Automated identification of patients with a diagnosis of binge eating disorder from narrative electronic health records

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ABSTRACT

Binge eating disorder (BED) does not have an International Classification of Diseases, 9th or 10th edition code, but is included under 'eating disorder not otherwise specified' (EDNOS). This historical cohort study identified patients with clinician-diagnosed BED from electronic health records (EHR) in the Department of Veterans Affairs between 2000 and 2011 using natural language processing (NLP) and compared their characteristics to patients identified by EDNOS diagnosis codes. NLP identified 1487 BED patients with classification accuracy of 91.8% and sensitivity of 96.2% compared to human review. After applying study inclusion criteria, 525 patients had NLP-identified BED only, 1354 had EDNOS only, and 68 had both BED and EDNOS. Patient characteristics were similar between the groups. This is the first study to use NLP as a method to identify BED patients from EHR data and will allow further epidemiological study of patients with BED in systems with adequate clinical notes.

BACKGROUND AND SIGNIFICANCE

Binge eating disorder (BED) is characterized by regular, excessive consumption of food (occurring, on average, once per week for at least 3 months), without an associated inappropriate compensatory behavior such as purging, fasting, or engaging in compulsive exercise.[1] The lifetime prevalence of BED in adults in the USA ranges from 2.0% to 3.5%,[2 3] but may be underestimated because individuals with BED tend to conceal their illness.[4]

The advancement of electronic health records (EHR) to gather and store patient data[5–8] has enabled researchers greater access to patient information.[9 10] However, BED was not officially classified as an eating disorder until the release of the Diagnostic and Statistical Manual of Mental Disorders (DSM), fifth edition in 2013.[1] Before this, BED was included in the DSM, fourth edition (IV) as an area for further research under eating disorder not otherwise specified (EDNOS).[11] In addition, DSM diagnoses are not captured in structured data and the International Classification of Diseases, 9th and 10th edition (ICD-9 and ICD-10) billing codes only include disorders from the DSM-IV. Thus, BED is currently captured using the EDNOS ICD-9 code, which includes other eating disorders.[12 13] Therefore, despite an increased ability of clinicians to screen for BED,[14–17] it remains difficult to study in large populations. Epidemiological research in BED has relied on time and resource-intensive prospective questionnaires and patient registries,[3 4 18–21] which do not allow the identification of patients with BED in other datasets.

Natural language processing (NLP) includes a set of methods developed to recognize distinctive word and phrase patterns from written text, in a manner similar to human chart review.[10 22–25] NLP has been used to identify patients with diseases that do not have diagnosis codes, or for which the diagnosis codes are poorly documented, and for test results absent in structured EHR data.[24 26 27] The objective of this study was to identify patients with clinician-diagnosed BED from narrative clinic notes in the Department of Veterans Affairs (VA) EHR using NLP; then, compare characteristics (ie, demographics, comorbidities, and medication use) of patients identified to have only BED, only EDNOS, and both BED and EDNOS.

MATERIALS AND METHODS

Data acquisition and management

This historical cohort study used EHR data from the national population of US veterans who received care in the VA. Administrative and clinical information recorded in the EHR during patient–provider interactions within the VA was obtained, including patient demographics, diagnostic codes, vital signs, medications, and narrative clinical notes. Examining both diagnostic codes and clinical notes allowed for a comparison of how a BED diagnosis appears in the EHR (figure 1). This study was reviewed and approved by the University of Utah Institutional Review Board and the VA Salt Lake City Health Care System Research and Development Service.

NLP development for BED patient identification

Initial term identification

To identify patients with clinician-diagnosed BED, narrative clinic notes from inpatient and outpatient encounters were selected from 1 January 2000 to 31 December 2011. A random set of 1000 of these notes was sampled from adult patients (≥18 years) with at least one diagnosis of EDNOS (ICD-9 307.50). Clinicians and informaticists reviewed this sample of notes for terms and phrases used by clinicians to describe a diagnosis of BED.

