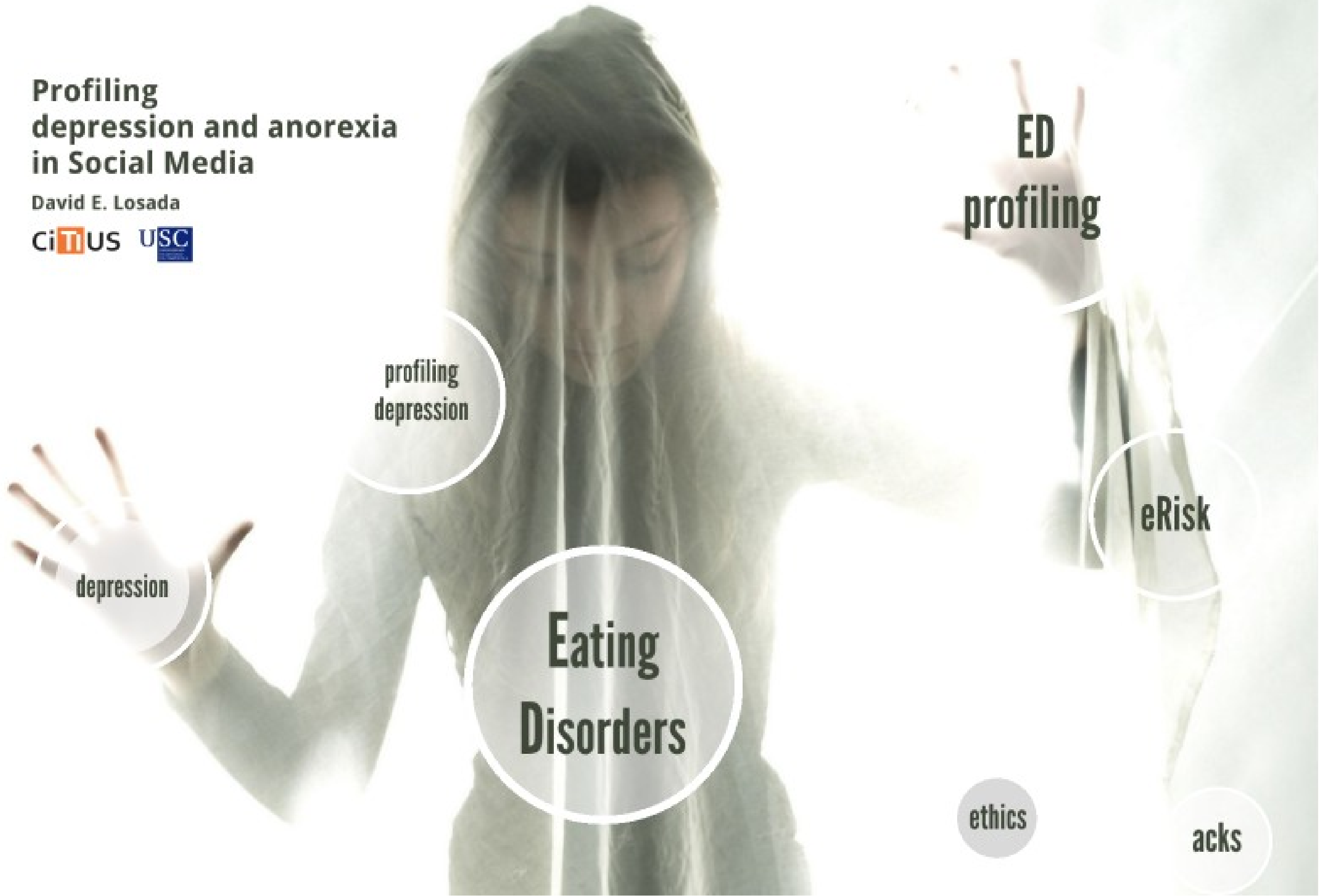
Profiling depression and anorexia in Social Media

David E. Losada

CiTIUS USC



depression

common mental disorder

persistent sadness

self-harm

loss of energy

hopelessness

restlessness

indecisiveness

loss of interest

change of appetite

suicide

sleeping problems

worthlessness

inability to carry out daily activities

reduced concentration

anxiety

guilt

World Health Organization

key facts

World Health Organization

Fact sheet, Feb 2017

http://www.who.int/mediacentre/factsheets/fs369/en/

300 MILLION people

ALL ages

more women than men

World Health Organization

Fact sheet, Feb 2017 http://www.who.int/mediacentre/factsheets/fs369/en/

800k people die due to suicide

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

World Health Organization

Fact sheet, Feb 2017 http://www.who.int/mediacentre/factsheets/fs369/en/

leading cause of disability

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

World Health Organization

Fact sheet, Feb 2017 http://www.who.int/mediacentre/factsheets/fs369/en/

and the burden of depression is on the rise

Profiling
depression and anorexia
in Social Media
David E. Losada
ED
profiling
profiling
depression
depression
Eating
Disorders
eRisk
ethics
acks

profiling depression

online profiling
as a **complementary** tool

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

key components

refs

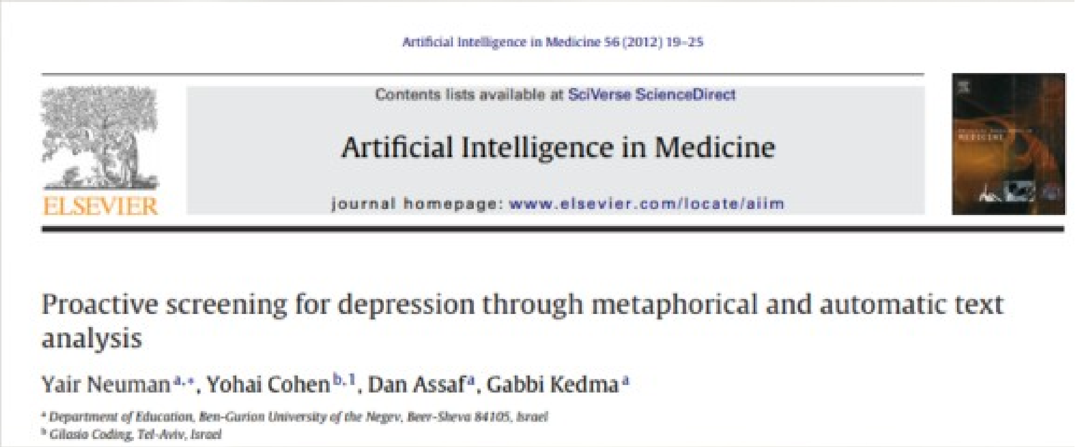
key components

- **text/content analysis**: extraction of symptoms, detection of depression, doc search, ...
- network/phone **usage** statistics
- **resources/data**: LIWC, ontologies, discussion boards, support communities, questionnaires, ...

profiling depression - refs

construction of a **depression lexicon** (assisted by experts)

to evaluate the level of depression in texts



Artificial Intelligence in Medicine 56 (2012) 19–25

Contents lists available at SciVerse ScienceDirect

Artificial Intelligence in Medicine

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

ELSEVIER

Proactive screening for depression through metaphorical and automatic text analysis

Yair Neuman[a,*], Yohai Cohen[b,1], Dan Assaf[a], Gabbi Kedma[a]

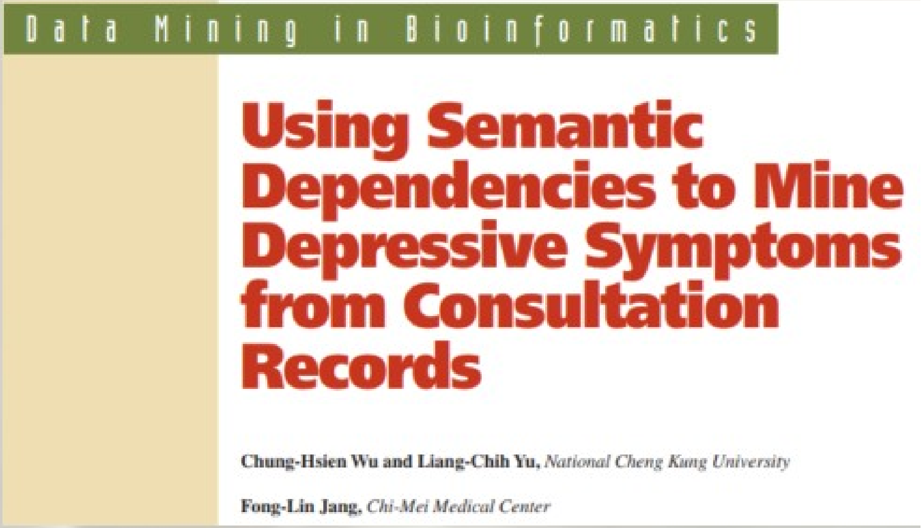
[a] Department of Education, Ben-Gurion University of the Negev, Beer-Sheva 84105, Israel
[b] Gilasio Coding, Tel-Aviv, Israel

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, ...)

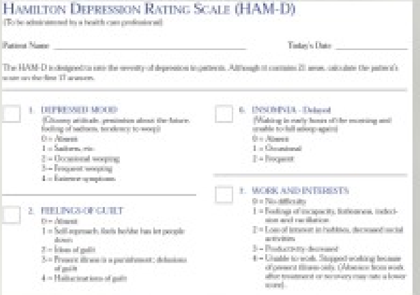

Data Mining in Bioinformatics

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*

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


HAMILTON DEPRESSION RATING SCALE (HAM-D)

Patient Name ______ Today's Date ______

1. DEPRESSED MOOD
0 = Absent
1 = Sadness, etc.
2 = Occasional weeping
3 = Frequent weeping
4 = Extreme symptoms

2. FEELINGS OF GUILT
0 = Absent
2 = Ideas of guilt
4 = Hallucinations of guilt

6. INSOMNIA - Delayed
0 = Absent
1 = Occasional
2 = Frequent

7. WORK AND INTERESTS
0 = No difficulty
3 = Productivity decreased

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

HAMILTON DEPRESSION RATING SCALE (HAM-D)

(To be administered by a health care professional)

Patient Name ______________________________ Today's Date ______________

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

☐ 1. DEPRESSED MOOD
(Gloomy attitude, pessimism about the future, feeling of sadness, tendency to weep)
0 = Absent
1 = Sadness, etc.
2 = Occasional weeping
3 = Frequent weeping
4 = Extreme symptoms

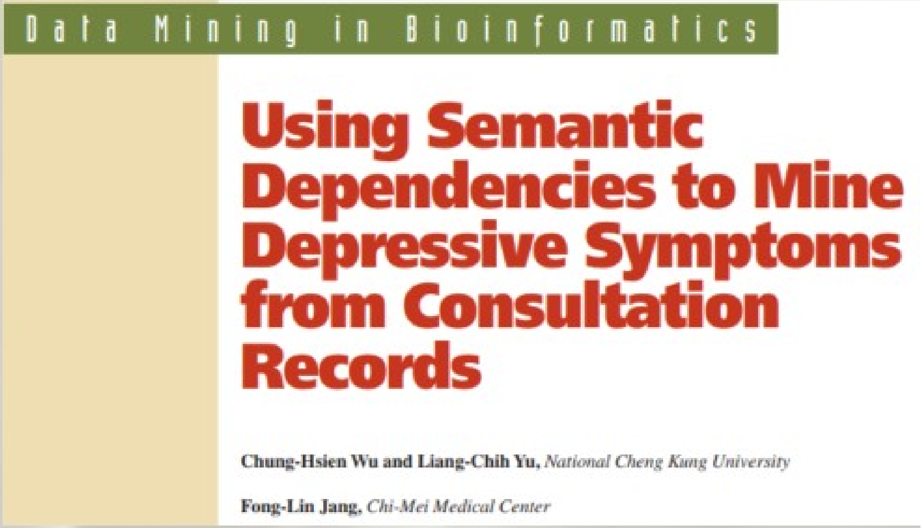
☐ 2. FEELINGS OF GUILT
0 = Absent
1 = Self-reproach, feels he/she has let people down
2 = Ideas of guilt
3 = Present illness is a punishment; delusions of guilt
4 = Hallucinations of guilt

☐ 6. INSOMNIA - Delayed
(Waking in early hours of the morning and unable to fall asleep again)
0 = Absent
1 = Occasional
2 = Frequent

☐ 7. WORK AND INTERESTS
0 = No difficulty
1 = Feelings of incapacity, listlessness, indecision and vacillation
2 = Loss of interest in hobbies, decreased social activities
3 = Productivity decreased
4 = Unable to work. Stopped working because of present illness only. (Absence from work after treatment or recovery may rate a lower score).

consultation records

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



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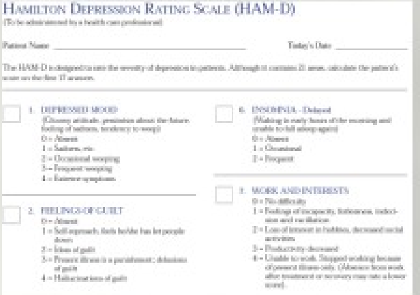

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Experiments done with PsychPark,
a **virtual psychiatric clinic** maintained
by a group of volunteer professionals

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**

Artificial Intelligence 173 (2009) 817–829

Contents lists available at ScienceDirect

Artificial Intelligence

www.elsevier.com/locate/artint

ELSEVIER

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?

