did this happen to me, I	Self-obsessed (me, my)	15.87	Priority
1-grain: "How did this happen to me, I			Label: 1-grain: 0.00-0.01
1-grain: "How did this happen to me, I	Social	0	
1-grain: "How did this happen to me, I	Emotions	0	
1-grain: "How did this happen to me, I	Overly-cognitive words	15.87	
#grains meta-data	User activity		User social network
Any 1-grain length	Number of		Number of:
Any 1-grain length	Posts by the face of		Friends
Any 1-grain length	Posts by the face of		Followers
Any 1-grain length	Posts between "Glas		People in extended
Any 1-grain length	and Sam		circle
Any 1-grain length	Relationships		
Any 1-grain length	Posts with LWFC		
Any 1-grain length	Relationships, 0-relationship		

[illegible]

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])			n-grams	LJWC	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-R ² ^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	Naive 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

¹ University of Pennsylvania, Philadelphia, PA, United States

²The University of Melbourne, Melbourne, Australia

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



TABLE 4

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

[illegible]

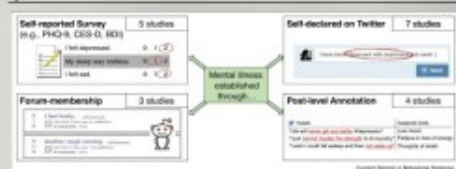
AUC: Area Under the Receiver Operating Characteristic (ROC) Curve. Precision: Fraction of cases that are positive that are truly positive. Accuracy: Fraction of cases that are correctly classified by the model. Sens: Sensitive. Match: Yes; No. Recall: Recall. Confusion Matrix: True - Right; False - Wrong.

^aWeighted with 100 Public Area 10.

*Using the *Journal* on basis of the Forensic and Toxicology by the International Forensic Ky. Term Fee (FPI) proxy to the S.O.P. 4. Personnel
FPI/00/01/01

Studies highlighted in green report B.Ca; B.Ca are not mass rate dependent and can be compared across studies

Figure 3



Each source used a strategy or assessment criteria to establish a study's 'true status'. The number of profiles selected to explore is the percent of all in a year end. The most summary score self-reported screening scores by depression is the PHQ-9 Patient Health Questionnaire (15, 16, 17) or the 10-item Patient Health Questionnaire Depression Scale (18, 19) or the 10-item Patient Health Questionnaire (20).

Journal of Business Ethics (2015) 129:101–117

© 2000 Blackwell Science Ltd *Journal of Internal Medicine* 247: 391–397

principle, he collected leaves and more strongly than through the utilization of sensors (see Table 1). In simple words, though sensor-based increment location at generally provides a higher degree of safety [1].

We first compare studies that attempt to distinguish causally all sorts from sociological methods (Sections A and B). Table 1 summarizes the methodological kinds of these studies.

Prediction based on survey responses

Psychometric self-report surveys for mental illness have a high degree of validity and reliability (e.g., see [1]). In epidemiological and epidemiological research, self-report surveys are second only to clinical interviews, which are used in clinical trials and in some research, which are used as data for use in some research. We discuss how studies that provide survey-based diagnosis status by collecting participants' responses to depression surveys in comparison with their social media data.

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

recognize that a depressive episode, combined with water on the canvas for Epidemiologic Studies Depression Scale Revised (CES-D-10) and Beck's Depression Inventory (BDI-10). This study revealed several distinctions in posting anxiety by depressed water, including: domestic, more negative emotion, less social interaction, more self-focus, and more negative/optimistic-related items throughout the year since depressive onset.

Rever et al. [11] produced near *depression* and post-traumatic stress disorder (PTSD) states from sets of 160000 words that provided a repeated text episode (see Figure 2) as examples of immediate, with relatively high rates under the Bayesian Operating Characteristic (BOC) model of [7] (*depression* and 50 PTSD). Data were aggregated to words, which somewhat outperformed aggregation to days, and modeled as linguistic conjunctions of activity patterns that differentiated high to low severity of onset.

Tsugawa *et al.* [11] predicted depression from Twelfth data in a Japanese sample, using the CES-D as their measurement criterion. Using errors from the most recent 6-18 weeks preceding the administration of the CES-D was sufficient for recognizing depression; predicting

Figure 1

Example post: How did this happen to me?

H-games

I-games: from old film, telegram, etc. I

I-games: "this bad", "nothing", "his

mother", "heaven", "I"

I-games: "his action", did his

mother? "his happen?"

LWC (dis)advantages

Category	% Score
Self-advantaged (no. neg)	15.87
Social words	-
Emotions	0
Good/negative words	16.97

Socialism

Subjectivity: zero (0)

Priority: I-games (0)

Label: I-games score: 0.2

I-games meta-data

Avg. I-game length:

Avg. number of I-games per user:

Avg. number of I-games per user:

...

User activity

Number of:

- Posts by the face of
- Posts by others
- Posts between I-Games
- Likes
- Retweets
- Posts with LWC's
- Hashtags, @ mentions

User social network

Number of:

- Friends
- Followers
- People in extended circles

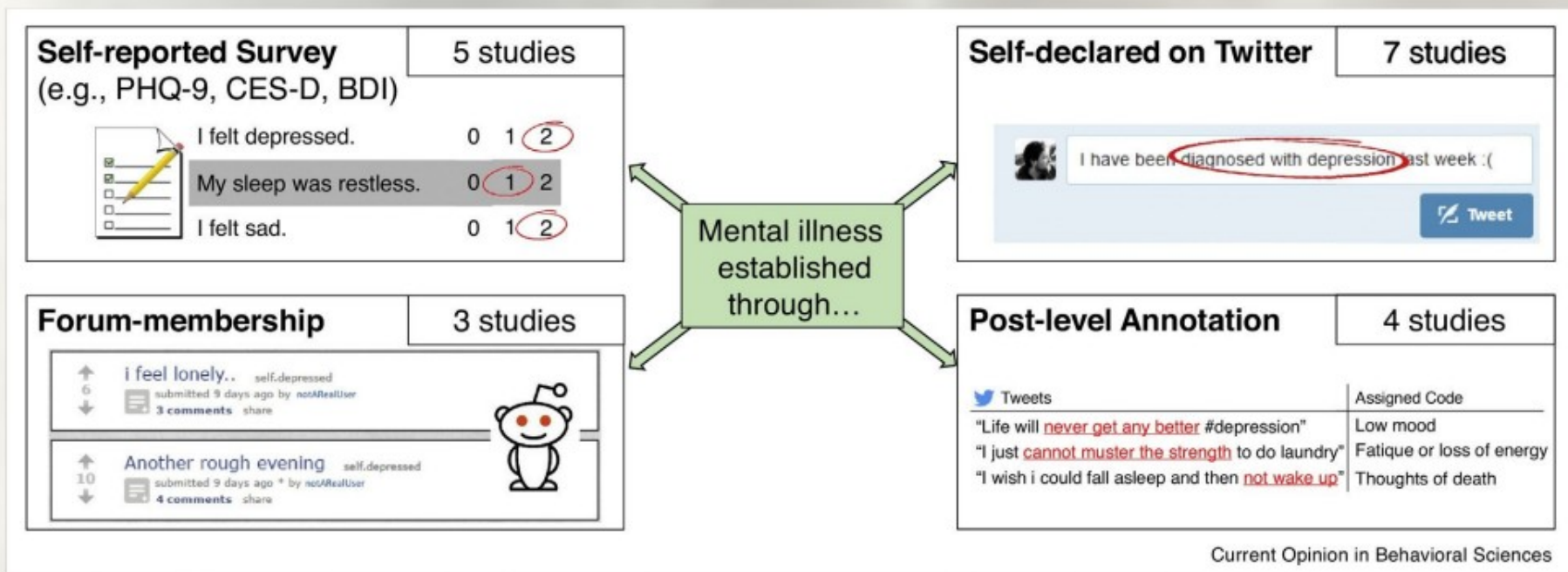
GameCognition 2014

Journal of Natural Products • The Official Journal of the American Chemical Society • Volume 71, Number 1, January 2008 • Pages 1–160 • ISSN 0022-2967 • DOI: 10.1021/jnp700001a

Source: *U.S. Census Bureau, 1997*

Current Estimates in Behavioral Sciences 77 / H. O'Neil

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

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[illegible]

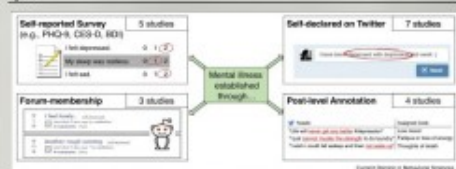
AUC: Area Under the Receiver Operating Characteristic (ROC) Curve. Precision: Fraction of cases that are positive that are truly positive. Accuracy: Fraction of cases that are correctly classified by the model. Sens: Sensitive. Match: Yes; No. Recall: Recall. Confusion Matrix: True - Right; False - Wrong.

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FPI/00/01/2001

Studies highlighted in green report B.Ca; B.Ca are not mass rate dependent and can be compared across studies

Figure 3



Each source used a strategy or assessment criteria to establish a study's 'true status'. The number of profiles selected to explore is the percent of all in a year end. The most summary score self-reported screening scores by depression is the PHQ-9 Patient Health Questionnaire (15, 16, 17) or C-SSRS for self-reported suicidal ideation scores (18, 19) or depression (20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100).

Journal of Human Capital Management 2012, 14(3), 39-49

© 2000 Blackwell Science Ltd *Journal of Internal Medicine* 247: 399–406

principle, he collected leaves and more strongly than through the utilization of sensors (see Table 1). In simple words, though sensor-based increment locusts do generally provide a higher degree of safety [1].