The initial set of terms and phrases found included different tenses of the words 'eat' or 'eater'; preceded by descriptors such as 'addictive', 'binge', or 'over'; or followed by 'disorder' or

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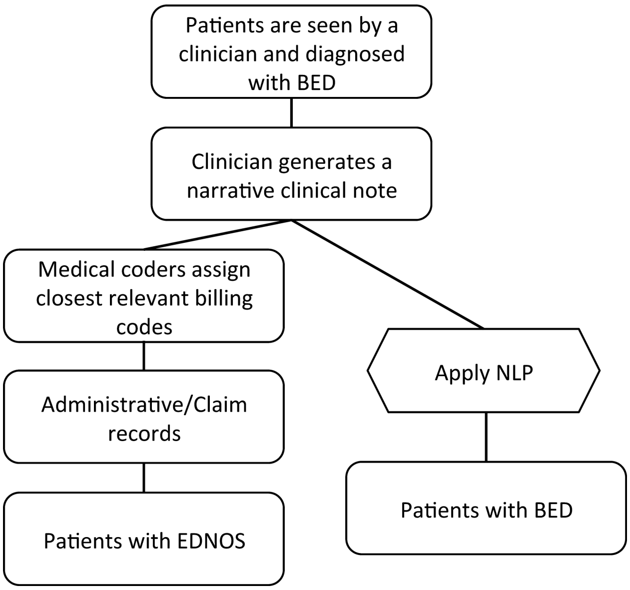

Figure 1 Current method of diagnosing EDNOS from structured data compared to NLP method for identifying patients diagnosed with BED. BED, binge eating disorder; EDNOS, eating disorder not otherwise specified; NLP, natural language processing.

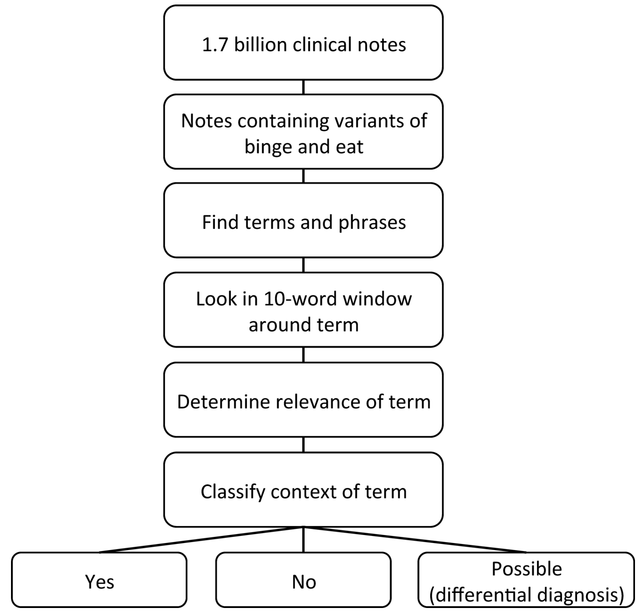

Figure 2 Diagram of the natural language processing algorithm.

'episode'. 'EDNOS', 'NOS', and 'NEC'—'not elsewhere classified' were also commonly found.

NLP development

The goal of the NLP algorithm was not to infer BED through descriptions of behavior, but to identify explicit physician-documented diagnoses (eg, medical record stated 'the patient has BED'). A rule-based approach was used and was iteratively developed starting with the initial terms and phrases found in the EDNOS patient notes. The VA EHR includes many templates (eg, questionnaires) and informative documents (eg, patient handouts) that may be used by providers, but do not necessarily indicate a diagnosis. Therefore a customized algorithm, similar to ConText,[28] was used to identify instances when a term or phrase was found in a clinical note indicating a diagnosis of BED was negated, hypothetical, historical, given to someone other than the patient, or included in informative text. This approach excluded references to family history, key terms used in other contexts (eg, alcoholic binge), and descriptions in informative text (eg, 'symptoms of BED include …'). Windows of 10 words were created around each instance to help distinguish whether a clinician was affirming ('yes'), ruling out ('no'), or considering a BED diagnosis as part of a differential diagnosis ('possible'). Each instance in a narrative clinical note was classified into one of these three diagnostic categories (figure 2). The NLP system did not use grammatical parsing and syntactic and semantic normalization were performed during rule development.

NLP validation

The NLP system went through five iterations of rule development, in which results were manually validated. Patterns of the most commonly missed or misclassified concepts were identified, and the rules were adjusted accordingly. For each of the five iterations, clinical annotators manually reviewed 1000 randomly selected (using an automated randomization sequence in Microsoft SQL server) instances to compare their classification to the NLP system output. Validation centered on two criteria: first, that the term found was actually relevant to BED, and second, that the inference made by the tool with regard to the 'yes,' 'no,' or 'possible' classification was correct. Accuracy results were then tabulated and reported. Error analyses were performed with each iteration to determine the utility of each term in the full set of notes. Frequency analysis helped find commonalities occurring in the surrounding text in both correct and incorrect NLP system classifications. This process identified related terms along with misspellings, abbreviations, and synonyms of the concepts of interest. Terms with the least entropy, that is, terms with a large number of instances but a small percentage of which were relevant to BED diagnosis, were identified and removed. Through the validation process, the initial set of phrases was narrowed down until it only included variations of 'BED', including acronyms, abbreviations, and differences in word order (more information available in the supplementary data, available online only). After final validation, the BED NLP tool was then run on all notes associated with inpatient and outpatient encounters in the VA system from 1 January 2000 to 31 December 2011. In order to assess the sensitivity of the NLP tool, a random sample of 200 patient records containing any of the initial terms and phrases and 530 patient records of patients with an EDNOS diagnosis that were not identified and classified by NLP as having BED was manually reviewed.