Internet Interventions 2 (2015) 183–188

Contents lists available at ScienceDirect

Internet Interventions

journal homepage: www.invent-journal.com/

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 Vimiera 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**

DEPRESSION AND ANXIETY 28:447–455 (2011)

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]

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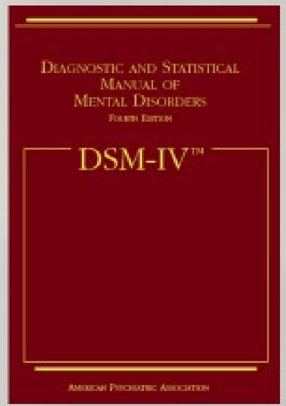

users categorized according to DSM

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

Diagnostic and Statistical Manual of Mental Disorders

Fourth Edition

DSM-IV™

publicly available
profile updates

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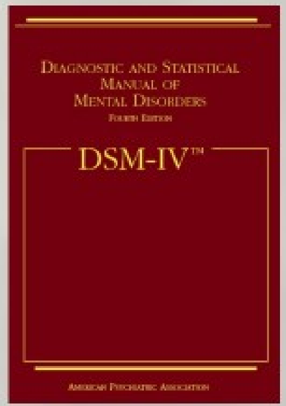

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Diagnostic and Statistic Manual (DSM)

users categorized according to DSM

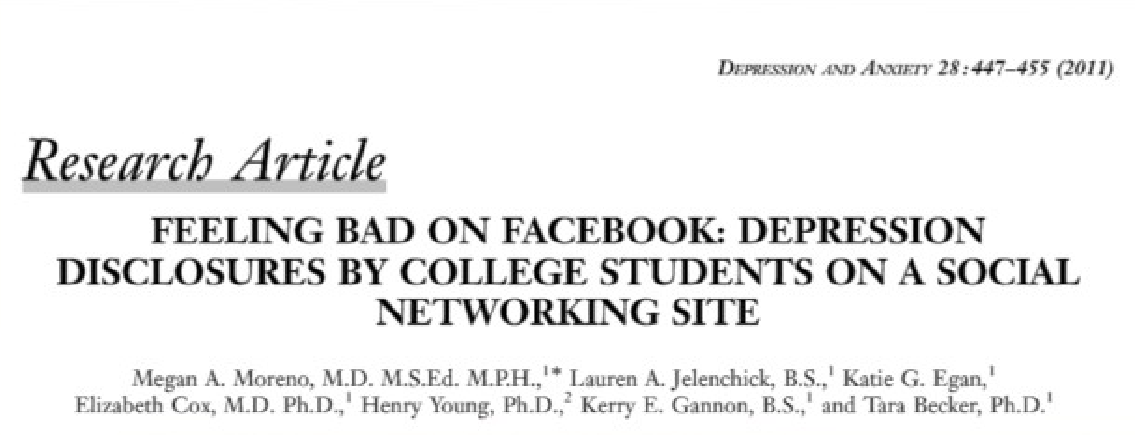
relationship between **depression on profile** and **age**, **graduation year**, **gender**, **relationship status**, **facebook activity**, ...

Major Depression Episodes (MDE): symptoms
depressed mood, loss of interest/pleasure in activities, appetite changes, sleep problems, psychomotor agitation/retardation, energy loss, feeling worthless or guilty, decreased concentration or suicidal ideation.

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

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

publicly available
profile updates



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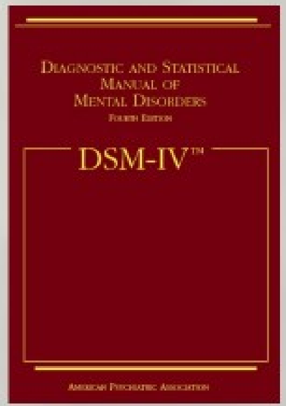

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relationship between **depression on profile** and **age**, **graduation year**, **gender**, **relationship status**, **facebook activity**, ...

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
Balitmore, 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**

amazon mechanical turk

crowdsourcing

AAAI-13
July 14-18, 2013
IAAI-13
July 16-18, 2013
BELLEVUE, WASHINGTON, USA

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

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

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

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

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

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.

ty, ...)

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.

amazon mechanical turk

crowdsourcing

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crowdsourcing

AMT turkers: aske
standard **clinical**
Beck Depression I

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.

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

categorization of tweets:

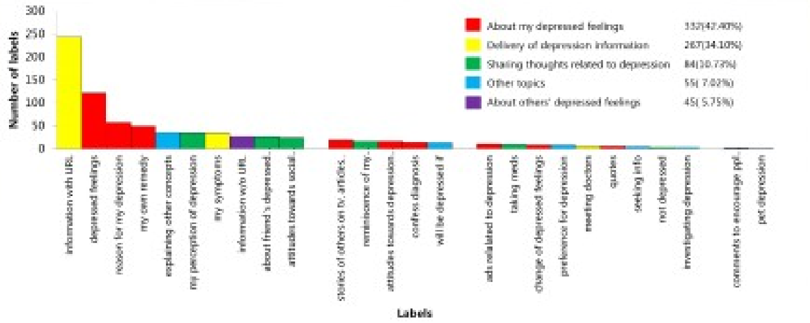

Figure 1: Labeled and categorized language usage in relation to depression

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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Chiyoung Cha
Ewha Womans University
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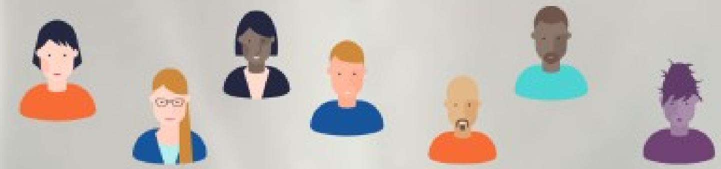
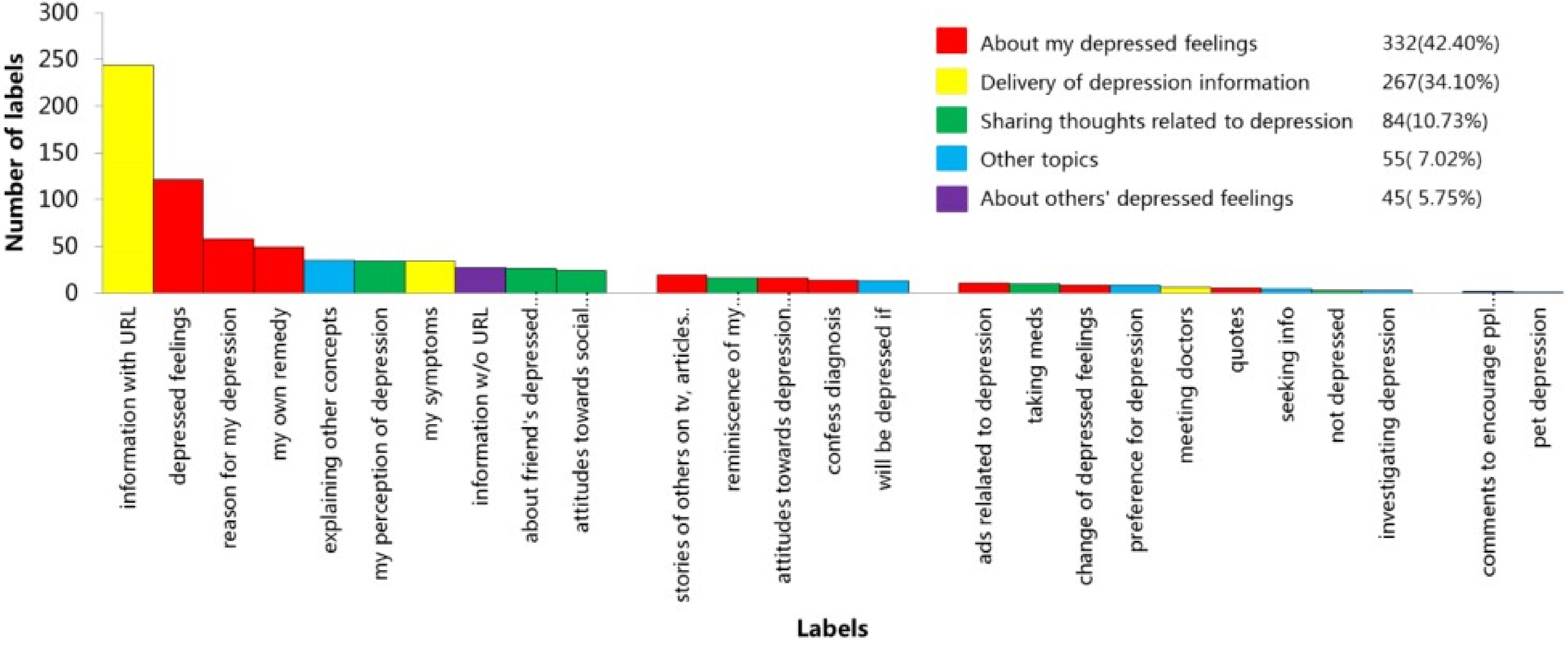


also performed a **screening test** (69 young adults):

- 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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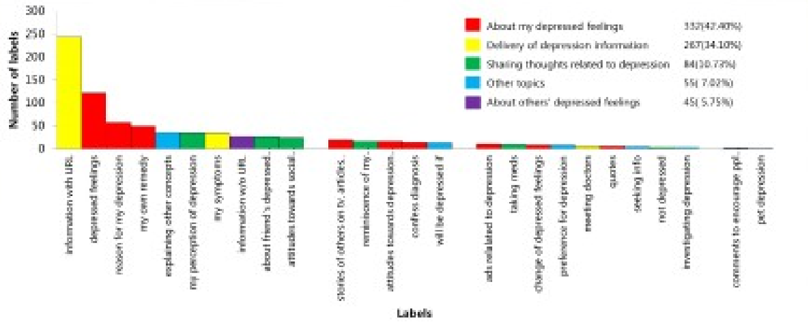

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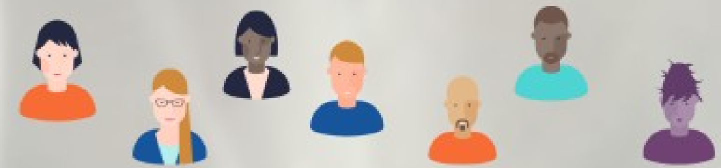

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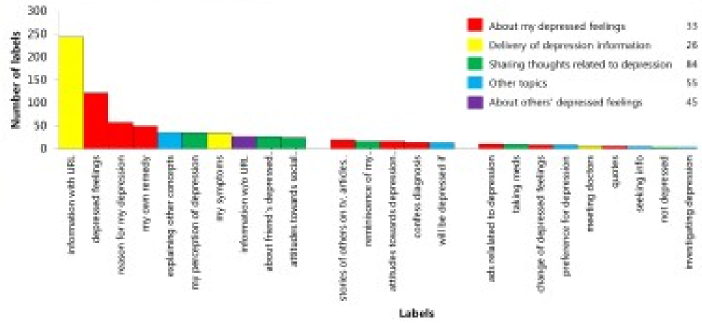

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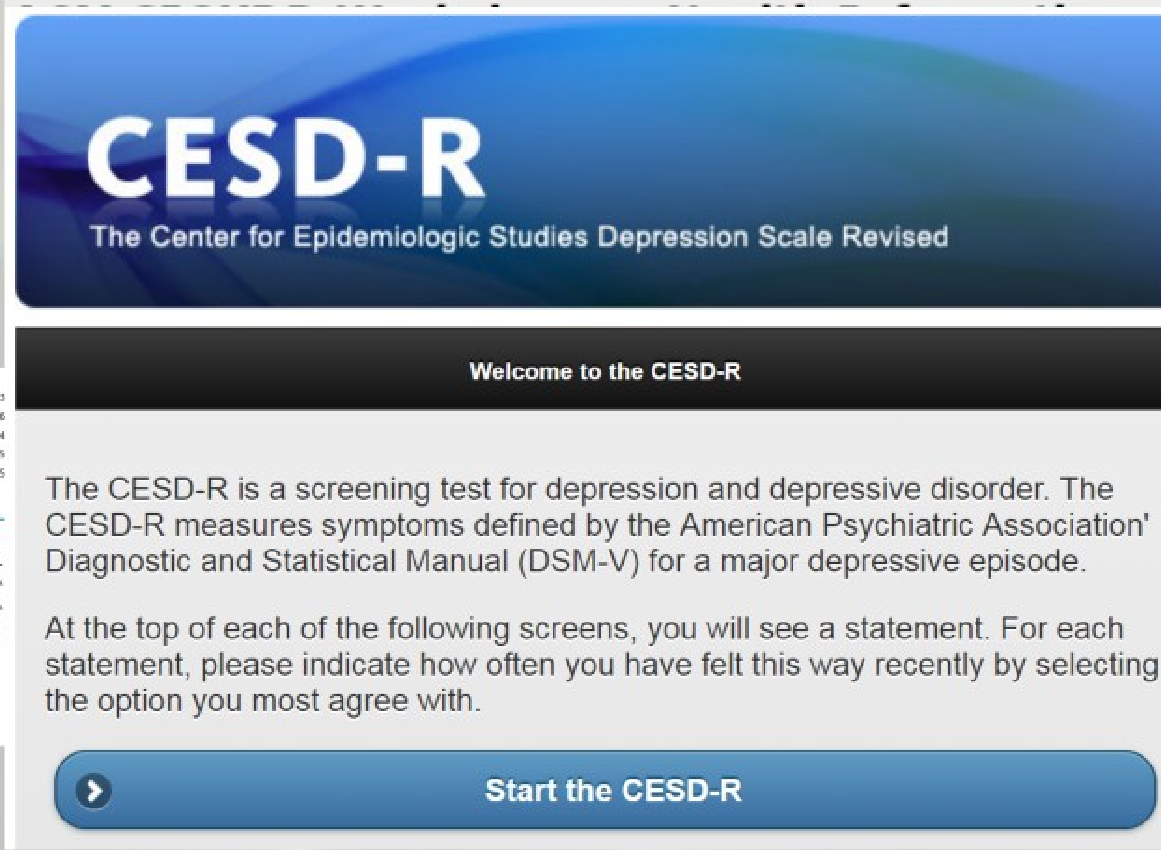

collecting tweets of the same users

comparing depression levels vs sentiments & language

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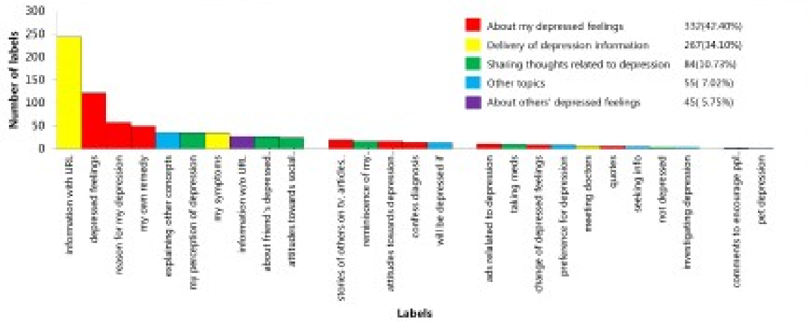

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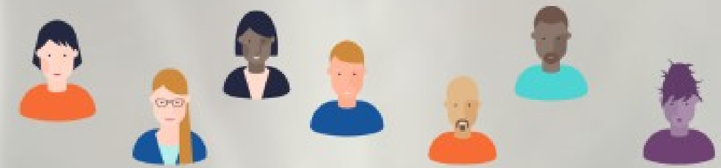

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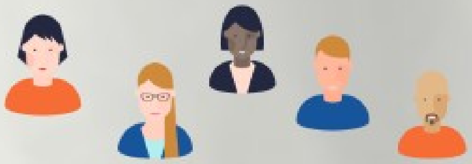
recruited participants (**screening survey**)

ICWSM-13
JULY 2013
BOSTON, USA
THE 7TH INTERNATIONAL AAAI CONFERENCE ON WEBLOGS AND SOCIAL MEDIA



demographic data

Twitter ID

depression quotient (CES-D)

7 7

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

Minsu Park
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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 partipants' **friends**

216 **college** students

CES-D questionnaires

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

network data (campus)
usage statistics
contents not recorded!