We first compare studies that attempt to distinguish causally all sorts from sociological methods (Sections A and B). Table 1 summarizes the methodological kinds of these studies.

Prediction based on survey responses

Psychometric self-report surveys for mental illness have a high degree of validity and reliability (e.g., see [1]). In epidemiological and epidemiological research, self-report surveys are second only to clinical interviews, which are used in clinical trials and in some research. We discuss how studies that provide survey-based diagnosis status by collecting participants' responses to depression surveys in comparison with their clinical data.

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recognize that a depressive episode, combined with water on the Canis for Epidemiologic Studies Depression Scale Revised (CES-D14) and Beck's Depression Inventory (BDI-II). This study revealed several distinctions in posting activity by depressed users, including: greater cyber, more negative emotion, less social interaction, more self-focus, and mentioning depression-related terms throughout the year since the depressive onset.

Rever et al. [11] produced near *depression* and post-traumatic stress disorder (PTSD) states from sets of 160000 words that provided a repeated text episode (see Figure 2) for examples of immediate, with relatively high rates under the Bayesian Operating Characteristic (BOC) curve (AUC of 0.7) depression and 0.6 PTSD). Data were aggregated to words, which somewhat outperformed aggregation to days, and modeled as linguistic conjunctions of activity patterns that differentiated high from low severity of onset.

Tsugawa *et al.* [11] predicted depression from Twelfth data in a Japanese sample, using the CES-D as their measurement criterion. Using errors from the most recent 6-18 weeks preceding the administration of the CES-D was sufficient for recognizing depression; predicting

Figure 1

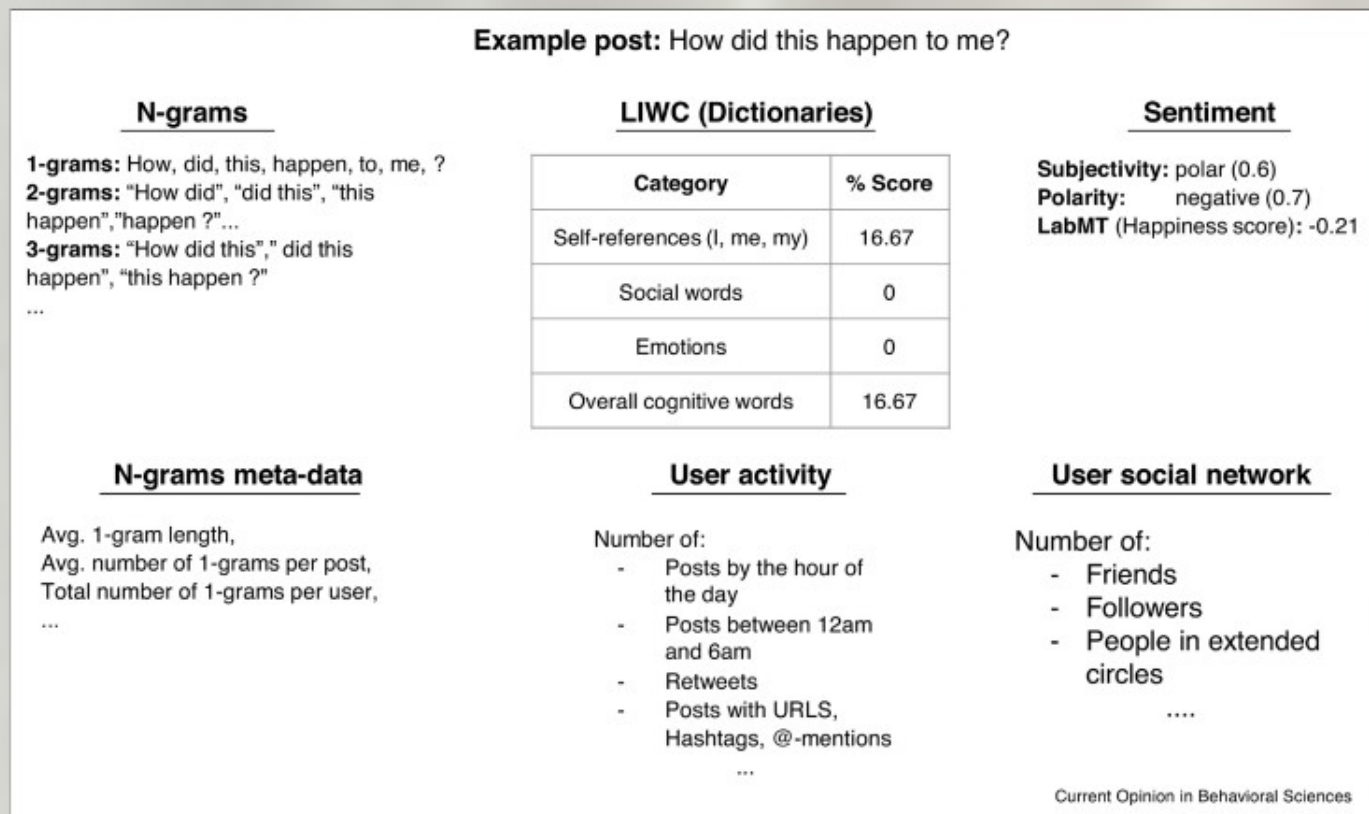
Example post: How did this happen to me?												
#hashtags	LWC (dislikes)	SocialRank										
<p>1-gram: how, did, this, happen, to, me, ?</p> <p>2-gram: "how did", "happen to", "this happen", "happen to", "me ?"</p> <p>3-gram: "how did", "did this happen", "this happen ?"</p>	<table> <tr> <th>Category</th><th>% Score</th></tr> <tr> <td>Self-advocacy (me, my)</td><td>10.0%</td></tr> <tr> <td>Social words</td><td>0</td></tr> <tr> <td>Emotions</td><td>0</td></tr> <tr> <td>Other cognitive words</td><td>10.0%</td></tr> </table>	Category	% Score	Self-advocacy (me, my)	10.0%	Social words	0	Emotions	0	Other cognitive words	10.0%	<p>Subjectivity: 0.00 (0.0)</p> <p>Priority: 1 (0.0)</p> <p>Label: 1 (negative words: 0.0)</p>
Category	% Score											
Self-advocacy (me, my)	10.0%											
Social words	0											
Emotions	0											
Other cognitive words	10.0%											
#tags meta data	User activity	User social network										
<p>Any 1-gram length</p> <p>Any 2-gram or more</p> <p>Any number of 1-grams per post</p> <p>Any number of 1-grams per user</p>	<p>Number of:</p> <ul style="list-style-type: none"> Posts by the user of Posts by the user's friends Posts between 1-gram and 2-gram Retweets Posts with LWC Hashtags, @ mentions 	<p>Number of:</p> <ul style="list-style-type: none"> Friends Followers People in extended circles 										

Journal of Natural Products • The Official Journal of the American Chemical Society • Volume 71, Number 1, January 2008 • Pages 1–100 • ISSN 0022-0667 • DOI: 10.1021/jn700000a

Source: *U.S. Census Bureau, 1997*

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Figure 2



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

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

104 *Journal of Health Politics, Policy and Law*

TABLE 4

Publication performance achieved by different mental illness studies reviewed in this paper. The relevant dataset, features, and similarity settings are provided.

[illegible]

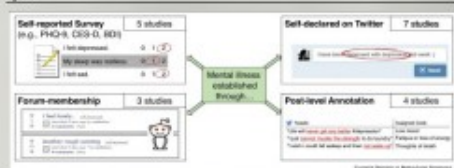
NJC Area Under the Receiver Operating Characteristic (ROC) Curve: Fraction of cases used as positive that are in y positive. No overlap between cases that are correctly classified by the model (true). Support vector machine (SVM) (Cortez et al., 2001) – 100% (100%)

^aWashed with 100 mM NaCl.

¹Using the measures on board the Fawcett on factor structures by the bifactorial Penna & Jorm-Pass (1997) proxy to the M.D.P. & Penna (1997) D.M.

Median logs (light to green) represent ΔG_{ox} . ΔG_{ox} are not mass rate dependent and not too comparable across studies.

Figure 10



Key words used: studies as assessment; trials to establish efficacy; breast cancer. The number of studies selected for review is the percent of the population. The most commonly used self-reported screening surveys for physicians include the PHQ-9 (Patient Health Questionnaire) and the C-STAR-10 (Cancer Health Status Assessment).
DOI: 10.1002/jbm.b.10008

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Blended (Hybrid) Instruction: an essential reading • <http://www.ck12.org/Blended-Instruction>

principle, he collected more and more strongly than through the utilization of sensors (see Table 1). In simple words, though sensor-based treatment (section A) generally provides a higher degree of safety [4].

We first compare studies that attempt to distinguish causally of events from nonbiological outside factors A and B. Table 1 summarizes the methodological details of these studies.

Estimation based on survey responses

Psychometric self-report surveys for mental illness have a high degree of validity and reliability (e.g., see [12]). In psychological and epidemiological research, self-report surveys are second only to clinical assessments, which are costly and used only in clinical circumstances, which are usually made up of data from used as an outcome measure. We discuss five studies that produce survey-based diagnostic status by collecting participants' responses to depression surveys in comparison with their social media data.