Patient selection

Patients with at least one diagnosis of BED identified by NLP in a clinical note were classified as having BED (first diagnosis defined index date). EDNOS patients were identified by ICD-9 code (first diagnosis defined index date). Patients were included in the final cohort if they were aged 18 years or over, had 1 year or more of activity (eg, an office visit, prescription fill, hospital visit) before and after the index date, had a body mass index (BMI) value within ±60 days of the index date, and no diagnosis for other eating disorders (ie, bulimia nervosa (ICD-9 307.51), anorexia nervosa (307.1), pica (307.52), rumination disorder (307.53), and psychogenic vomiting (307.54)). Three groups were created for comparison of patient characteristics

Table 1 Measurement properties of the final iteration of the NLP tool

Accuracy*

Instances reviewed	Instances annotator agreed with NLP classification		BED diagnosis 'Yes' NLP-identified	'Yes' Annotator agreed		'No' NLP-identified	'No' Annotator agreed		'Possible'† NLP-identified	'Possible'† Annotator agreed	
N	N	%	N	N	%	N	N	%	N	N	%
1000	918	91.8	731	663	90.7	177	171	96.6	92	84	91.3

Sensitivity‡

Sample selection category	Patient records reviewed N	Missed BED diagnoses N	Sensitivity %
Initial keyword list§	200	1	99.5
EDNOS¶	530	27	94.7
Total	730	28	96.2

*Used 1000 randomly selected instances of variants of the phrase 'BED'.
†Includes differential diagnoses.
‡Used 200 patient records containing any of the initial terms and phrases and 530 patient records of patients with an EDNOS diagnosis that were not identified and classified by NLP as having BED.
§Patient records were selected that contained one of the initial keywords or phrases ('addictive eating', 'BED', 'binge eat', 'binge eater', 'binge eating', 'eating disorder', 'EDNOS', 'eating episode', 'over eat', 'over eater', 'over eating').
¶Patient records were selected that contained a diagnosis code for EDNOS (ICD-9 307.50).
BED, binge eating disorder; EDNOS, eating disorder not otherwise specified; ICD-9, International Classification of Diseases, 9th edition; NLP, natural language processing.

based on the method of identification: patients with only NLP-identified BED (BED only), patients with only EDNOS (EDNOS only), and patients with both BED and EDNOS (BED +EDNOS).

Statistical analysis

Descriptive statistics (frequencies and percentages for categorical variables; means and SD for continuous variables) were used to characterize patients in terms of demographics (age,