Associating Internet Usage with Depressive Behavior Among College Students

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

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

IEEE TECHNOLOGY AND SOCIETY MAGAZINE | WINTER 2012 1932-4529/12/$31.00©2012IEEE | 73

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

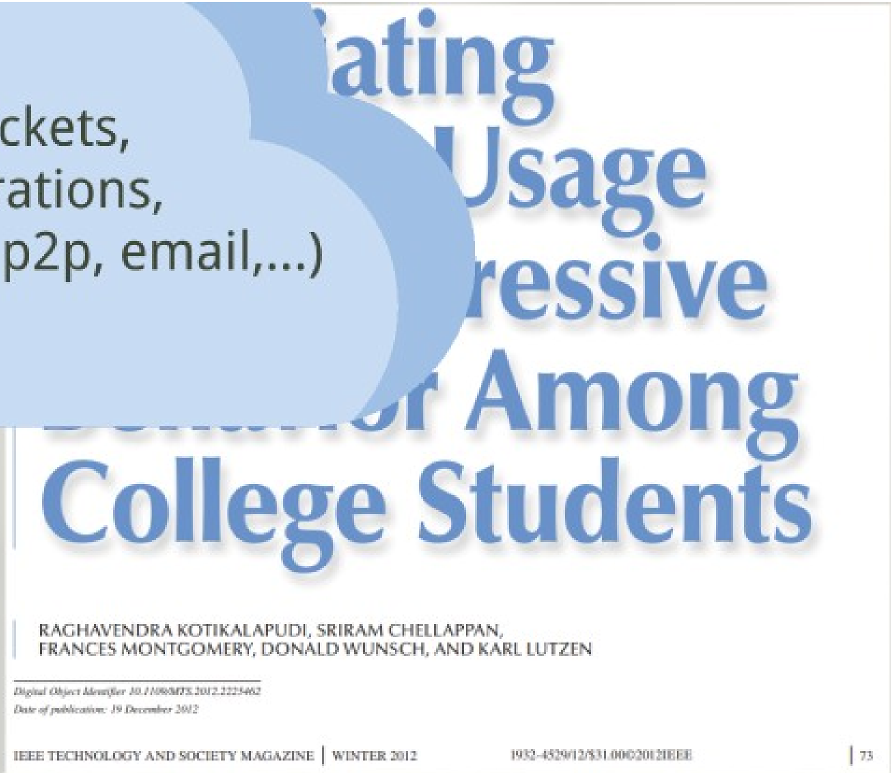
216 **college** studen

CES-D questio

30% met min.
for **depression**

network data (c pus)
usage statisti
contents not recorded!

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


iating
Usage
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r Among
College Students

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

user's phone data

Patient Health
Questionnaire-9

JOURNAL OF MEDICAL INTERNET RESEARCH Saeb et al

Original Paper

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

Sohrab Saeb[1,2], PhD; Mi Zhang[3], PhD; Christopher J Karr[1], MA; Stephen M Schueller[1], PhD; Marya E Corden[1], MPH; Konrad P Kording[2], PhD; David C Mohr[1], PhD

[1]Center for Behavioral Intervention Technologies, Department of Preventive Medicine, Northwestern University, Chicago, IL, United States
[2]Rehabilitation Institute of Chicago, Department of Physical Medicine and Rehabilitation, Northwestern University, Chicago, IL, United States
[3]Department 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

th
aire-9

PATIENT HEALTH QUESTIONNAIRE-9 (PHQ-9)

Over the <u>last 2 weeks</u>, 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 <u>any</u> problems, how <u>difficult</u> have these problems made it for you to do your work, take care of things at home, or get along with other people?

Not difficult at all	Somewhat difficult	Very difficult	Extremely difficult
☐	☐	☐	☐

Sohrab Saeb
Konrad P K
[1]Center for Bel
[2]Rehabilitation
[3]Department o

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user's phone data

Patient Health Questionnaire-9

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

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essays by college students

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

Linguistic Inquiry and Word Count **(LIWC)**

depressed participants:

▲negatively valenced words, **neg emotions**

▲1st person singular (I,me,my)

(think a great deal about **themselves**)

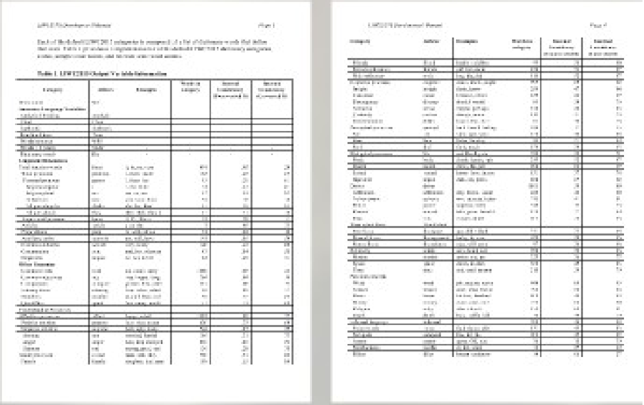
▴slightly more positive emotions than never-depressed

COGNITION AND EMOTION, 2004, *18* (8), 1121–1133

Language use of depressed and depression-vulnerable college students

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

University of Texas at Austin, USA



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	Sixltr	-	-	-	-
Dictionary words	Dic	-	-	-	-
Linguistic Dimensions					
Total function words	funct	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	mate, 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	TimeOrient				
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
Netspeak	netspeak	btw, lol, thx	209	.42	.82
Assent	assent	agree, OK, yes	36	.10	.39
Nonfluencies	nonflu	er, hm, umm	19	.27	.69
Fillers	filler	Imean, youknow	14	.06	.27

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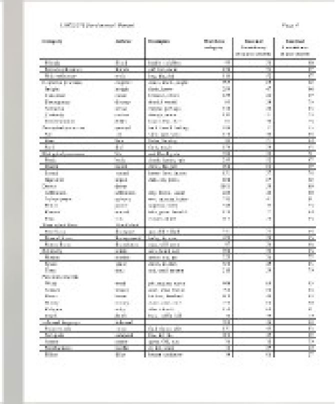

Linguistic Inquiry and Word Count **(LIWC)**

depressed participants:

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

essays by college students

BDI score

linear **regression**

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

Qualitative analysis: LDA extracts **topic**s
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

Sharath Chandra Guntuku[1], David B Yaden[1], Margaret L Kern[2], Lyle H Ungar[1] and Johannes C Eichstaedt[1]

[1] University of Pennsylvania, Philadelphia, PA, United States
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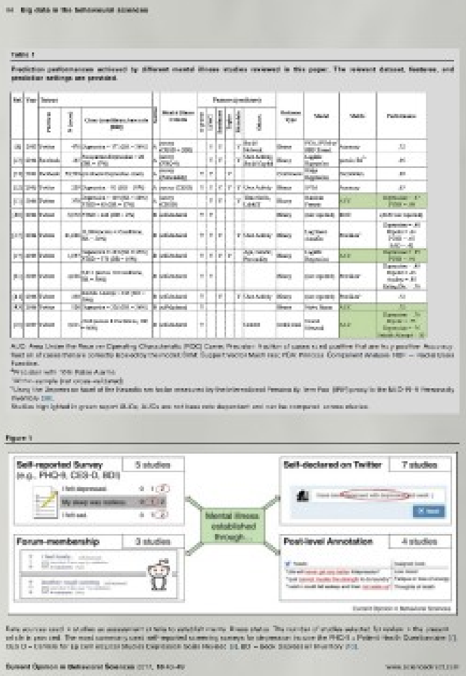
Current Opinion in Behavioral Sciences 2017, **18**:43–49



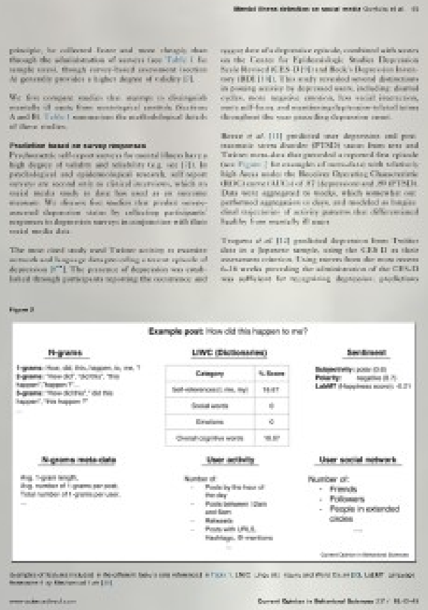


Table 1

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

Ref.	Year	Dataset: Platform	Dataset: N (users)	Dataset: Cases (conditions; base rate [BR])	Section	Mental Illness Criteria	Features (predictors): n-grams	LIWC	Sentiment	Topics	Metadata	Others	Outcome Type	Model	Metric	Performance
[8]	2013	Twitter	476	Depression = 171 (BR = 36%)	A	survey (CESD + BDI)		Y	Y		Y	Social Network	Binary	PCA, SVM w/ RBF Kernel	Accuracy	.72
[13]	2014	Facebook	165	Post-partum Depression = 28 (BR = 17%)	A	survey (PHQ-9)		Y	Y		Y	User Activity, Social Capital	Binary	Logistic Regression	pseudo-R2[b]	.36
[14]	2014	Facebook	28,749	(continous 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.

[a]Precision with 10% False Alarms.

[b]Within-sample (not cross-validated).

[c]Using 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

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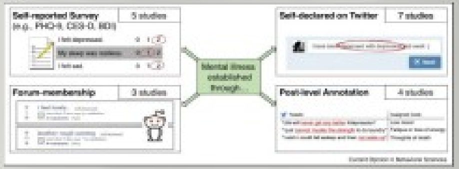


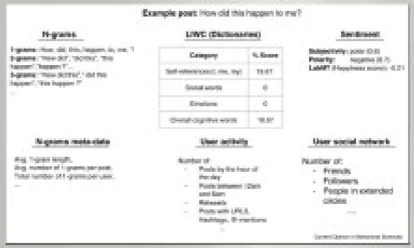
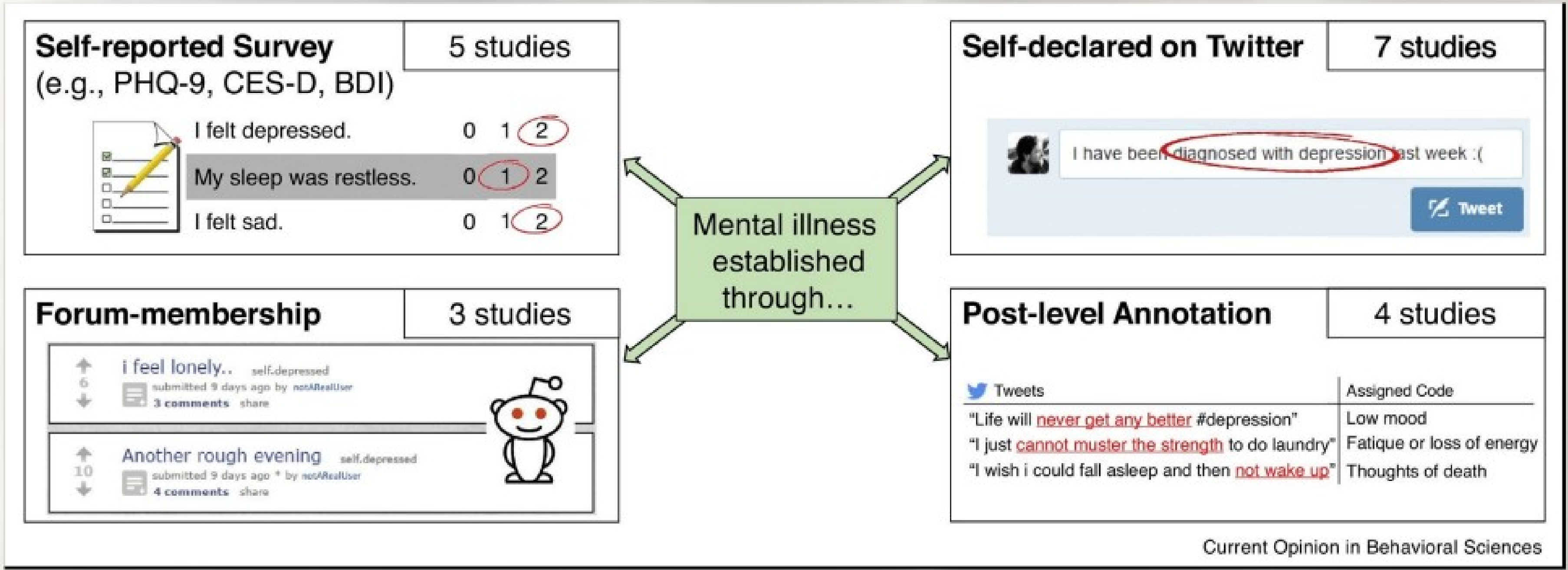


Figure 1



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].

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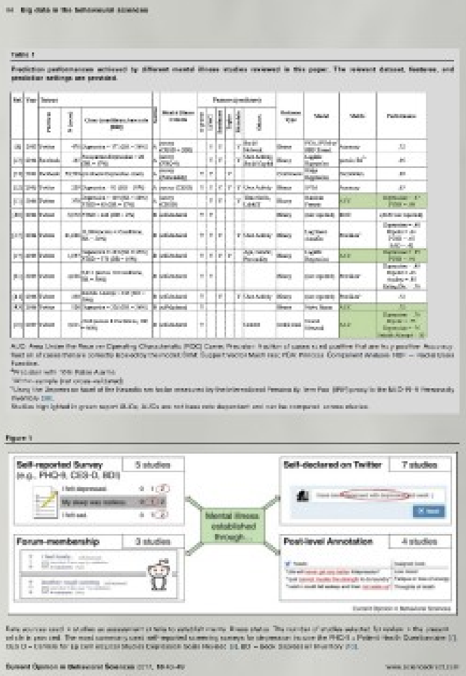

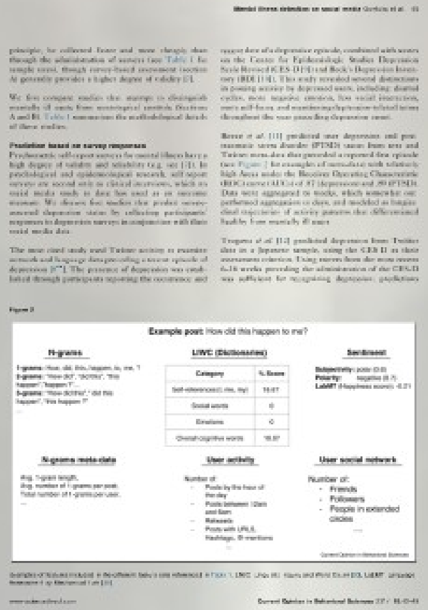

Figure 2

Example post: How did this happen to me?