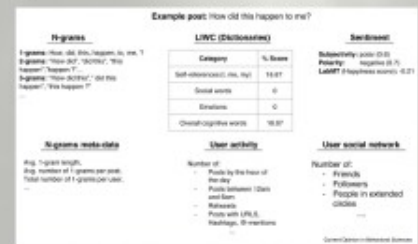
The most cited study used Yalom's writing to examine network and language first preceding a recent episode of depression [37]. The presence of depression was confirmed through participants reporting the occurrence and

recurrent depressive episode, combined with work on the Center for Epidemiologic Studies Depression Scale Revised (CES-D10) and Beck's Depression Inventory (BDI-10). This study revealed several distinctions in posting activity by depressed users, including: daily entries, more negative emotion, less social interaction with self, friends, and members, and depression-related posts throughout the year preceding depression onset.

Herein we describe a [111] produced over deposition and post-annealing surface disorder (PTSD) seen from x-ray scattering measurements that generated a reported first spinodal (see Figure 1) for examples of intermediate work released. High Access modes: the Bayesian Overlaying Characterization (BOC) model (List of 37) (deposition and 20 PTSD) data were aggregated to models, which were then performed aggregation to days, and modeled as long-term global trajectories of activity patterns that differentiate. Results from essentially 80 cases.

Togawa *et al.* [12] predicted depression from Twitt data in a Japanese sample, using the CDS II as the measurement collection. Using scores from the most recent 6.18 weeks preceding the administration of the CDS, it was sufficient for recognizing depressive psychosis.

Figure 1



Downloaded from <http://ajph.org/> by guest on September 11, 2012

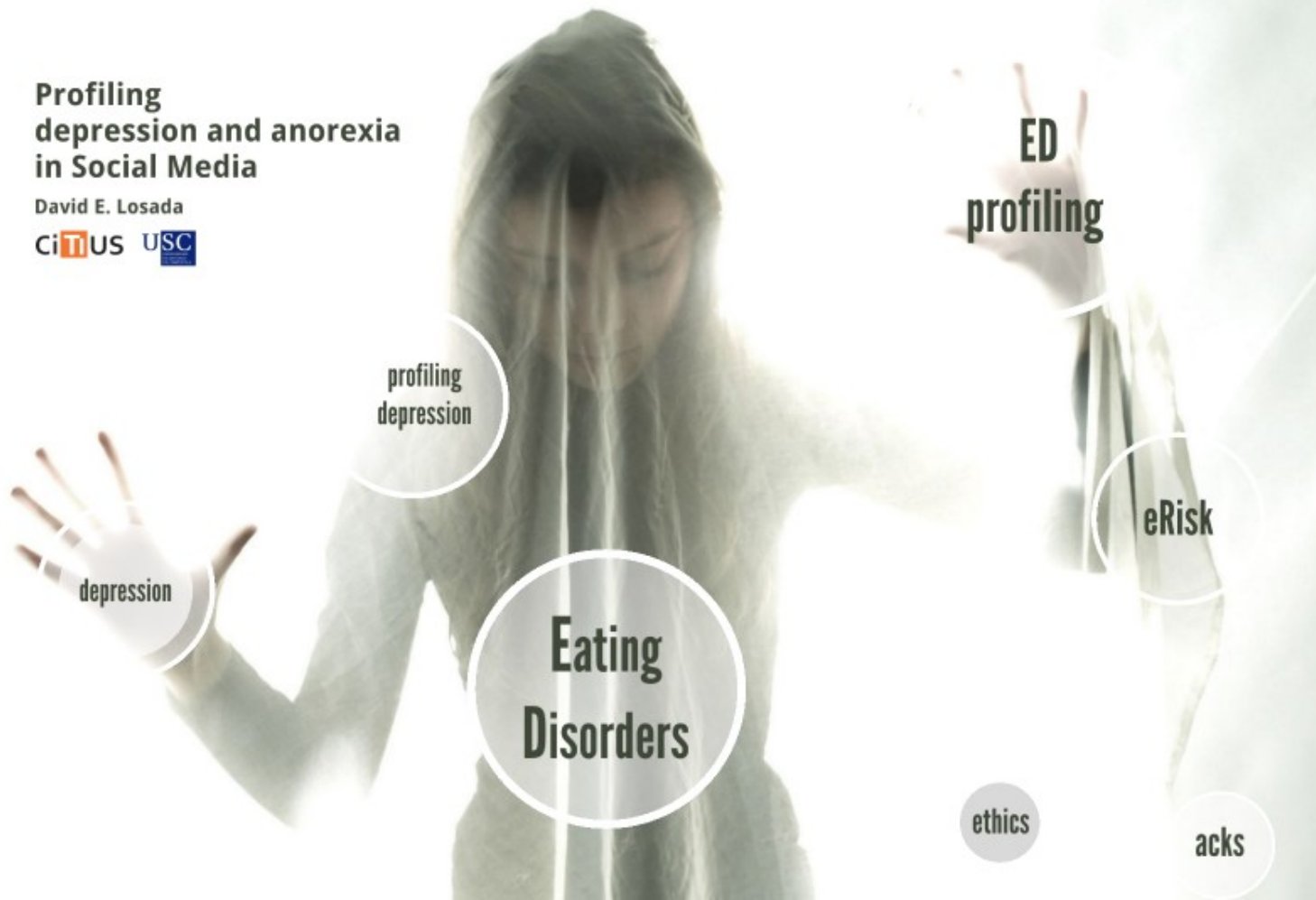
www.elsevier.com/locate/jbiotec

Current Reviews in Behavioral Sciences 27 / 44-45-46

Profiling depression and anorexia in Social Media

David E. Losada

CiMUS USC



depression

profiling
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 NERVOSA

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
purging



eating disorders symptoms

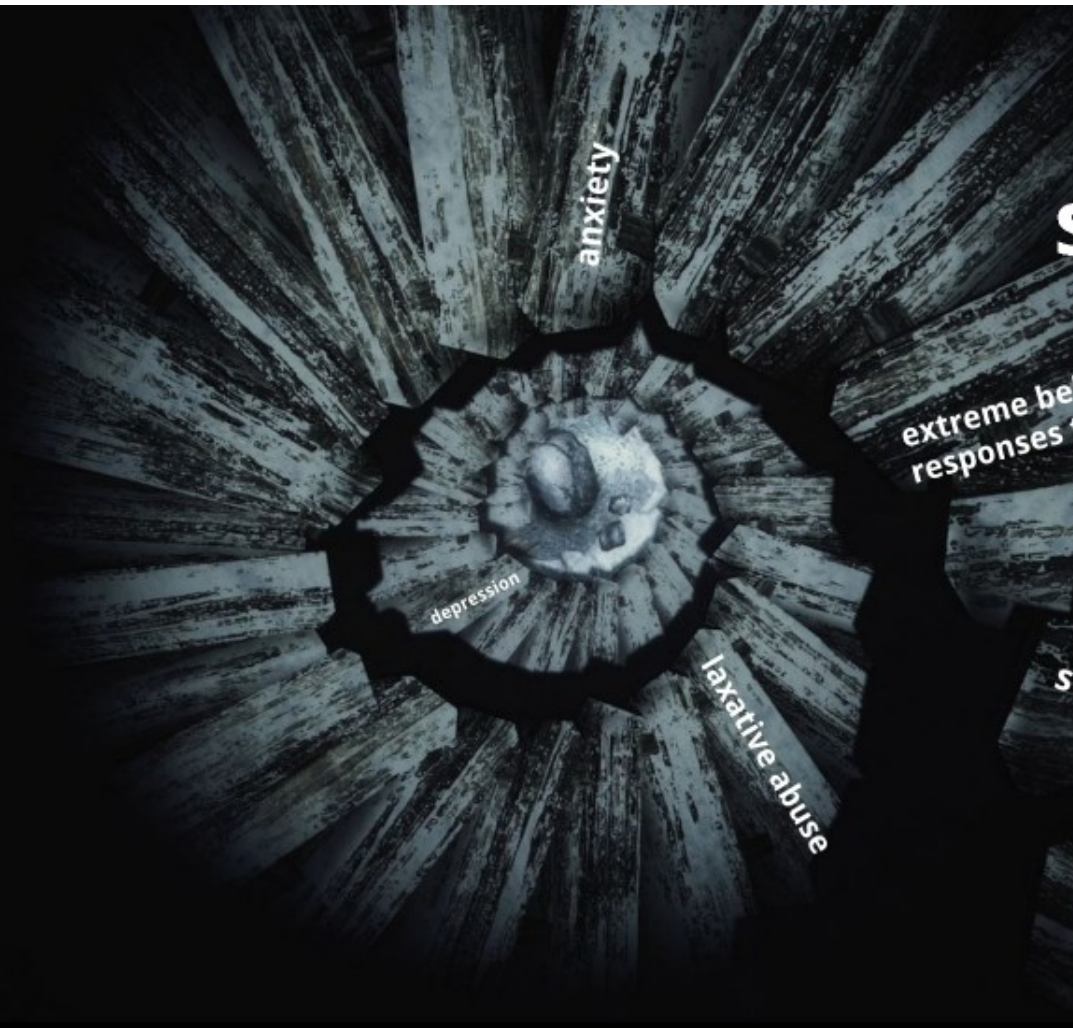
extreme behavioural/emotional
responses to eating food & gaining weight

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
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February 2015



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

Separately from prevalence data research (involving GP data) the ISE indicates an increase in the age-standardised annual incidence of all diagnosed eating disorders (in ages 10-49) from 32.2 to 37.2 per 100,000 between 2000 and 2006. It is increase appears to be due to an increase in the unspecified eating disorder category as AN and BN numbers remained fairly stable¹¹.

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 (bureaux a standard) is increasing prevalence over time with a 14% increase in admissions since 2009-10 – 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 recording¹².