N-grams

1-grams: How, did, this, happen, to, me, ?
2-grams: "How did", "did this", "this happen","happen ?"...
3-grams: "How did this"," did this happen", "this happen ?"
...

LIWC (Dictionaries)

Category	% Score
Self-references (I, me, my)	16.67
Social words	0
Emotions	0
Overall cognitive words	16.67

Sentiment

Subjectivity: polar (0.6)
Polarity: negative (0.7)
LabMT (Happiness score): -0.21

N-grams meta-data

Avg. 1-gram length,
Avg. number of 1-grams per post,
Total number of 1-grams per user,
...

User activity

Number of:
- Posts by the hour of the day
- Posts between 12am and 6am
- Retweets
- Posts with URLS, Hashtags, @-mentions

...

User social network

Number of:
- Friends
- Followers
- People in extended circles

....

Current Opinion in Behavioral Sciences

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

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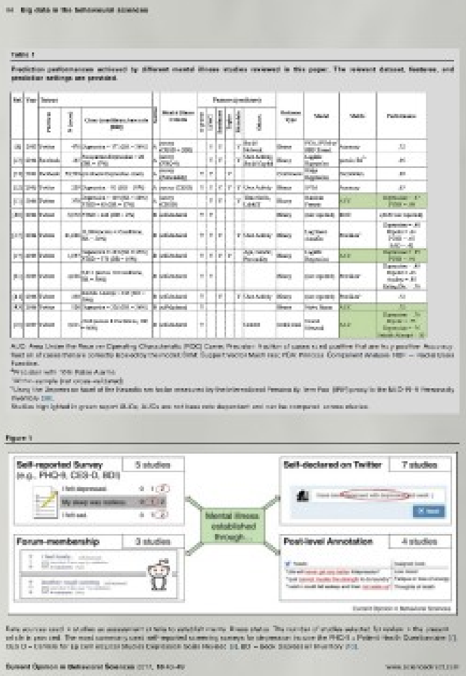
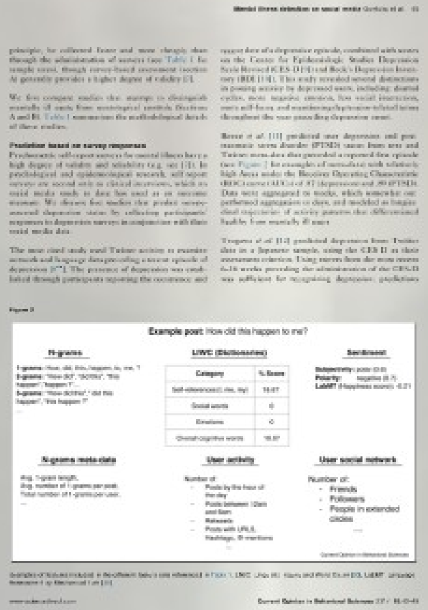




Profiling depression and anorexia in Social Media

David E. Losada

CiTIUS USC

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"

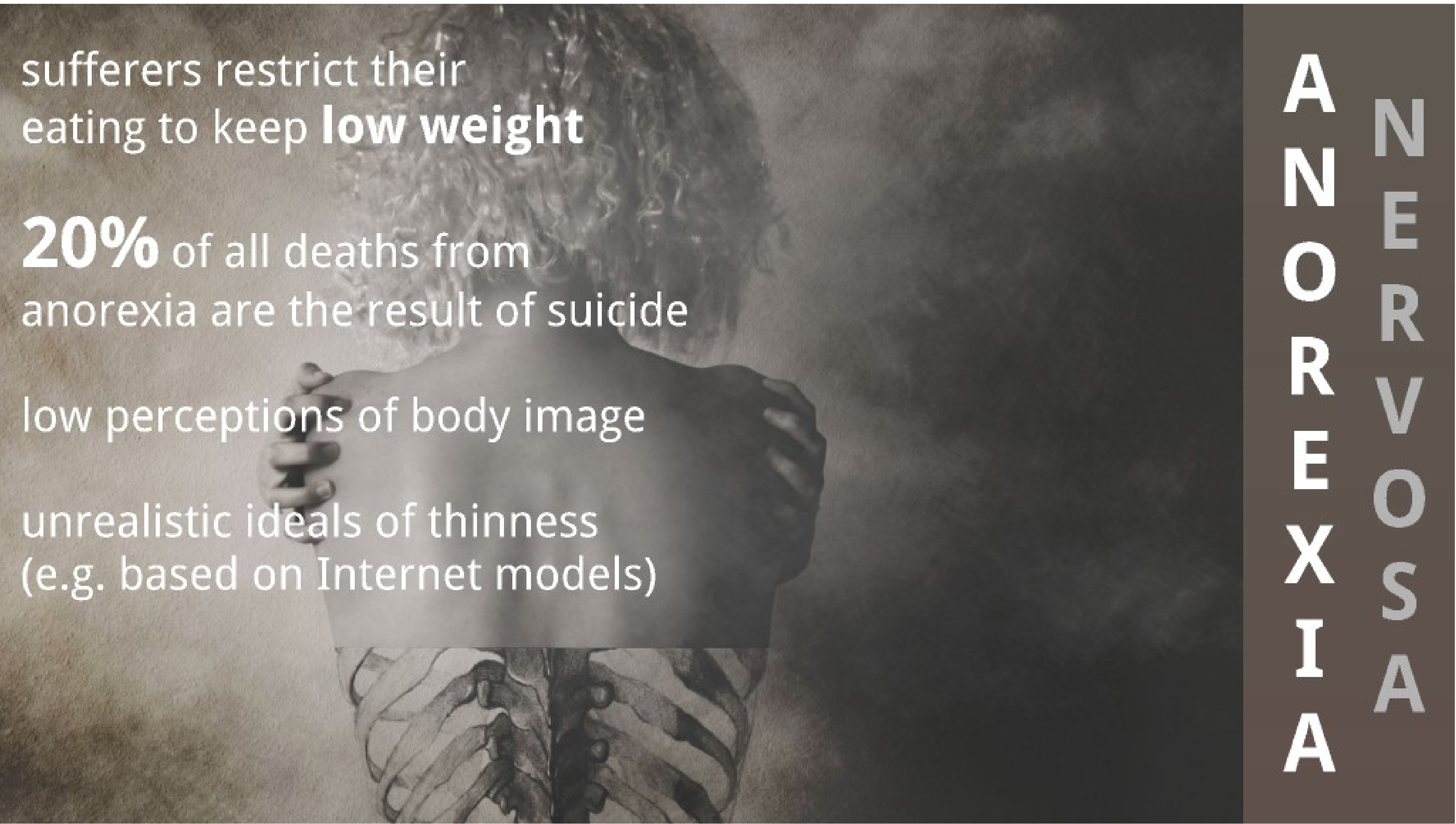
desire to be thin

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

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

beat

beating eating disorders

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beat™
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beat
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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 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 stable[13].

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 recording[14].

Table 3.3

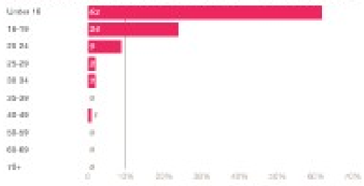
Count of FAEs with primary diagnosis of eating disorder in England, 2005-2014

	Count of Finished Admissions Episodes (FAEs) where the primary diagnosis was of eating disorders (England)
2005-2006	1,952
2006-2007	[illegible]
2007-2008	[illegible]
2008-2009	[illegible]
2009-2010	[illegible]
2010-2011	[missing data]
2011-2012	[illegible]
2012-2013	[illegible]
2013-2014	[illegible]

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



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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

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Table 3.3

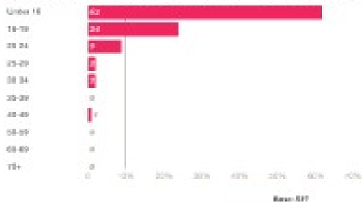
Count of FAEs with primary diagnosis of eating disorder in England, 2005-2014

	Count of Finished Admissions Episodes (FAEs) where the primary diagnosis was of eating disorders (England)
2005-2006	1,952
2006-2007	1,824
2007-2008	1,812
2008-2009	1,868
2009-2010	2,287
2010-2011	[missing data]
2011-2012	2,205
2012-2013	2,388
2013-2014	2,655

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



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

beat

beating eating disorders

prevalence of ED has significantly grown


The costs of eating disorders

Social, health and economic impacts

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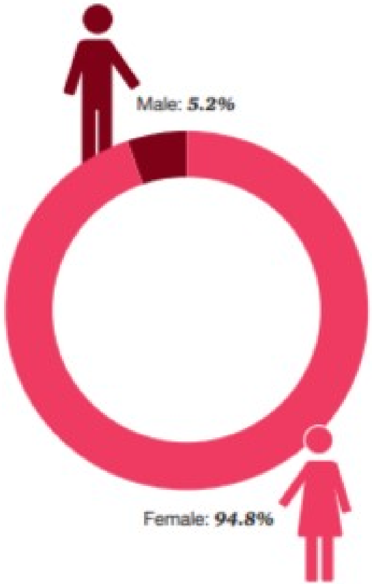
February 2015

beat

Figure 3.3

Gender breakdown of survey respondents



prevalence of ED has significantly **grown**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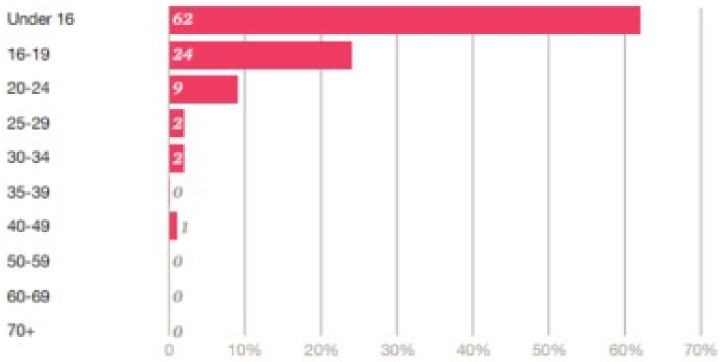


Base: 517

prevalence of ED has significantly grown


The costs of eating disorders
Social, health and economic impacts

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

February 2015

beat

prevalence of ED has significantly grown


The costs of eating disorders
Social, health and economic impacts

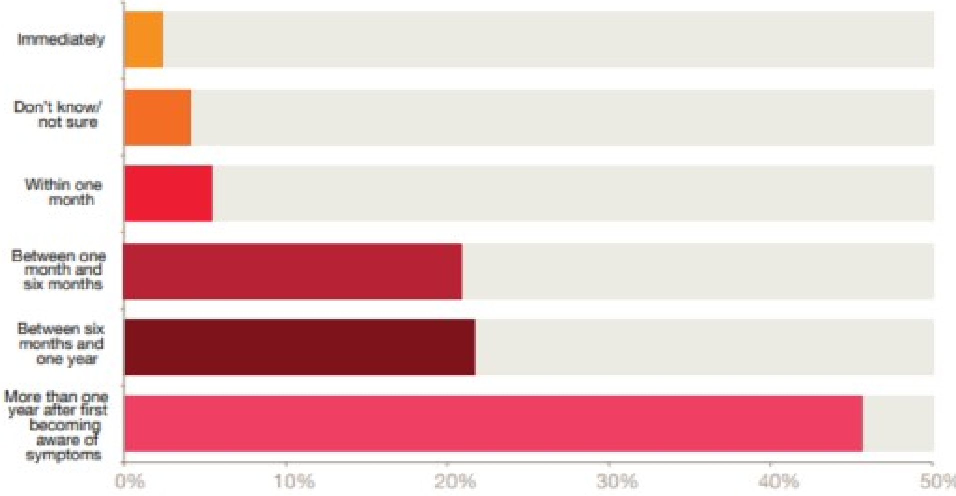
Assessing the impact of eating disorders across the UK on behalf of BEAT.

February 2015

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

Figure 4.1

Time between recognising symptoms and seeking help



Base: 517

clinical studies

surveys & interviews

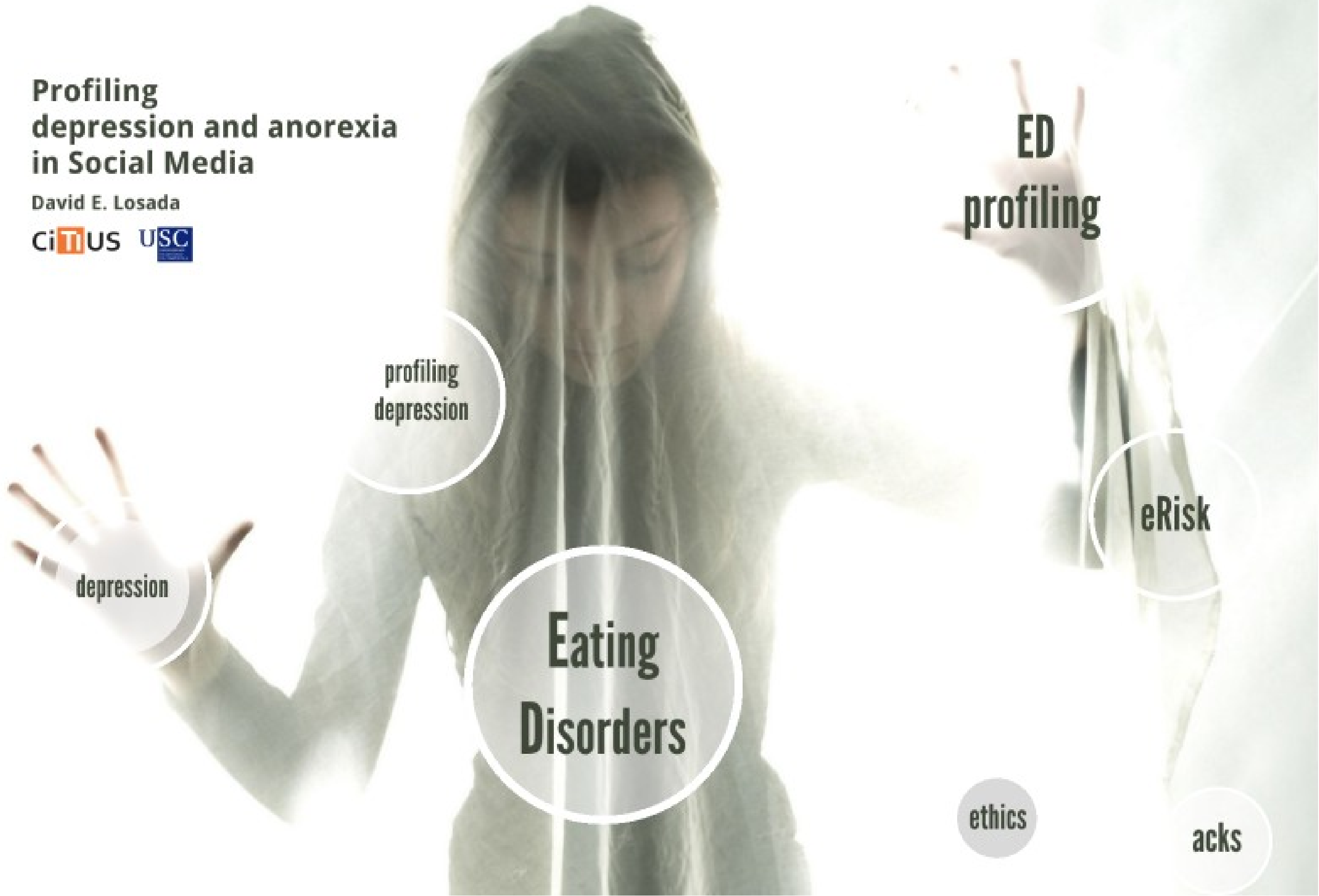
limitations:

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

Profiling depression and anorexia in Social Media

David E. Losada

CiTIUS USC



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

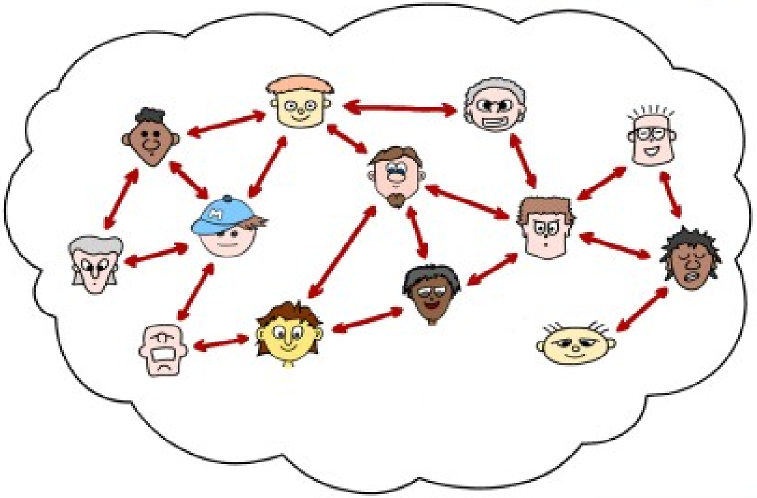
(semi-)anonymous & **open** nature of SM: encourages people to **socialize** and **self-disclose**

naturally occurring data in a non-reactive way.

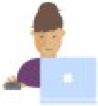
SM data complements **conventional data**

harmful content
vs
useful **recommendations** & **advice**

pro-ED **communities**
(support engagement
with ED lifestyles)



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**

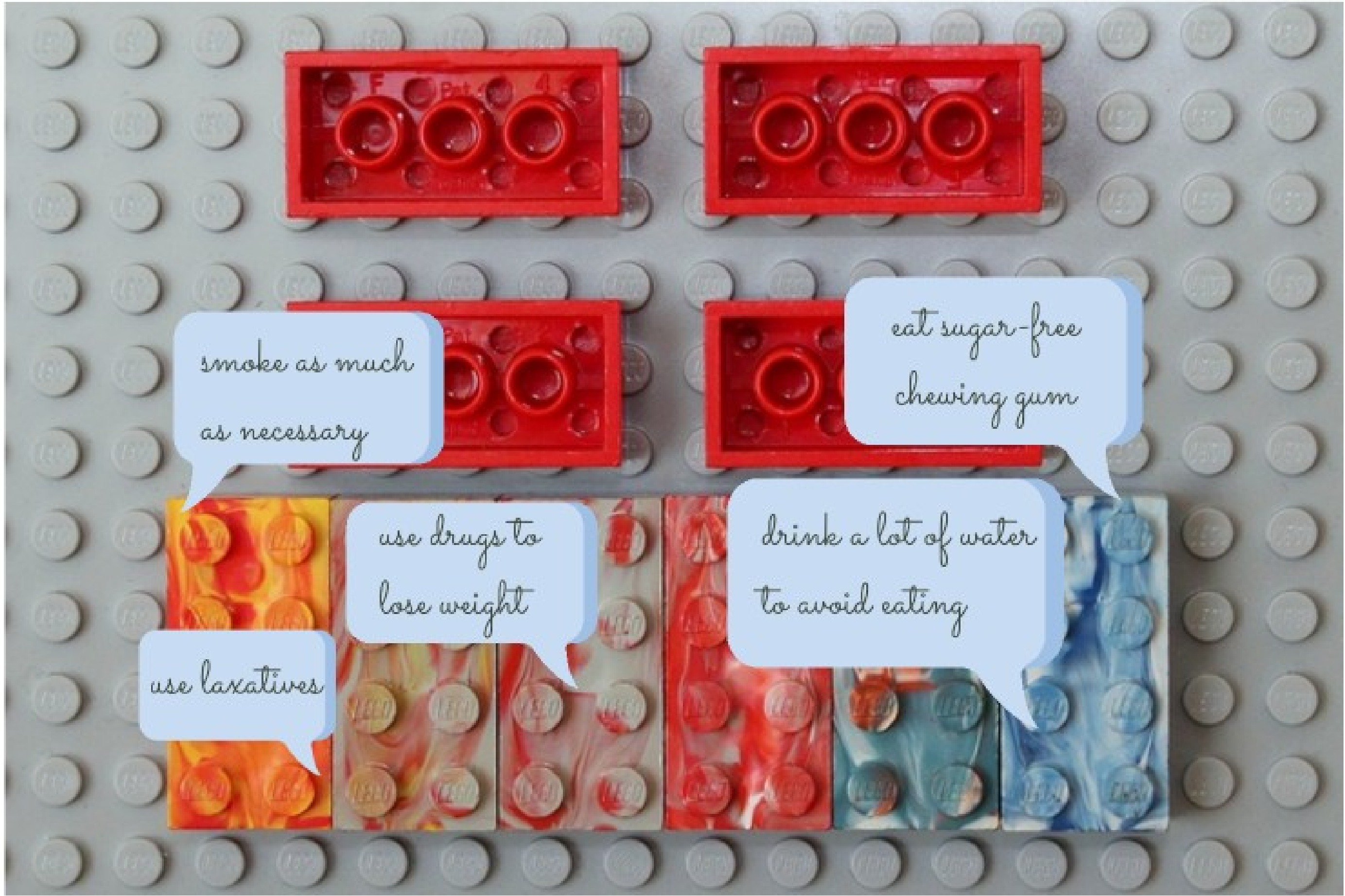
pro-ED communities:
- often "**hidden in plain sight**"
- use of **atypical language or tags**
  (seek to avoid outsiders encountering and reporting them)

pro-anorexia communities:

claim to provide support

promote disordered eating

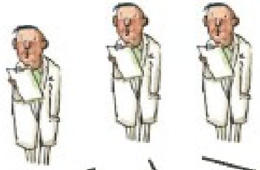
discourage people from seeking help or trying to recover



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 S[1], Fernandez-Luque L, Jian WS, Li YC, Crain S, Hsu MH, Wang YC, Khandregzen D, Chuluunbaatar E, Nguyen PA, Liou DM.

Author information

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

top viewers

13 years-old 17 years-old

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**

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

myspace

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

ISSN: 1064-0266 print/1532-530X online
DOI: 10.1080/10640266.2010.511918

Routledge
Taylor & Francis Group

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

ADRIENNE S. JUARASCIO
Department of Psychology, Drexel University, Philadelphia, Pennsylvania, USA

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

C. ALIX TIMKO
Department of Behavioral and Social Sciences, University of the Sciences, Philadelphia, Pennsylvania, USA

ED & SM: relevant refs

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

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

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

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

Markus Wolf[1], Florian Theis[1], and Hans Kordy[1]

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**

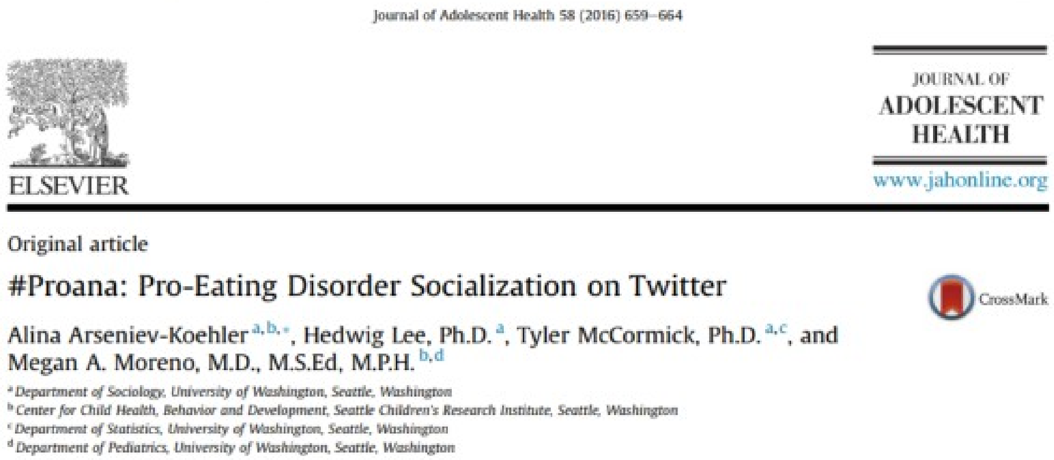
ED & SM: relevant refs

pro-ED Twitter profiles' refs to EDs

45 Pro-ED profiles

how the **followers** reference EDs

profile info + all tweets +
random sample of followers



Journal of Adolescent Health 58 (2016) 659–664

ELSEVIER

JOURNAL OF ADOLESCENT HEALTH

www.jahonline.org

Original article

#Proana: Pro-Eating Disorder Socialization on Twitter

CrossMark

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

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

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

ED & SM: relevant refs

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

investigated **pro-ED communities** in the **aftermath of moderation**

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

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

increasingly **complex lexical variants emerged over time**

more toxic, **self-harm**, and **vulnerable content**

CSCW 2016
San Francisco, CA

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

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

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

Instagram

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
PMCID: PMC3510717

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

Monitoring Editor: Gunther Eysenbach

Reviewed by Stephen Lewis

Elad Yom-Tov, PhD,[1] Luis Fernandez-Luque, MSc,[2,3] Ingmar Weber, PhD,[4] and Steven P Crain, PhD[5]

[1]Microsoft Research, Herzliya, Israel
[2]Northern Research Institute, Tromsø, Norway
[3]Computer Science Department, University of Tromsø, Tromsø, Norway
[4]Yahoo Research, Barcelona, Spain
[5]Department 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)

Detecting and Characterizing Eating-Disorder Communities on Social Media

Tao Wang, ESRC DTC, IfLS
Markus Brede, Department of ECS
Antonella Ianni, Department of Economics
Emmanouil Mentzakis, Department of Economics
University of Southampton, UK
{t.wang, Markus.Brede, A.Ianni, E.Mentzakis}@soton.ac.uk

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

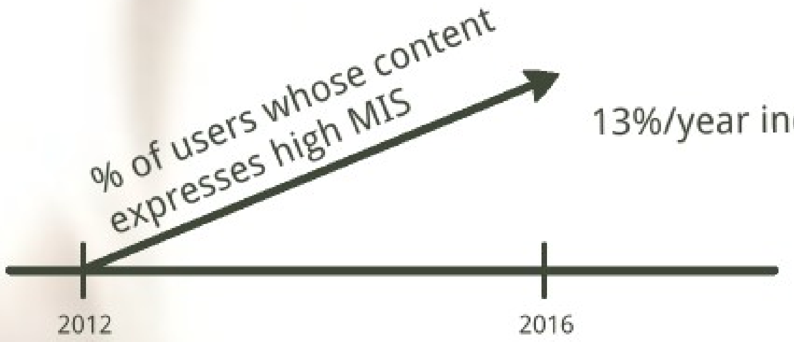
Instagram **posted content** on **pro-ED tags**

LDA topic modelling + novice/clinicial 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



13%/year increase

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

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

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Zhiyuan (Jerry) Lin
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Erica L. Goodman
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munmund@gatech.edu

26M posts

100k users

ED & SM: relevant refs

tumblr. **pro-anorexia** and **pro-recovery** communities

Digital Health

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

Anorexia on Tumblr: A Characterization Study

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

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)

ED & SM: relevant refs

San Jose, CA, USA

May 7-12

2016 #chi4good

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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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**

ED & SM: relevant refs

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.