Table 3.3

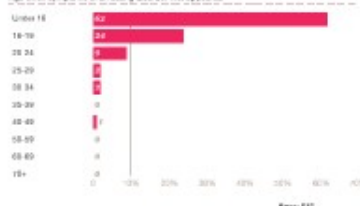
Count of EDs with per every 4 signs of eating disorder in England, 2000-2014

	Count of Perceived Atypical Symptoms (PAS) where the primary diagnosis was an eating disorder (England)
2000-2005	1,952
2006-2011	1,804
2012-2013	1,812
2009-2010	1,818
2010-2011	2,007
2012-2013	2,065
2013-2014	2,368
2014-2015	2,825

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



¹¹Wells, N., Haycraft, S., Rutter, M., & Treasure, J. (2013). The incidence of eating disorders in the UK in 2009-2008: first signs from the General Practice Research Database. *BMJ Open*, 3, 1-7. doi:10.1136/bmjopen-2013-000488. Available at: <http://dx.doi.org/10.1136/bmjopen-2013-000488>

¹²International Society for Eating Disorders (2013) *Prevalence of eating disorders*. Available at: <http://www.ised.org.uk/what-is-eating-disorders/prevalence>

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

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

Separately from prevalence data research (modeling GP data in the ISE indicates an increase in the age-standardised annual incidence of all diagnosed eating disorders for ages 10-49 from 32.2 to 37.2 per 100,000 between 2000 and 2006. This increase appears to be due to an increase in the unspecified eating disorder category as AN and BN numbers remained fairly stable¹.

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 steady trend in increasing prevalence over time with a 14% increase in admissions since 2009-10 – 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 recording².

Table 3.3

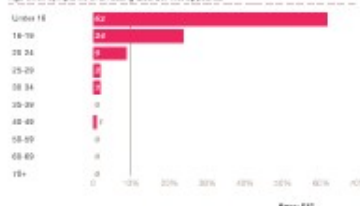
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2014-2015	2,455

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



¹Wolke, M., Haycraft, S.W., Rutter, M., & Treasure, J.L. (2013) The incidence of eating disorders in the UK in 2009-2008: first steps from the General Practice Research Database. *BMJ Open*, 3, no. 1-9 (in press). Available at: <http://dx.doi.org/10.1136/bmjopen-2013-000484>

²International Society for Eating Disorders (2013) *Prevalence of eating disorders*. Available at: <http://www.ised.org.uk/what-is-eating-disorders/prevalence>

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The costs of eating disorders

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prevalence of ED has significantly grown

The costs of eating disorders

Social, health and economic impacts

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Figure 3.3

Gender breakdown of survey respondents



prevalence of ED has significantly grown

The costs of eating disorders

Social, health and
economic impacts

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prevalence of ED has significantly grown

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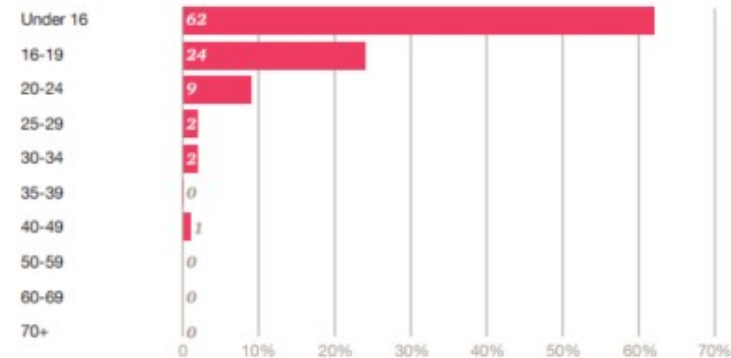
February 2015



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

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prevalence of ED has significantly grown

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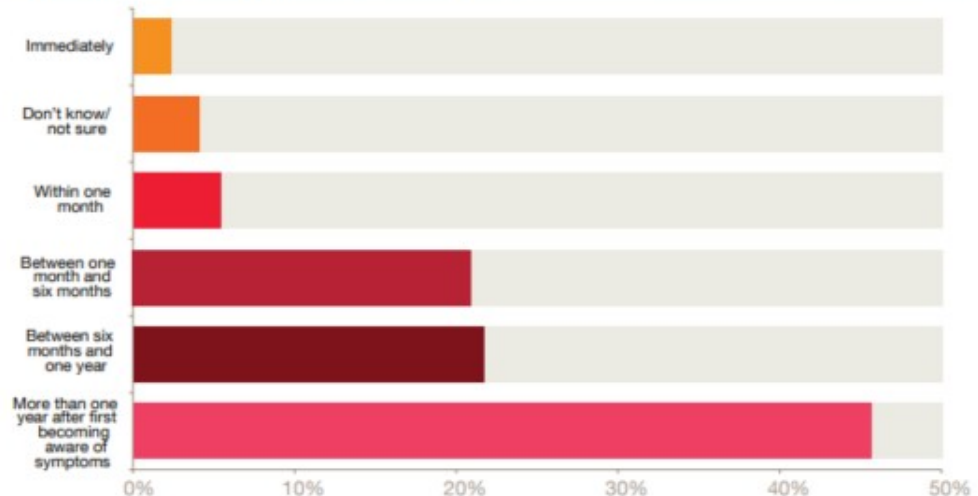
February 2015



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

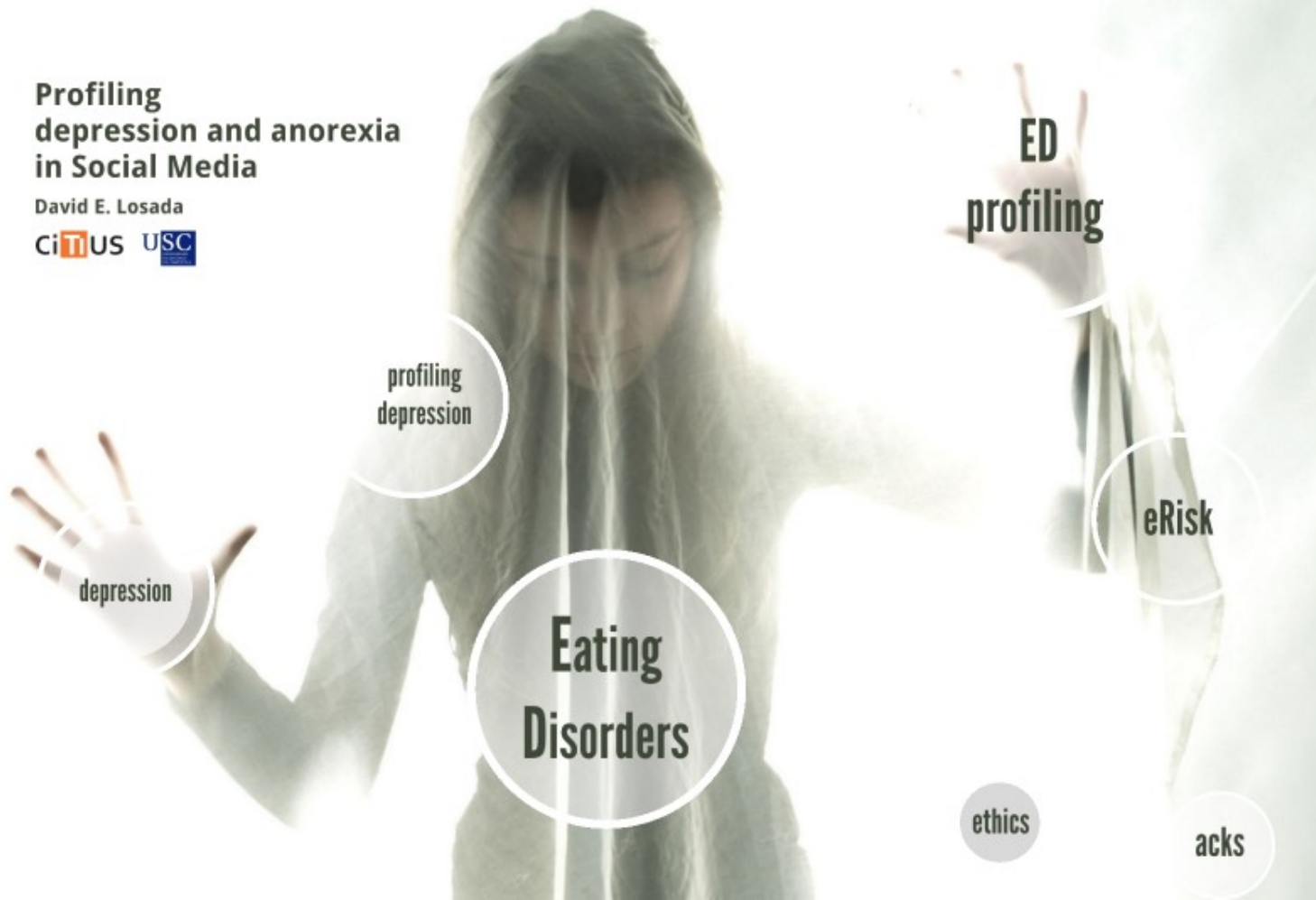
limitations:

- **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

CiMUS 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



(**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**

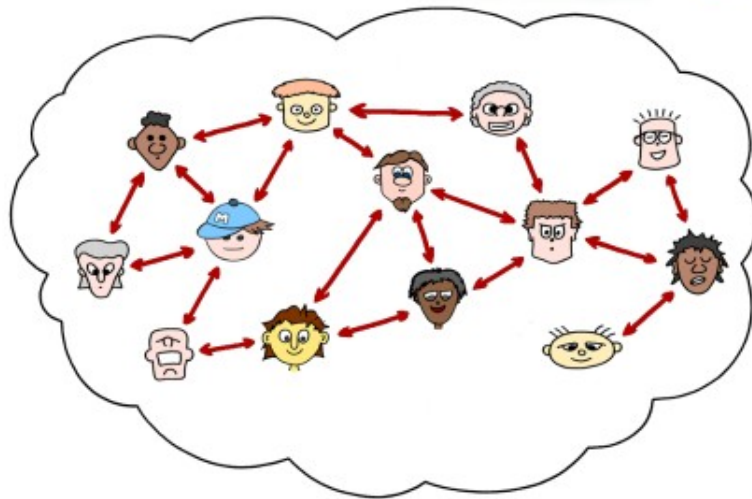


harmful content

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 YouTube

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-Lugue 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



13 years-old

17 years-old

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

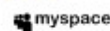
health authorities: study the content dissemination strategies used by the pro-anorexics & design their own **dissemination strategies for informative content**



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

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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**

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

Markus Wolf¹, Florian Theis¹, and Hans Kordy¹

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

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

expressions of **disordered** eating patterns & **notable audience of followers**

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

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}

^a Department of Sociology, University of Washington, Seattle, Washington

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

^c Department of Statistics, University of Washington, Seattle, Washington

^d Department of Pediatrics, University of Washington, Seattle, Washington

JOURNAL OF
ADOLESCENT
HEALTH
www.jahonline.org



CrossMark

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
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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,⁰²³ [Ingmar Weber](#), PhD,⁴ and [Steven P. Crain](#), PhD⁵

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

242,710 pics



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)



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ESRC DTC, ILS

Markus Brede
Department of ECS

Antonella Ianni
Department of Economics

Emmanouil Mentzakis
Department of Economics

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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

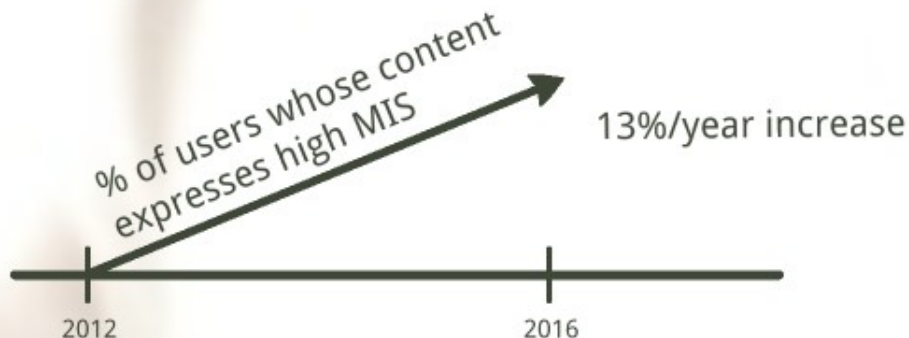
LDA topic modelling + novice/clinical annotations



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

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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

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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**

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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

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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)



A word cloud containing the following terms: Body Mass Index, purge, lbs, kgs, proana, lowest weight, Ultimate Goal Weight, legspo, Current Weight, and binge. The words are arranged in a circular pattern, with 'Body Mass Index' at the top and 'binge' at the bottom right.

Profiling depression and anorexia in Social Media

David E. Losada

CiMUS USC

ED
profiling

profiling
depression

depression

Eating
Disorders

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

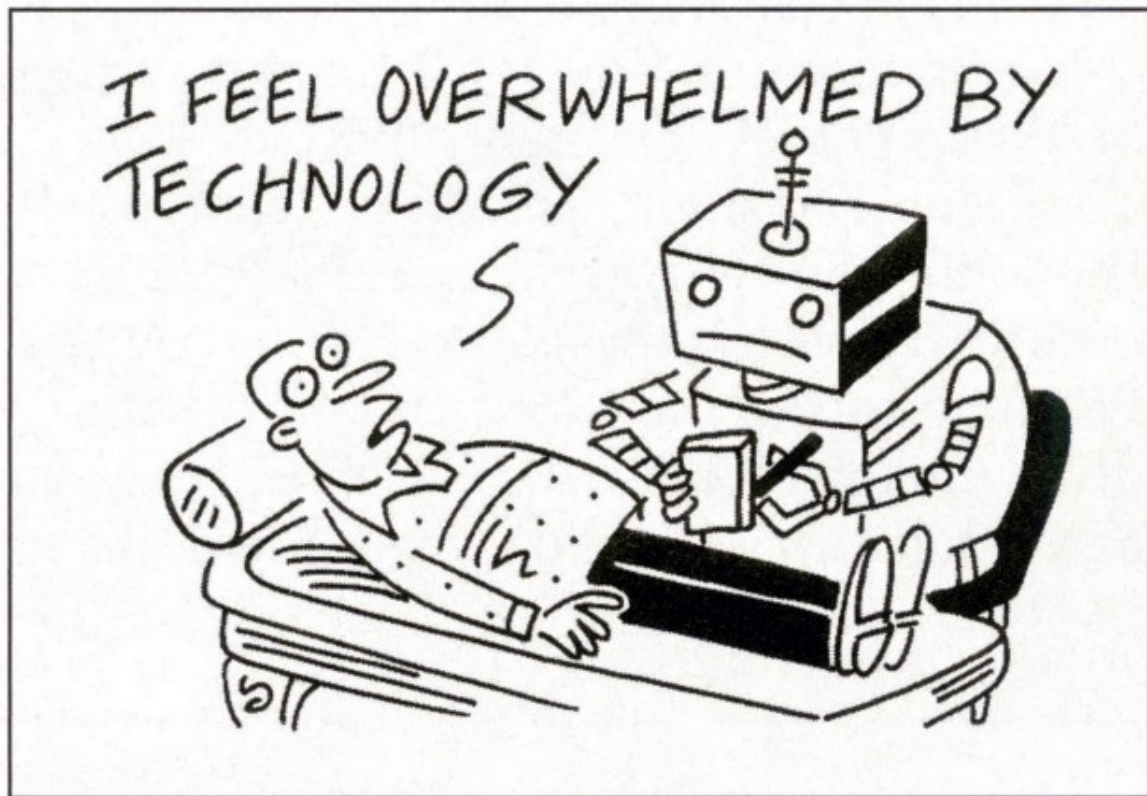
use cases

automatic assessments?



use cases

automatic assessments?

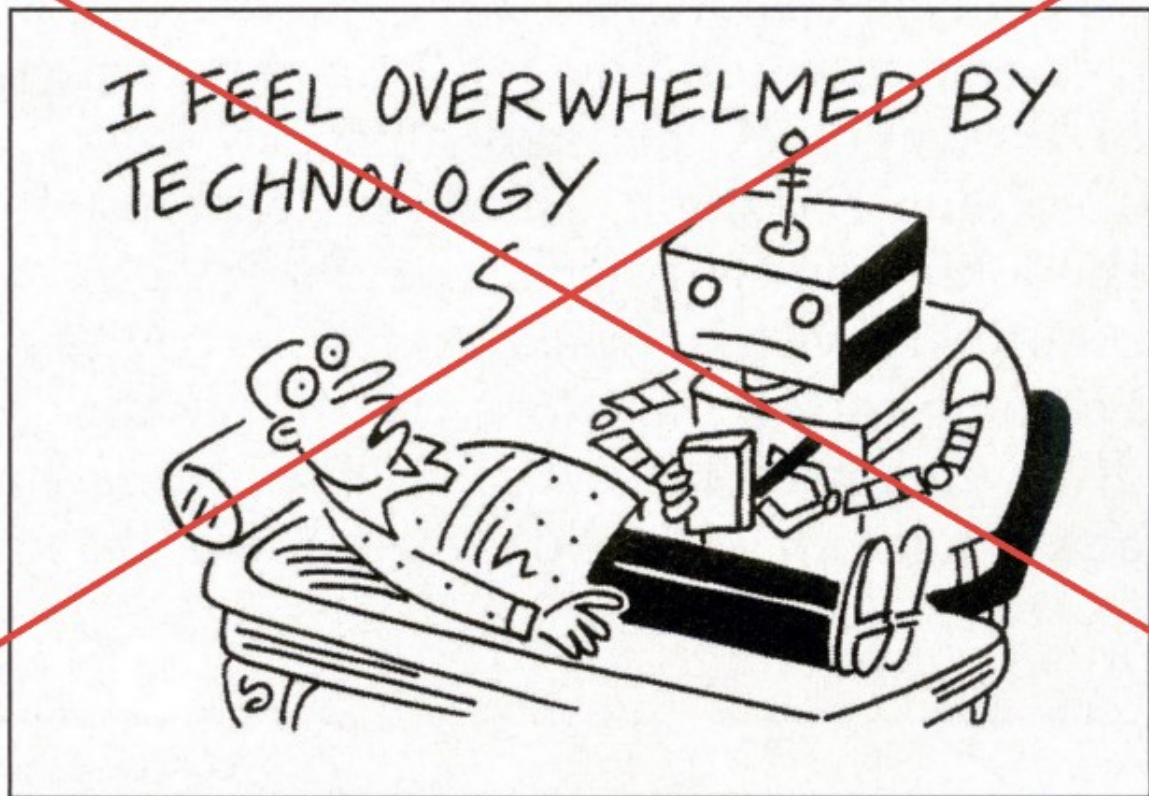


© HALDANE/THE TIMES/NEWS SYNDICATION

use cases

automatic assessments?

NO WAY!!!