CHI'17
Proceedings of the 2017 ACM SIGCHI Conference on
Human Factors in Computing Systems

Multimodal Classification of Moderated Online Pro-Eating Disorder Content

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David A. Shamma
Centrum Wiskunde & Informatica (CWI)
Amsterdam, Netherlands
aymans@acm.org

annotated data for training

ED & SM: main research themes

impact/prevalence of **ED-related** contents in SM

analysis of **communities** & **interactions**

content analysis, **psychometrics**

content moderation/ violation of SM guidelines

misleading health-related **info**

effect of moderation

learning technology (classification/regression)

Profiling depression and anorexia in Social Media

David E. Losada

CiTIUS USC

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

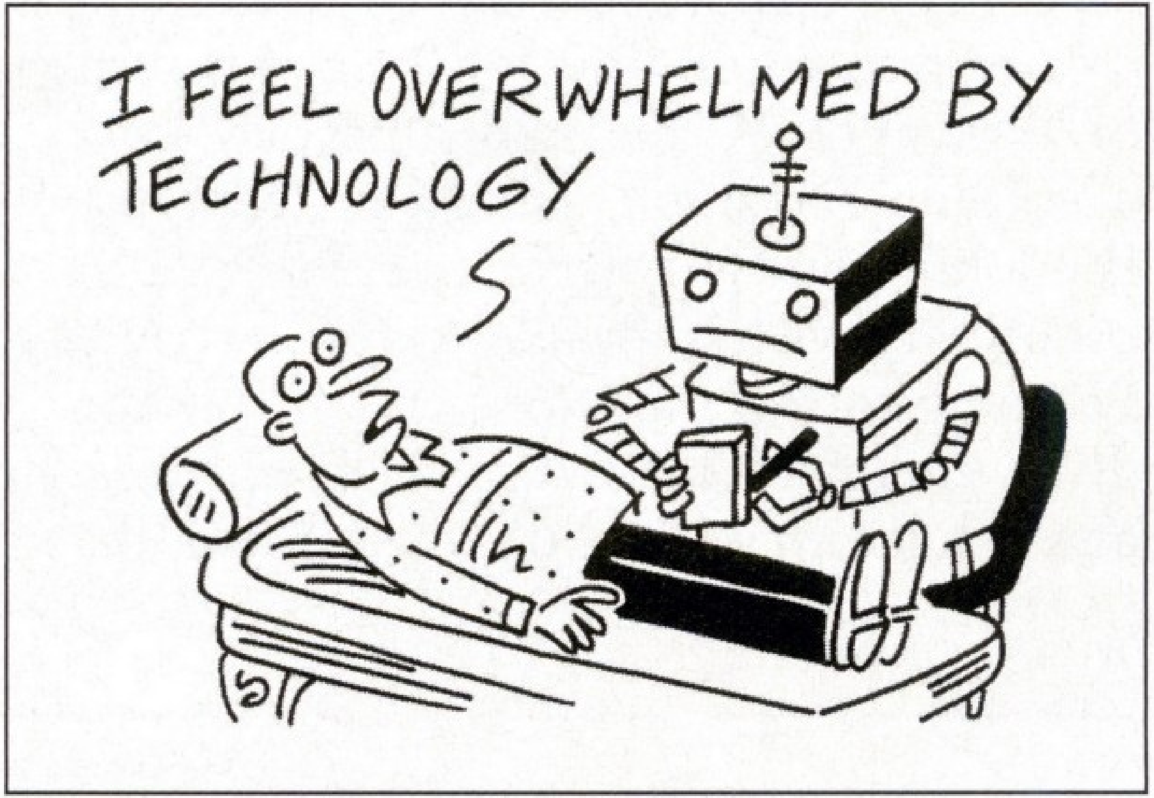
- **no interaction** with subjects
- **no need of** institutional review **approval**
- avoids the need of contacting subjects, which can be coercive and may change user behaviour

use cases

automatic assessments?

use cases

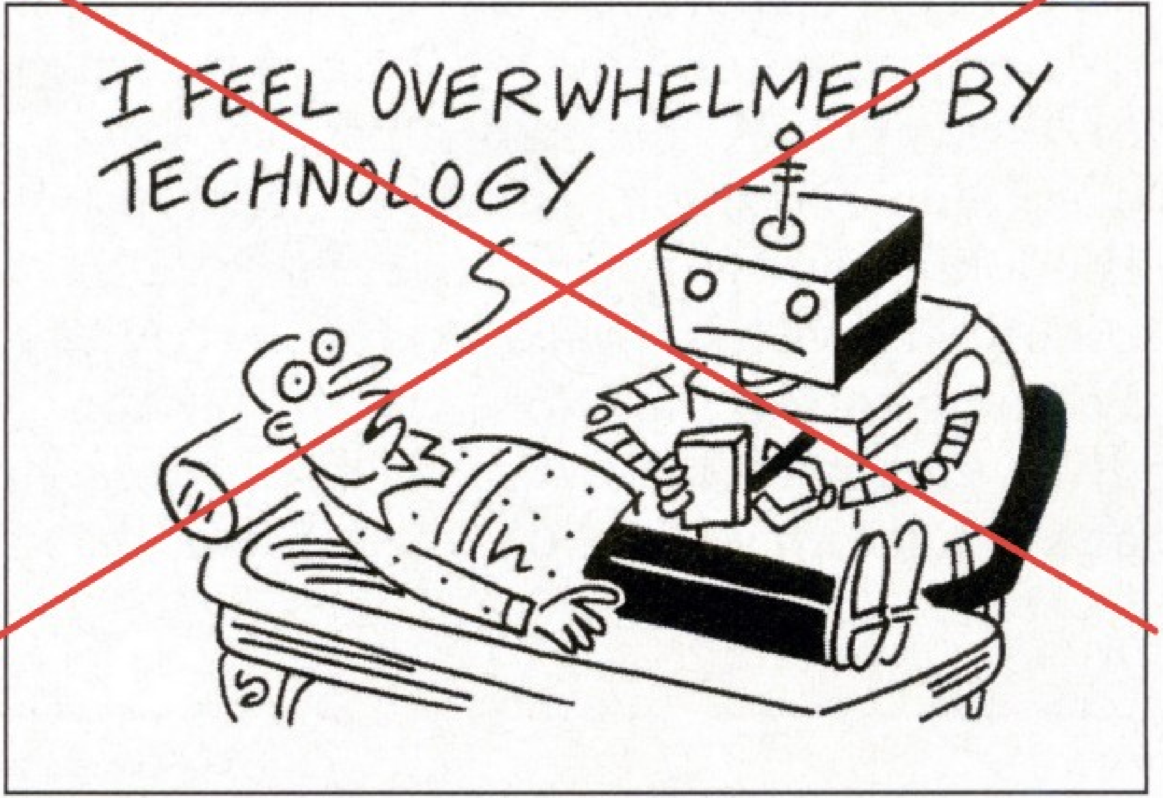
automatic assessments?



use cases

automatic assessments?

NO WAY!!!



use cases

automatic assessments?

NO WAY!!!

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

need to **involve clinicials/psychiatrists**

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

interventions?

By Frits Ahlefeldt

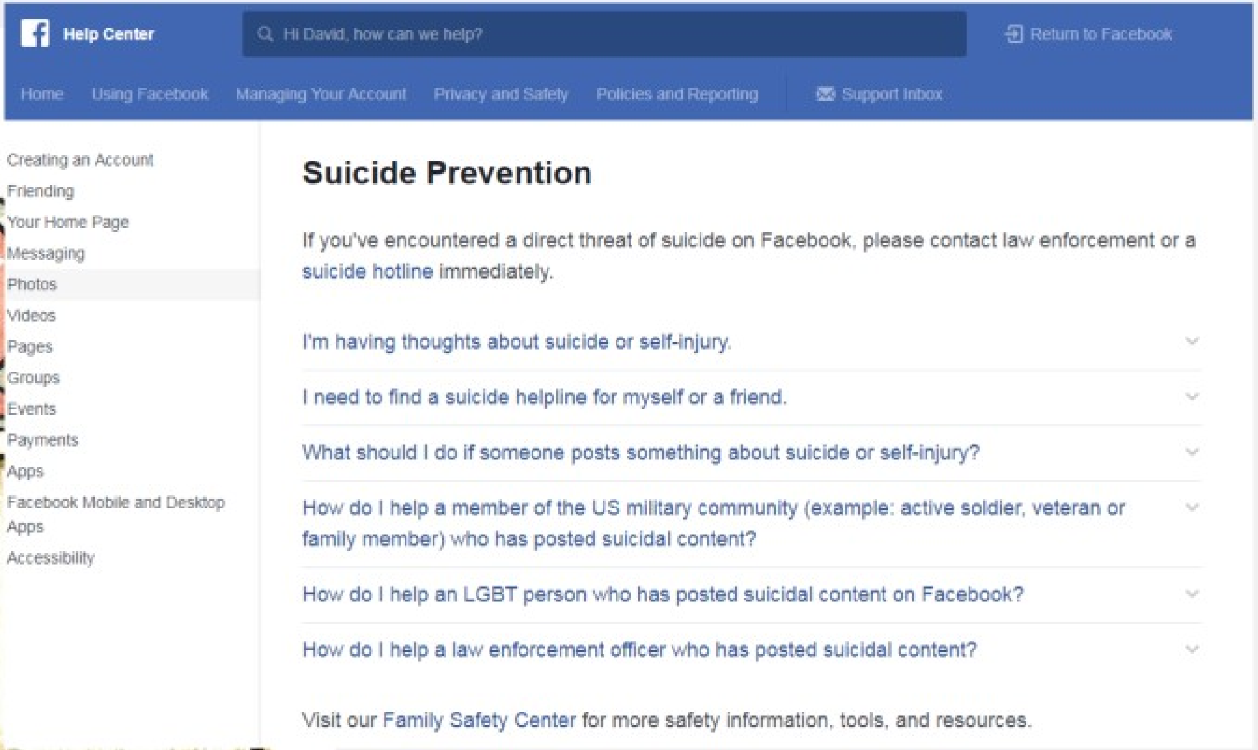
- ensure that the intended **benefits** of these interventions outweigh the **risks**

- **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



use cases: example

suggests possible uses of this technology:

Internet Interventions 2 (2015) 183–188

Contents lists available at ScienceDirect

Internet Interventions

journal homepage: www.invent-journal.com/

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 Vimiera and Pembroke Roads, Marsfield, NSW 2122, Australia
[c] National Institute for Mental Health Research, Building 63, The Australian National University, Canberra ACT 2601, Australia

users must **consent to**:

their tweets being **monitored** by an organisation or an individual

permission to be contacted if ‘strongly concerning’ tweet detected

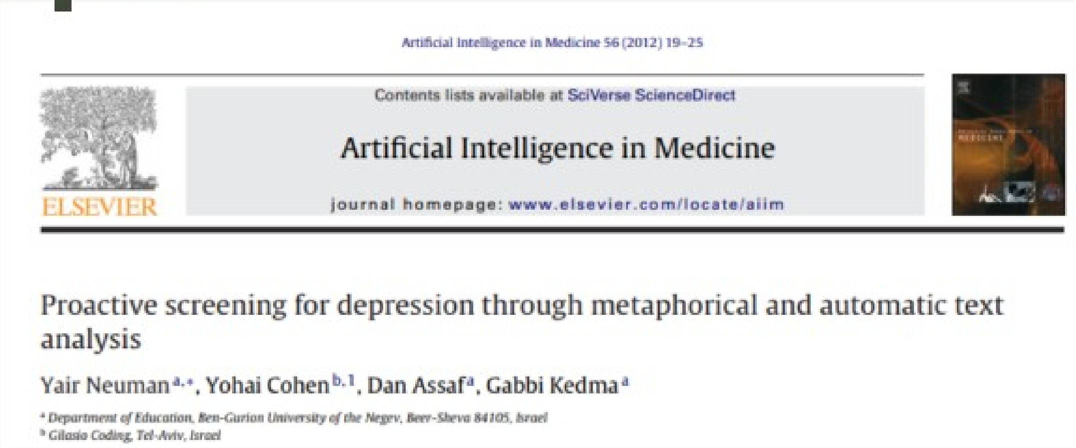
use cases: example

suggests possible uses of
this technology:

mental health agencies

tool for automatic screening
for depression

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


Artificial Intelligence in Medicine 56 (2012) 19–25

Contents lists available at SciVerse ScienceDirect

Artificial Intelligence in Medicine

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

ELSEVIER

Proactive screening for depression through metaphorical and automatic text analysis

Yair Neuman[a,*], Yohai Cohen[b,1], Dan Assaf[a], Gabbi Kedma[a]

[a] Department of Education, Ben-Gurion University of the Negev, Beer-Sheva 84105, Israel
[b] Gilasio Coding, Tel-Aviv, Israel

use cases: example

suggests possible uses of this technology:

mental healt

tool for auton
for depressio

given the sub
and **automat**
(e.g. within t


Artificial Intelligence in Medicine 56 (2012) 19–25

Contents lists available at SciVerse ScienceDirect

Artificial Intelligence in Medicine

atic text

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

signs of depression?

the questionnaire also identifies symptoms of depression ?

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

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

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freedom of speech vs security

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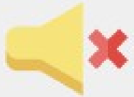
freedom of speech vs security



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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

- moderati
  that migh
- **avoids contagion**-like effects
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Profiling depression and anorexia in Social Media

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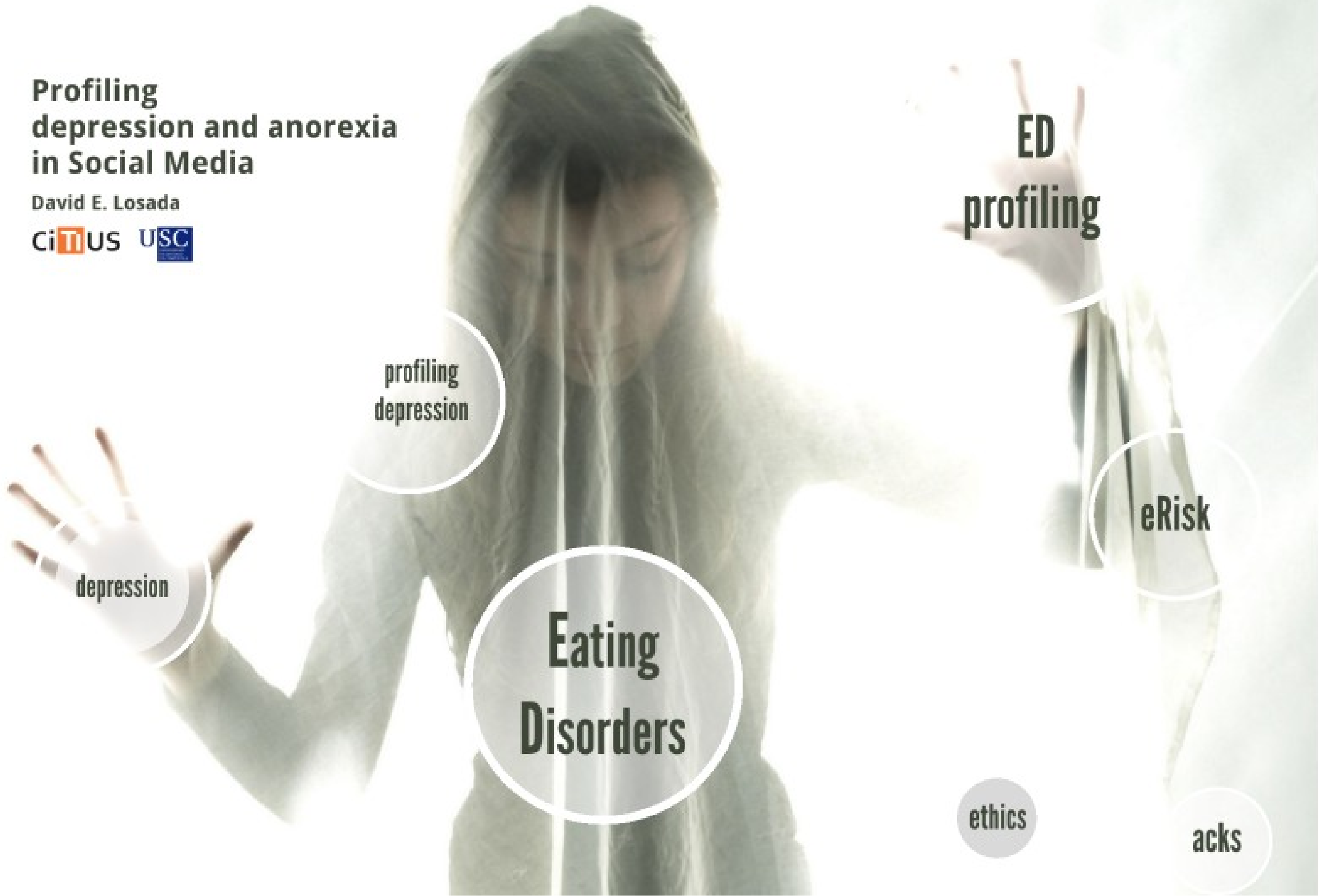
CiTIUS USC



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

USC UNIVERSIDADE DE SANTIAGO DE COMPOSTELA

CiTIUS Centro Singular de Investigación en Tecnoloxías da Información

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UNIVERSIDADE DA CORUÑA

IR Lab

eRisk @ clef 2017

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

eRisk @ clef 2018

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

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

data

early
intervention is crucial

current technology

doesn´t support early alerts

reactive

works with very explicit signals

current technology

too often, too late!

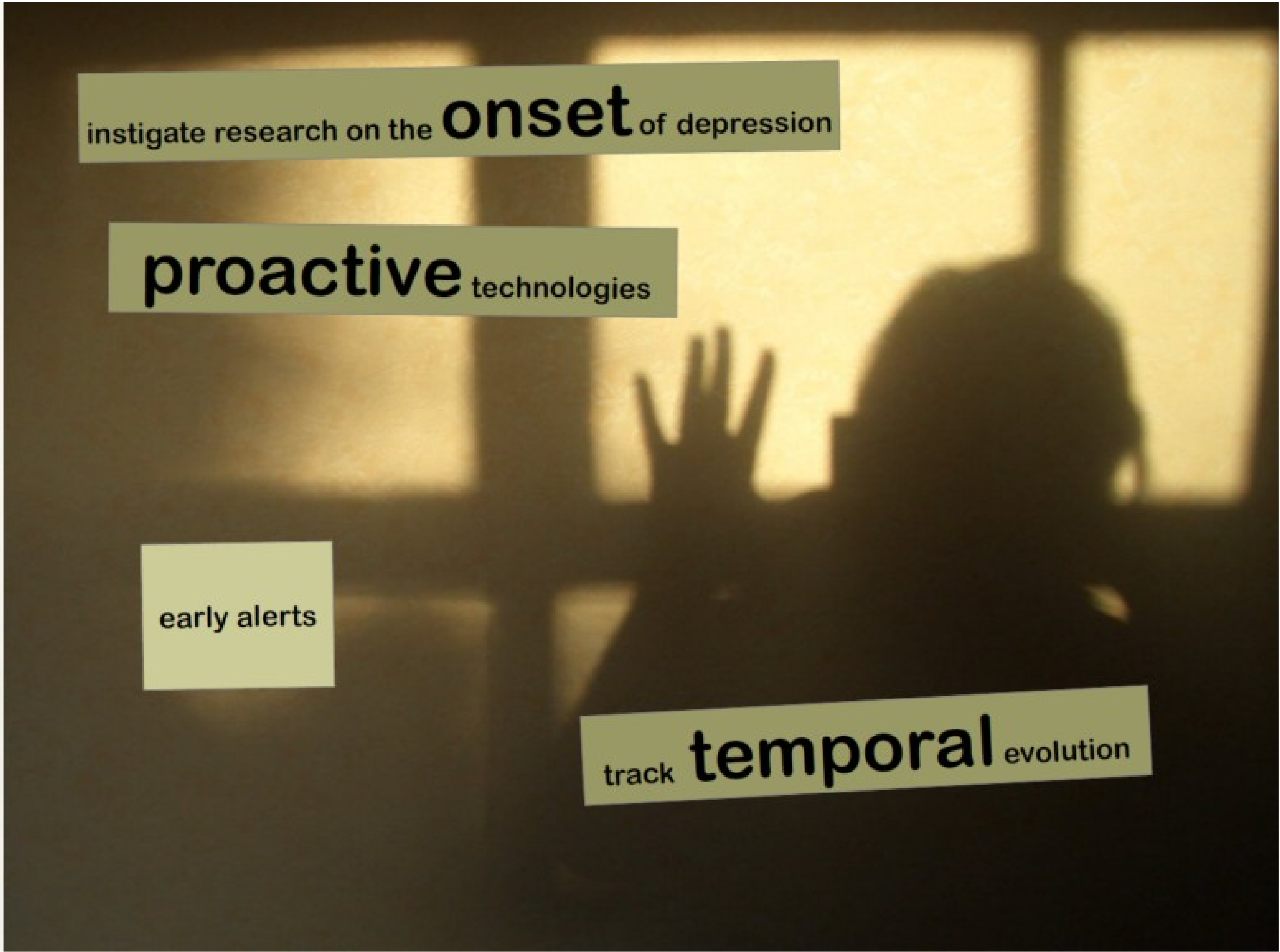
doesn´t support early alerts

reactive

works with very explicit signals

data

key aims

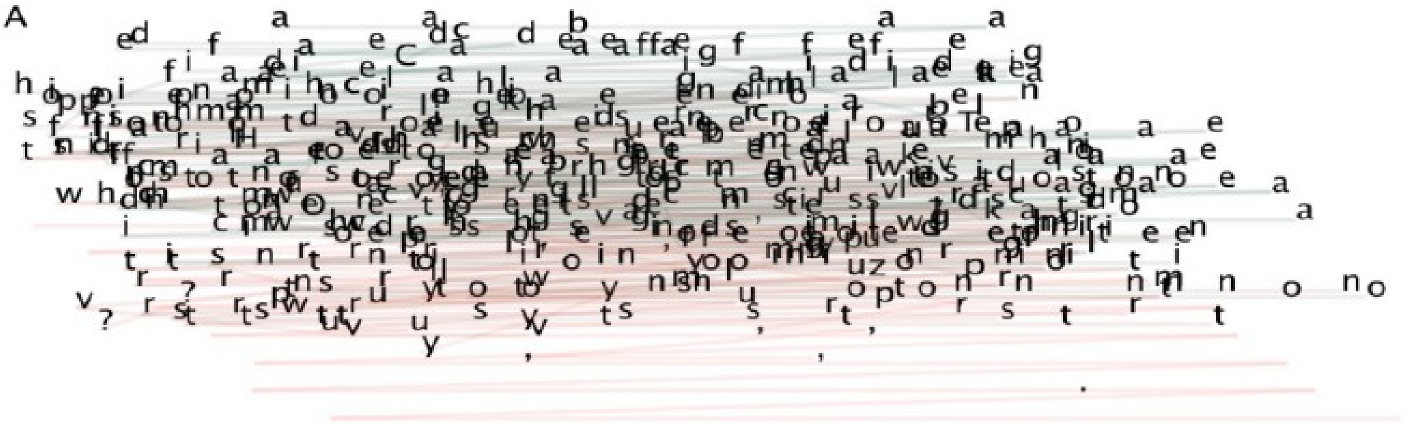


Lack of data on depression & language

few collections available

focus on 2-class categorisation

no temporal dimension, no early risk analysis

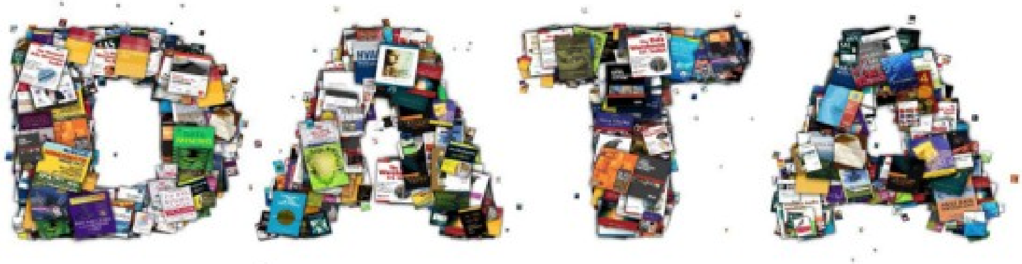


DATA

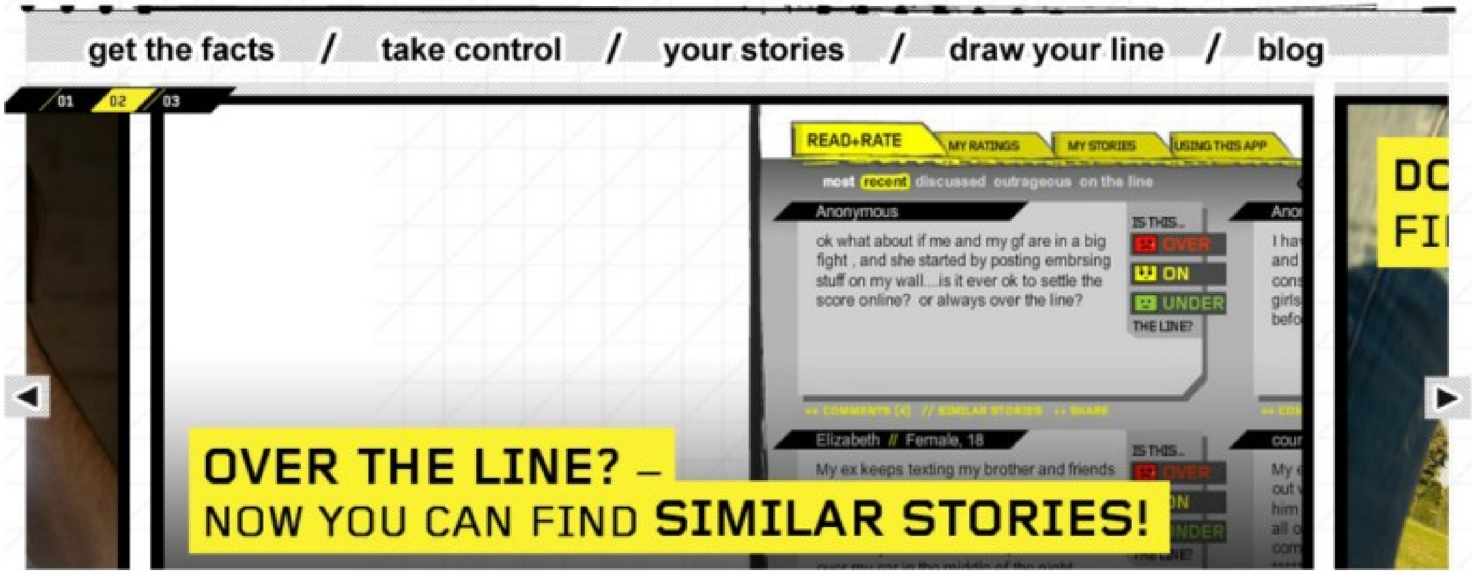
little context about the tweet writer

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

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


DATA

A Thin Line

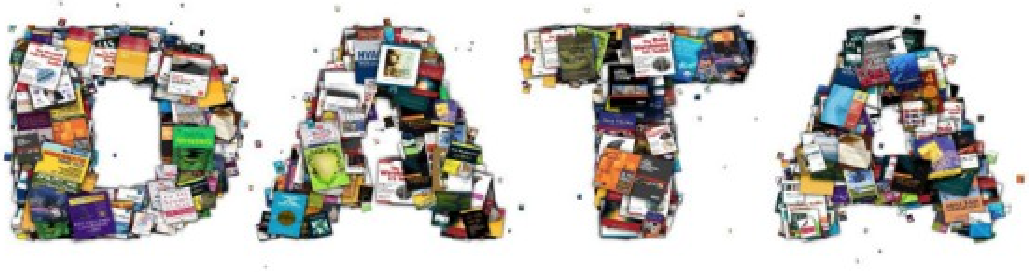

get the facts / take control / your stories / draw your line / blog
01 02 03
READ+RATE
MY RATINGS
MY STORIES
USING THIS APP
most recent discussed outrageous on the line
Anonymous
ok what about if me and my gf are in a big fight , and she started by posting embrsing stuff on my wall....is it ever ok to settle the score online? or always over the line?
IS THIS...
OVER
ON
UNDER
THE LINE?
Elizabeth // Female, 18
My ex keeps texting my brother and friends
OVER THE LINE? –
NOW YOU CAN FIND SIMILAR STORIES!

DATA

A Thin Line

no way to extract any **history**

short messages, little context




MIS SUBREDDITS PORTADA - TODOS - ALEATORIO | ASKREDDIT - FUNNY - PICS - VIDEOS - TODAYILEARNED - GAMING - GIFS - WORLDNEWS - MOVIES - NEWS
reddit DEPRESSION
activo
nuevo
subiendo
polémico
popular
con gold
patrocinados
384
(self.depression)
enviado hace 2 meses por
38 comentarios compartir
27
(self.depression)
enviado hace 7 días por
297 comentarios compartir
1 124
(self.depression)
enviado hace 8 horas por
25 comentarios compartir
2 37
enviado hace 6 horas por
5 comentarios compartir
3 43
enviado hace 8 horas por
21 comentarios compartir

DATA

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

reddit

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

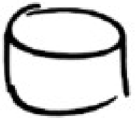
often several years of text

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

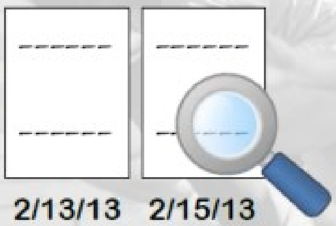
XML archives 

task format

detect **early traces** of depression

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

John Doe's writings
(post or comments)



2/13/13 2/15/13

chunk 1 (oldest writings)
10% of writings

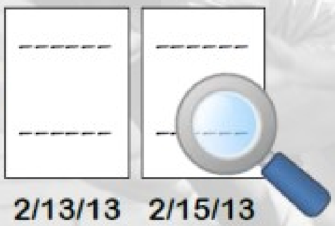
possible case of depression
no depression
no decision yet

task format

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

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

John Doe's writings
(post or comments)