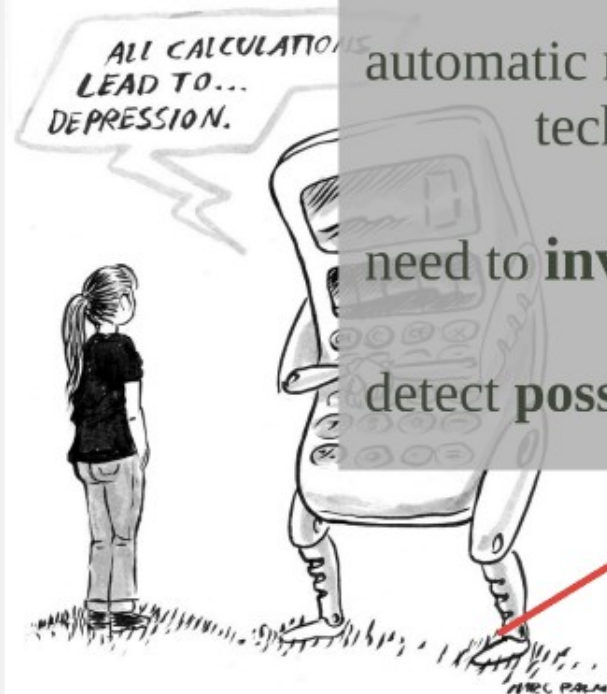


© HALDANE/THE TIMES/NEWS SYNDICATION

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?



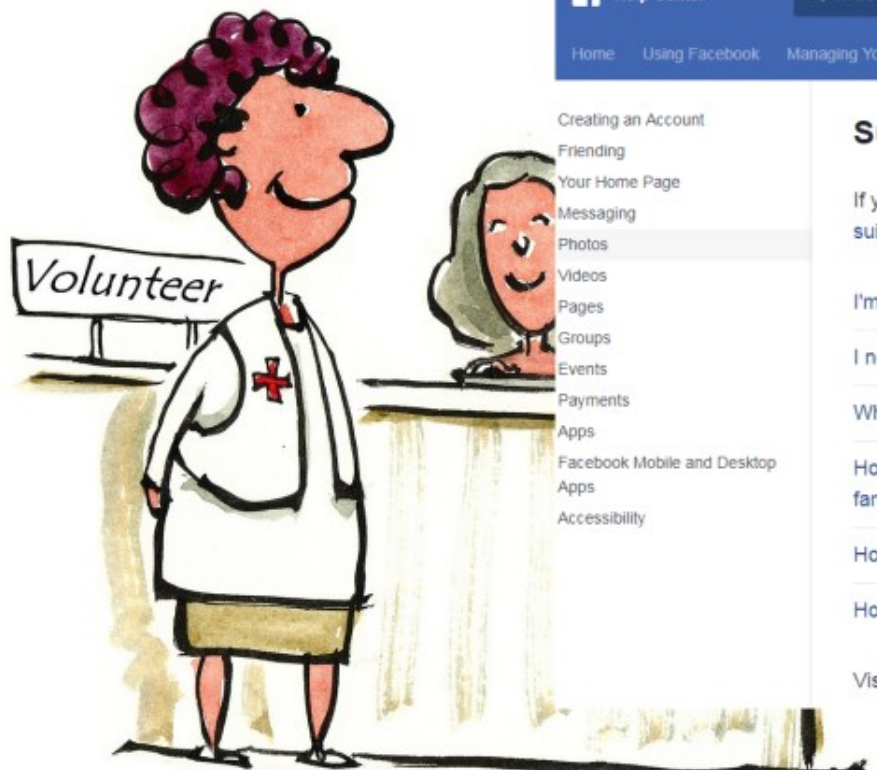
By Frits Ahlefeldt

- 👍 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?



By Frits Ahlefeldt

 **Help Center**

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.

use cases: example

suggests possible uses
of this technology:



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)



use cases: example

suggests possible uses of this technology:



mental health



tool for automating
for depression



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

signs of depression?

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



the questionnaire also identifies symptoms of depression ?

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



Artificial Intelligence in Medicine 56 (2012) 19–25

Contents lists available at SciVerse ScienceDirect

Artificial Intelligence in Medicine



atic 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



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avoids contagion-like effects





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freedom of speech vs security






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freedom of speech vs security






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freedom of speech vs security



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

Advantages



moderation
that might

that might harm individuals/communities



avoids contagion-like effects



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



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

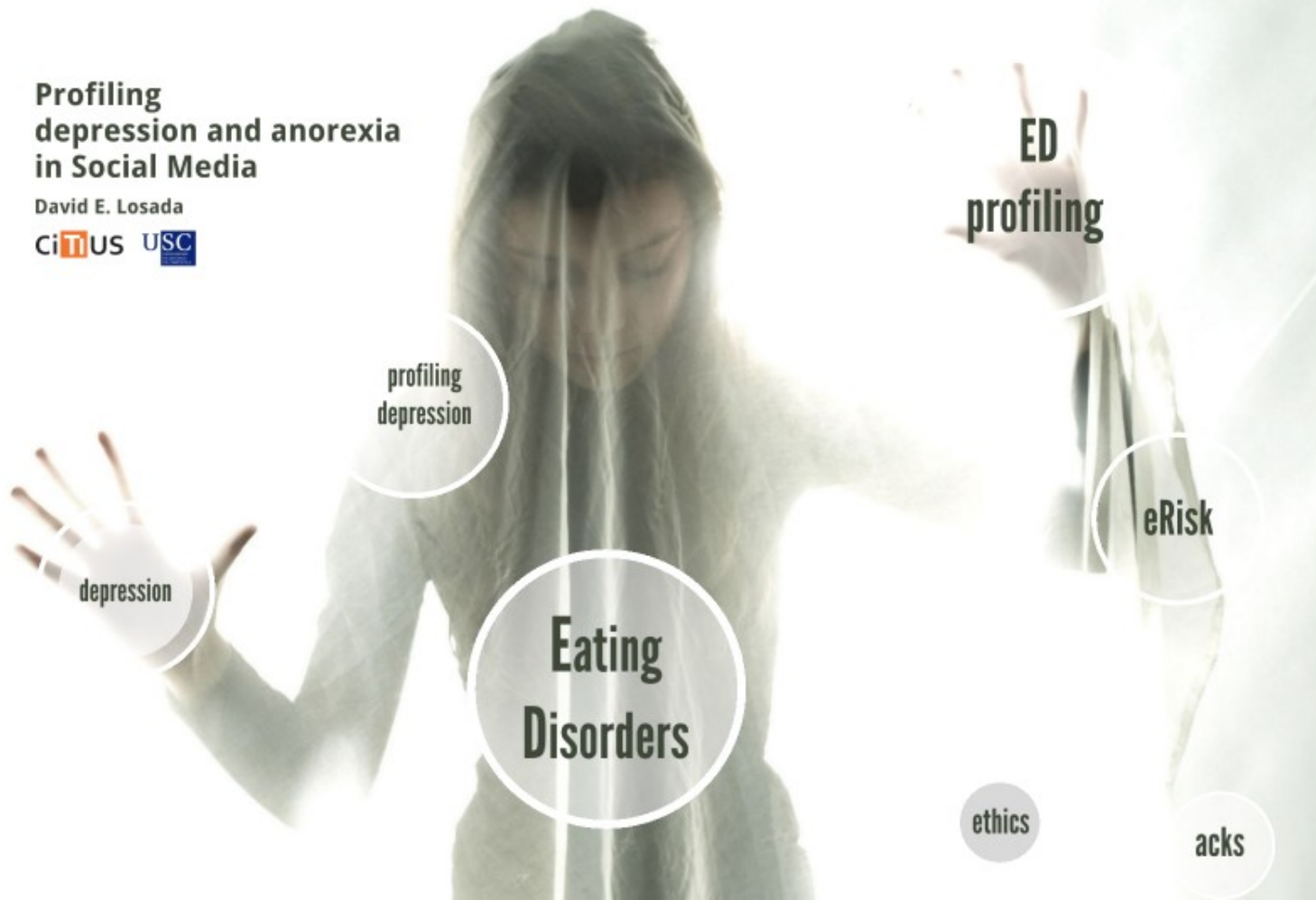


after banning certain contents, some communities became more **insular** and focused on more **dangerous** ideas

Profiling depression and anorexia in Social Media

David E. Losada

CiMUS USC



profiling
depression

depression

Eating
Disorders

ED
profiling

eRisk

ethics

acks

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

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

organizers



eRisk @
clef 2017



eRisk @
clef 2018

data

positive
vs
control

task
format

organizers

David E. Losada



Fabio Crestani



Javier Parapar



Centro Singular de Investigación
en Tecnoloxías da
Información



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

A row of vintage cars, with a yellow one in the foreground. The cars are parked on a street, and people are visible in the background. The image is used as a background for a presentation slide.