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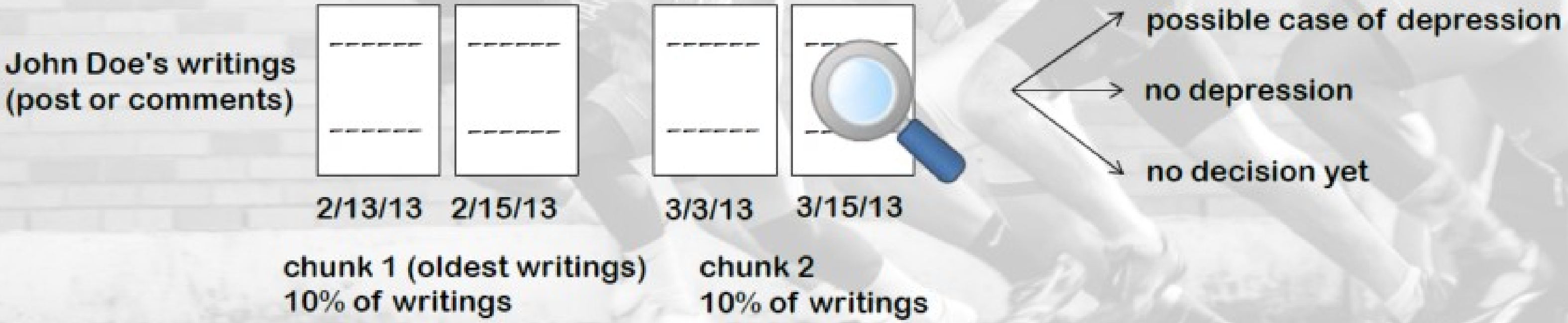

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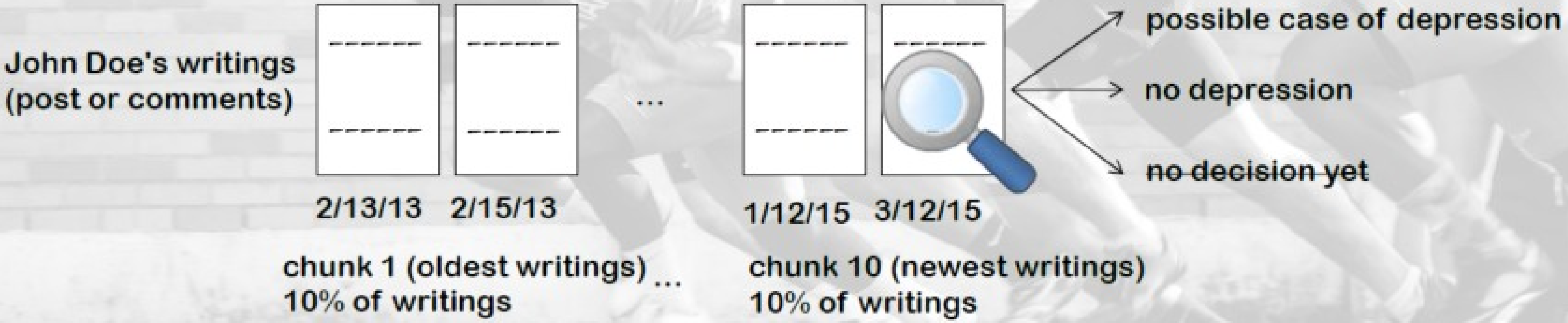
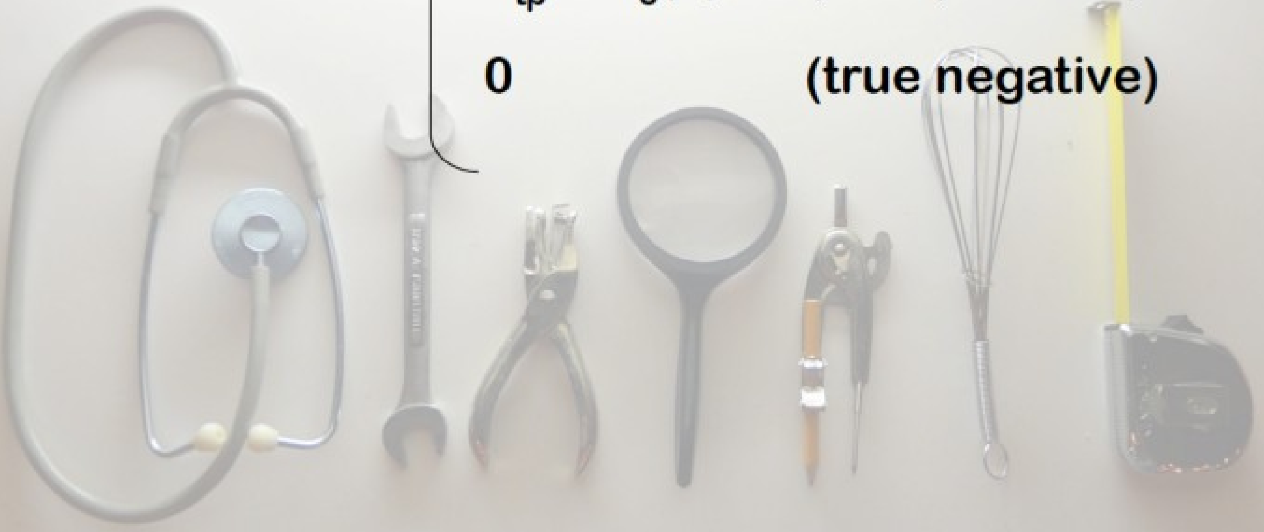


performance metric

Early Risk Detection Error:

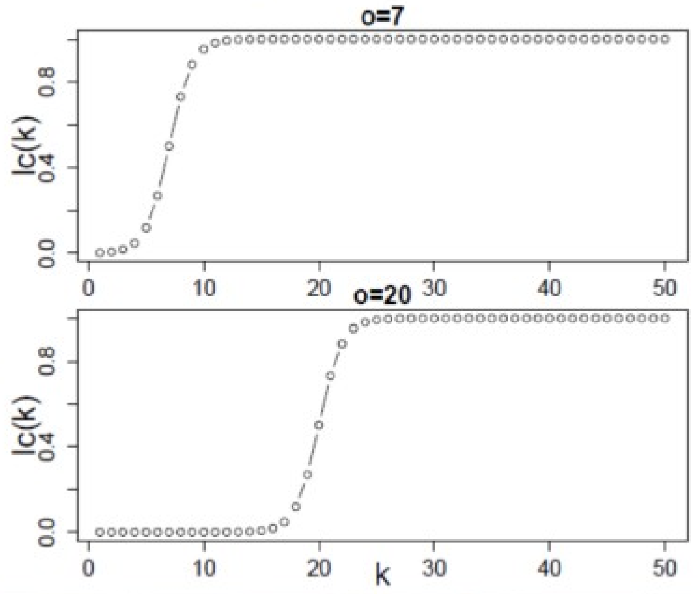
$$
ERDE_o(d,k) = \begin{cases} c_{fp} & \text{(false positive)} \\ c_{fn} & \text{(false negative)} \\ c_{tp} * lc_o(k) & \text{(true positive)} \\ 0 & \text{(true negative)} \end{cases}
$$



performance metric

True Positive cost

Latency cost function



penalty to late detections

splits

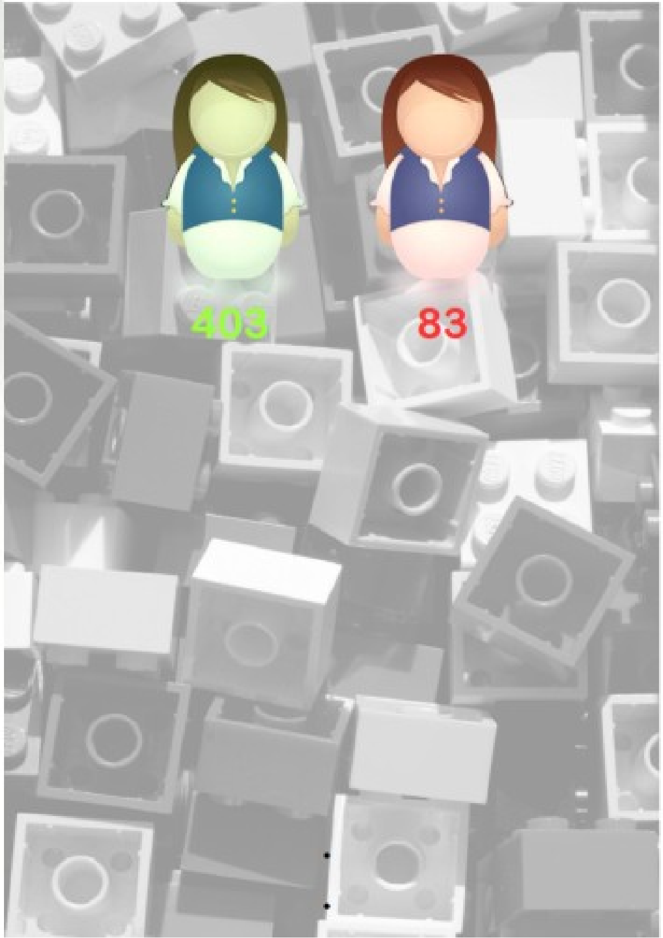
Training

Test

	Train		Test	
	Depressed	*Control*	*Depressed*	*Control*
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

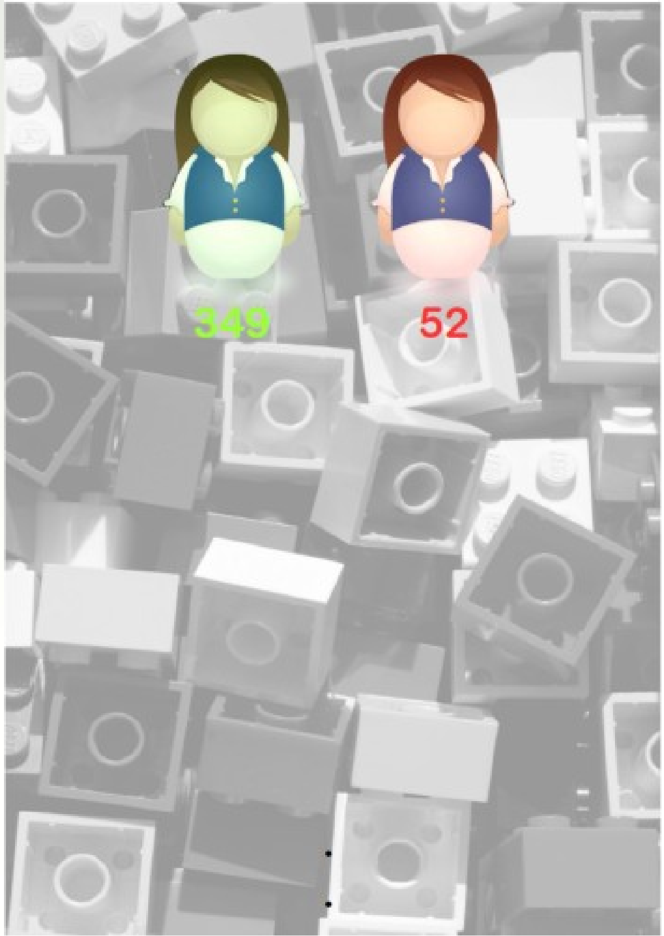
Training



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
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.

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

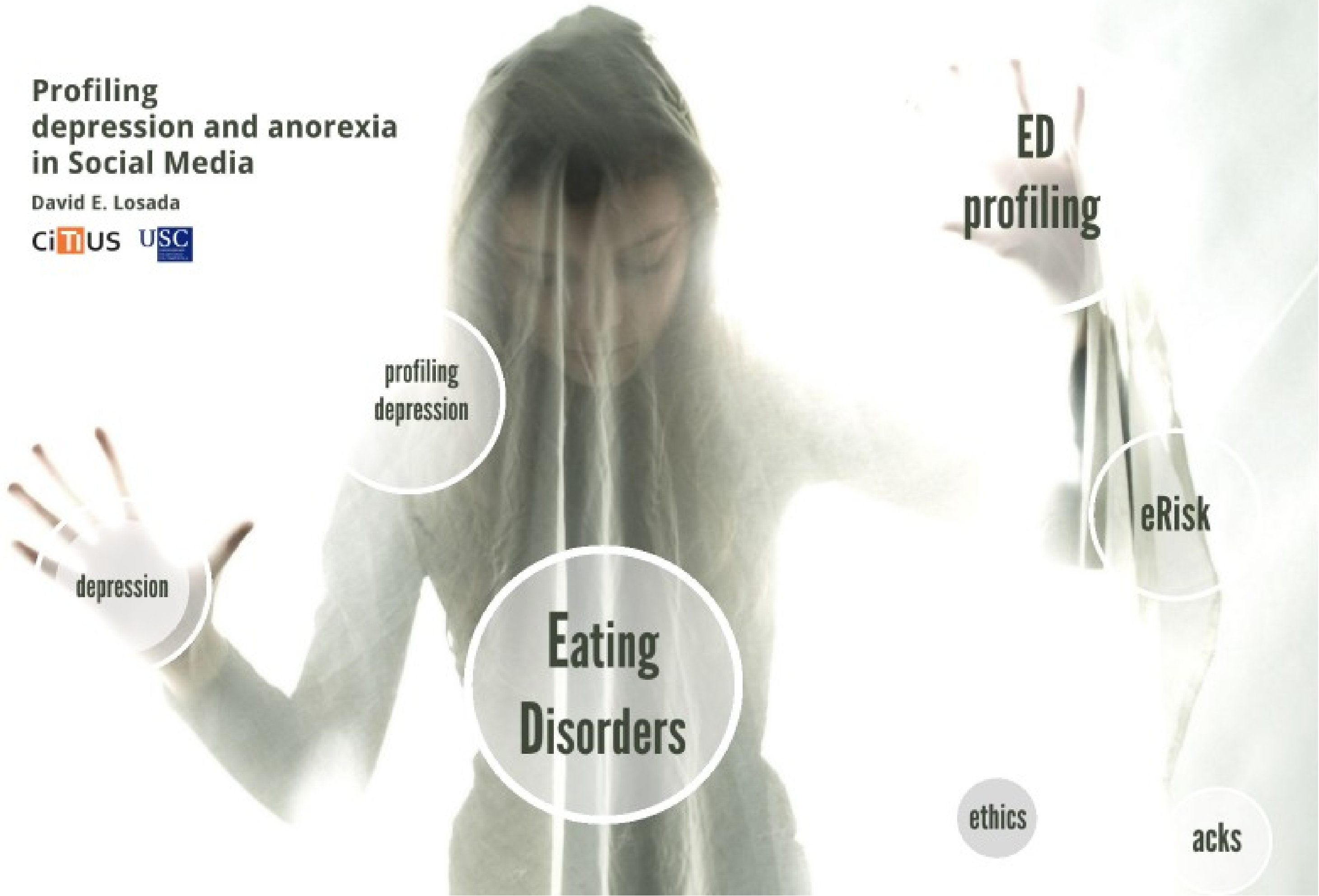
results

	$ERDE_5$	$ERDE_{50}$	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

CiTIUS USC



THANKS!

funding

resources

funding

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GOBIERNO DE ESPAÑA

MINISTERIO DE ECONOMÍA Y COMPETITIVIDAD

Unión Europea

Fondo Europeo de Desarrollo Regional
"Una manera de hacer Europa"

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FNSNF

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

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

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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