doesn't support
early alerts

reactive

works with very
explicit signals

current technology

**too often,
too late!**

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

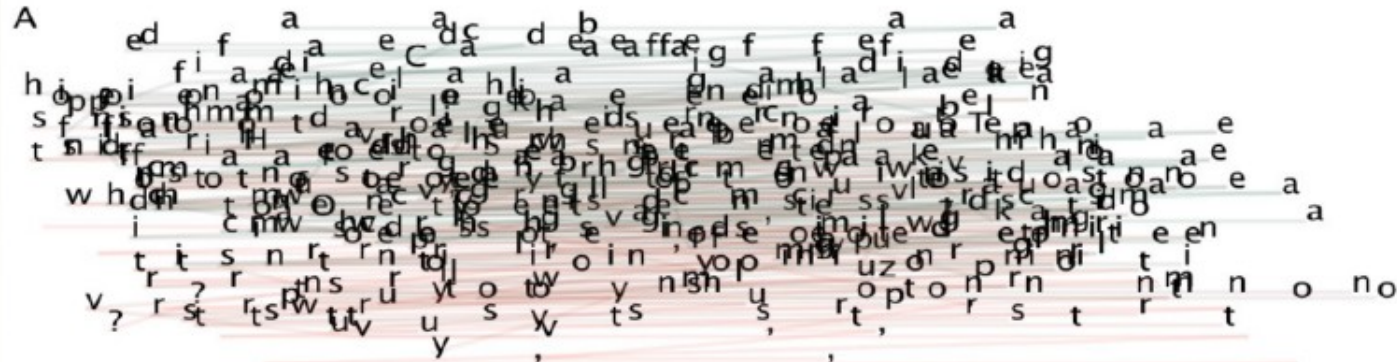
track **temporal** evolution

Lack of data on depression & language

few collections available

focus on 2-class categorisation

no temporal dimension, no early risk analysis





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

010203

READ+RATE

MY RATINGS

MY STORIES

USING THIS APP

most recent discussed outrageous on the line

Anonymous

ok what about if me and my gf are in a big fight , and she started by posting embrsing stuff on my wall...is it ever ok to settle the score online? or always over the line?

IS THIS...

OVER

ON

UNDER

THE LINE?

COMMENTS (4)

SIMILAR STORIES

SHARE

Elizabeth // Female, 18

My ex keeps texting my brother and friends

IS THIS...

OVER

ON

UNDER

THE LINE?

DC FI

OVER THE LINE? –

NOW YOU CAN FIND SIMILAR STORIES!



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



DEPRESSION

activo

nuevo

subiendo

polémico

popular

con gold

patrocinados

- ↑ 384 [Aa+] [I got from the 100 to the 1000 in 10 days. I'm feeling better. \(self,depression\)](#)
↓ enviado hace 2 meses por 1 comentario 38 comentarios compartir
- ↑ 27 [Aa+] [I'm feeling better. \(self,depression\)](#)
↓ enviado hace 7 días por 297 comentarios 297 comentarios compartir
- ↑ 124 [Aa+] [I got up. \(self,depression\)](#)
↓ enviado hace 8 horas por 25 comentarios 25 comentarios compartir
- ↑ 37 [Aa+] [The "little" stuff is not so bad. It's like, "I'm feeling better. \(self,depression\)](#)
↓ enviado hace 6 horas por 5 comentarios 5 comentarios compartir
- ↑ 43 [Aa+] [Tuddy, I'm feeling better. \(self,depression\)](#)
↓ enviado hace 8 horas por 21 comentarios 21 comentarios compartir



reddit



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

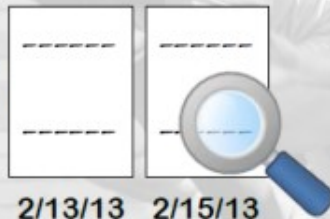
XML archives 

task format

detect **early traces** of depression

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

John Doe's writings
(post or comments)



chunk 1 (oldest writings)
10% of writings

possible case of depression

no depression

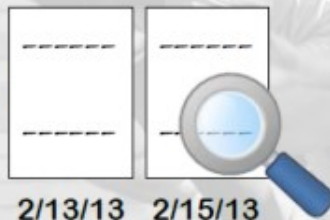
no decision yet

task format

detect **early traces** of ~~depression~~ **anorexia**

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~~ **anorexia**

no ~~depression~~ **anorexia**

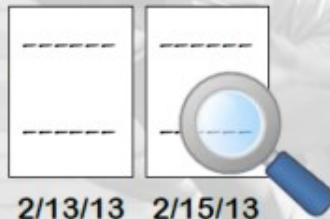
no decision yet

task format

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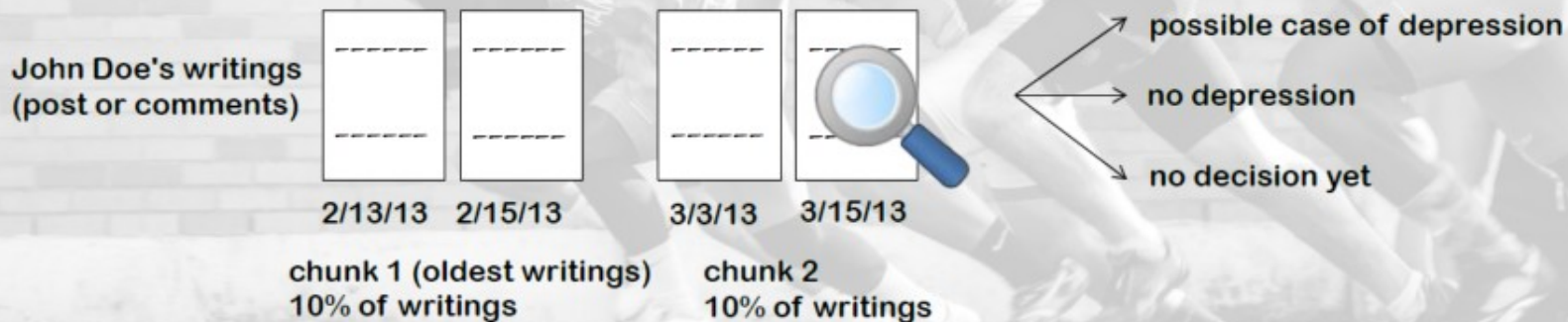
chunk 1 (oldest writings)
10% of writings

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

task format

detect **early traces** of depression

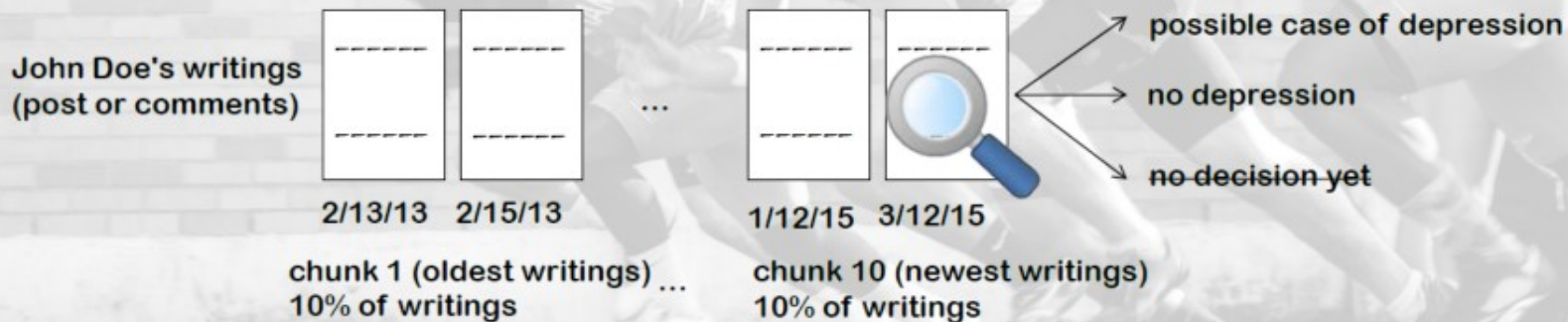
for each subject, **sequentially process**
pieces of evidence...



task format

detect **early traces** of depression

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



performance metric

Early Risk Detection Error:

$$\text{ERDE}_O(d, k) =$$

 c_{fp}

(false positive)

 c_{fn}

(false negative)

 $c_{tp} * lc_o(k)$

(true positive)

0

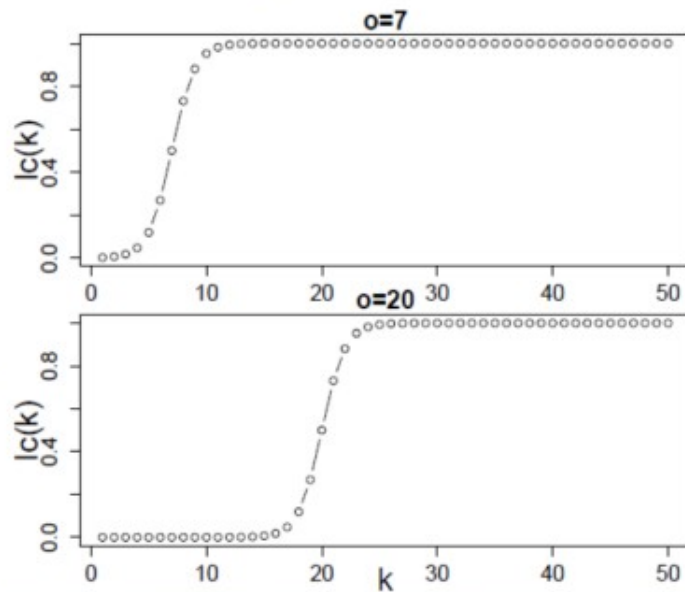
(true negative)



performance metric

True Positive cost

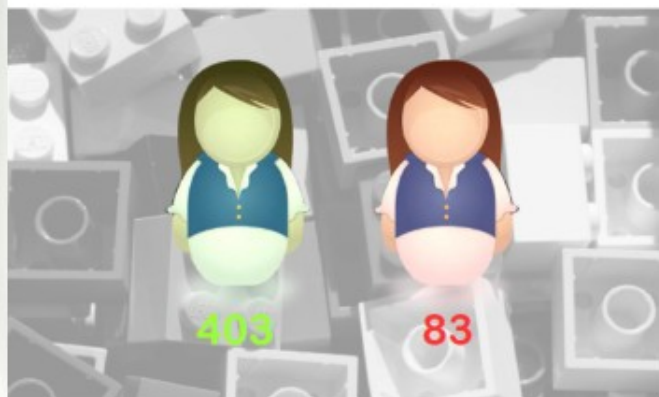
Latency cost function



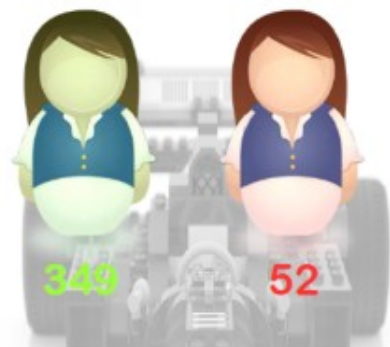
penalty to late detections

splits

Training



Test

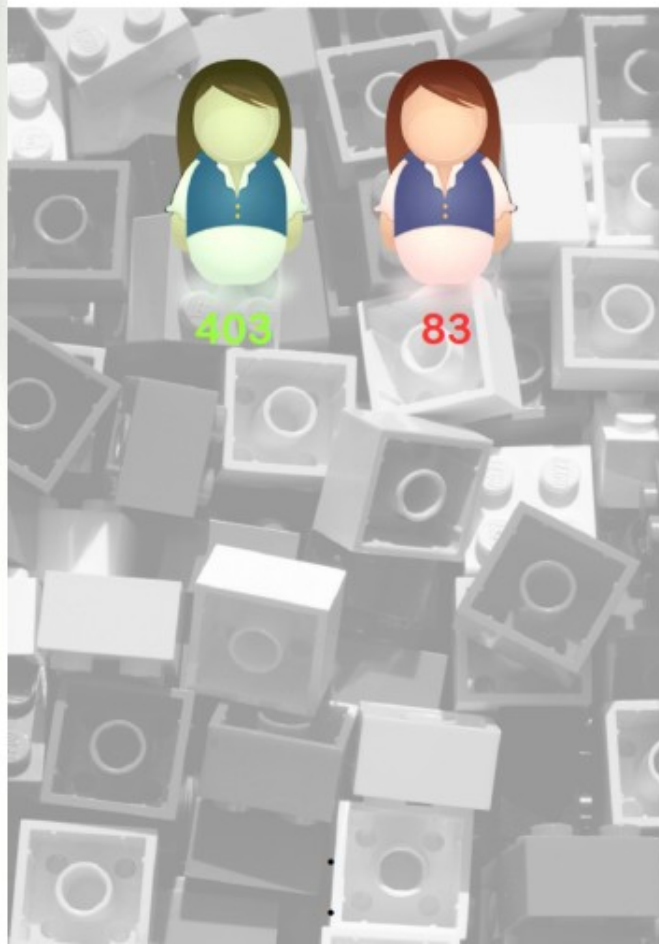


	Train		Test	
	<i>Depressed</i>	<i>Control</i>	<i>Depressed</i>	<i>Control</i>
Num. subjects	83	403	52	349
Num. submissions (posts & comments)	30,851	264,172	18,706	217,665
Avg num. of submissions per subject	371.7	655.5	359.7	623.7
Avg num. of days from first to last submission	572.7	626.6	608.31	623.2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

Table 1. Main statistics of the train and test collections



Training

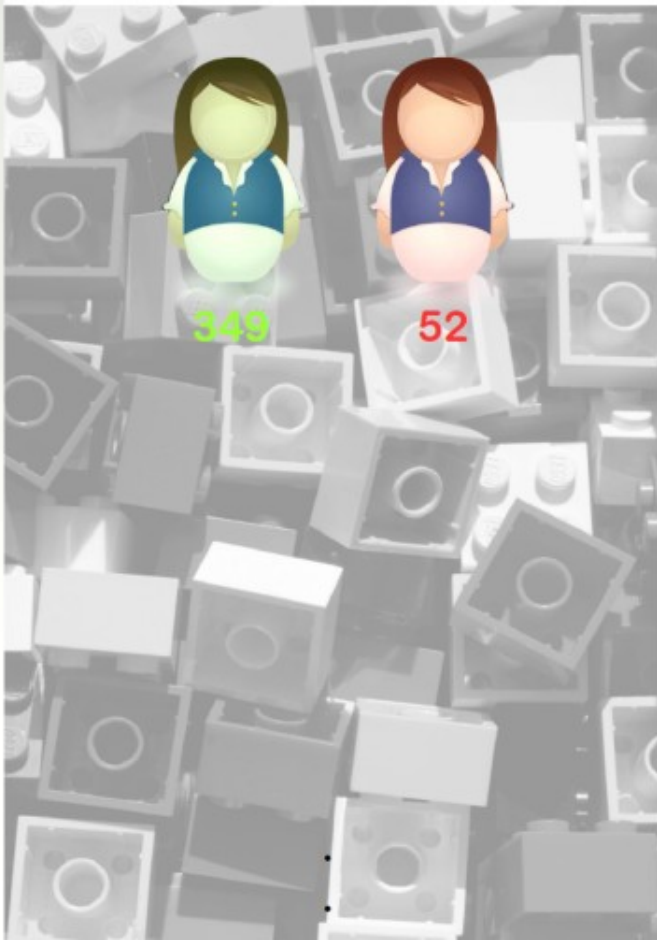


Nov 30th, 2016

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

	$ERDE_5$	$ERDE_{50}$	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

CiMUS USC



depression

profiling
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.**



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



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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



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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



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

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

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

resources



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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>

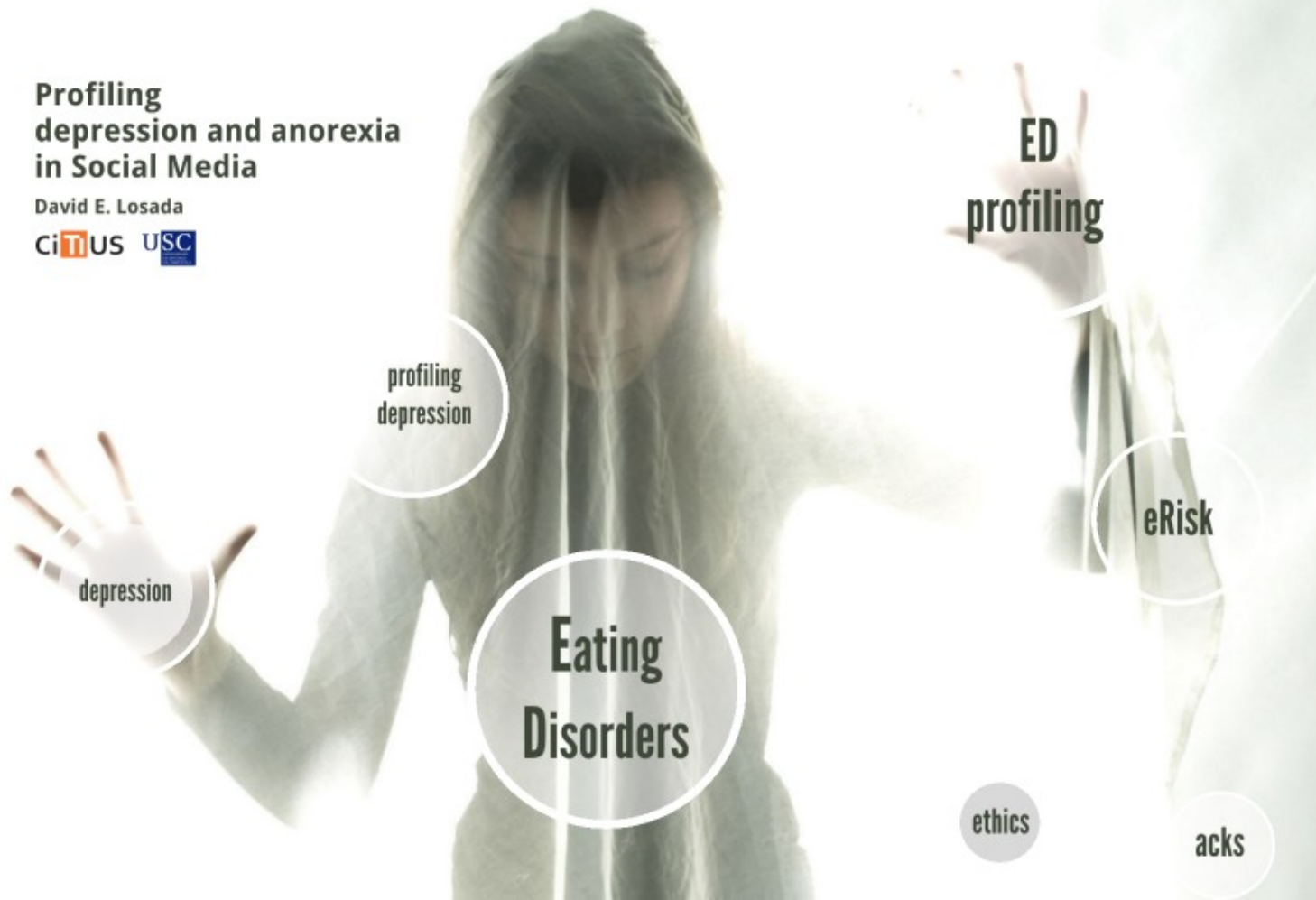
Andy Kennelly. grouping. <https://goo.gl/t8Y1Mh>

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

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