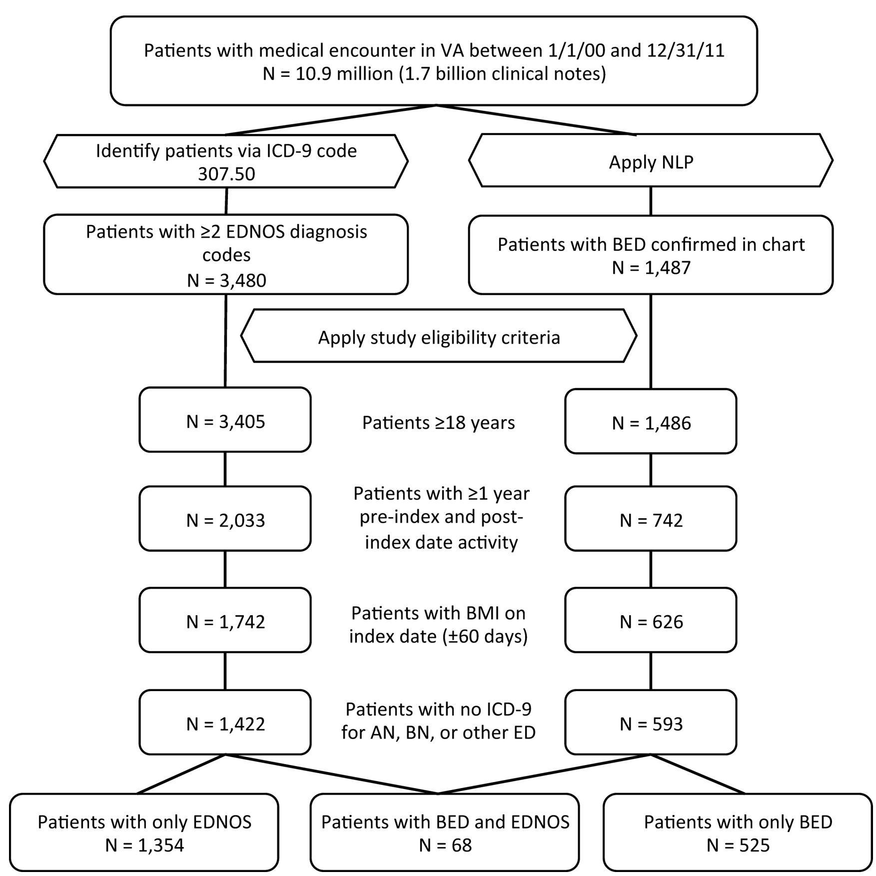

Figure 3 Attrition summary. AN, anorexia nervosa; BED, binge eating disorder; BN, bulimia nervosa; ED, eating disorder; EDNOS, eating disorder not otherwise specified; CD-9, International Classification of Diseases, 9th edition; NLP, natural language processing; VA, Department of Veterans Affairs.

Table 2 Characteristics of patients with only NLP-identified binge eating disorder (BED only), those with only a diagnosis of eating disorder not otherwise specified (EDNOS only) and those with both BED and EDNOS (BED+EDNOS)

	BED+EDNOS (N=68)		BED only (N=525)			EDNOS only (N=1354)			
Variable	N/mean	%/SD	N/mean	N/mean	p Value*	N/mean	%/SD	p Value*	p Value†
Age at index date (mean, SD), years	48.5	10.9	48.7	10.3	0.89	49.8	12.5	0.34	0.05
18–24	3	4.4	10	1.9	0.16	33	2.4	0.25	**<0.001**
25–34	7	10.3	40	7.6		165	12.2		
35–44	10	14.7	117	22.3		211	15.6		
45–54	22	32.4	198	37.7		427	31.5		
55–64	25	36.8	138	26.3		397	29.3		
65+	1	1.5	22	4.2		121	8.9		
Sex									
Male	45	66.2	383	73.0	0.24	850	62.8	0.57	**<0.001**
Race									
White	55	80.9	367	69.9	0.11	1024	75.6	0.65	**0.01**
Black	7	10.3	88	16.8		171	12.6		
Hispanic	2	2.9	6	1.1		29	2.1		
Other/unknown	4	5.9	64	12.2		130	9.6		
BMI at index date (mean, SD)	38.7	11.1	40.3	9.7	0.26	37.0	11.2	0.22	**<0.001**
<18.5	0	0	1	0.2	0.60	34	2.5	0.43	**<0.001**
18.5–24.9	5	7.4	24	4.6		194	14.3		
25.0–29.9	9	13.2	49	9.3		157	11.6		
30.0–34.9	9	13.2	80	15.2		196	14.5		
35.0–39.9	18	26.5	112	21.3		241	17.8		
40.0–44.9	10	14.7	116	22.1		221	16.3		
45.0–49.9	8	11.8	57	10.9		143	10.6		
50.0–54.9	3	4.4	49	9.3		83	6.1		
≥55.0	6	8.8	37	7.0		85	6.3		
Post-index comorbidities									
Depression	17	25.0	106	20.2	0.36	436	32.2	0.21	**<0.001**
Anxiety	20	29.4	64	12.2	**<0.001**	169	12.5	**<0.001**	0.86
Hyperlipidemia	36	52.9	265	50.5	0.70	640	47.3	0.36	0.21
Hypertension	41	60.3	316	60.2	0.99	709	52.4	0.20	0.002
Diabetes	28	41.2	188	35.8	0.39	492	36.3	0.42	0.83
Heart disease	8	11.8	80	15.2	0.45	196	14.5	0.53	0.68
Overweight	1	1.5	13	2.5	0.61	32	2.4	0.63	0.89
Obesity	44	64.7	336	64.0	0.91	799	59.0	0.35	**0.05**
Morbid obesity	20	29.4	169	32.2	0.64	364	26.9	0.65	**0.02**
Asthma	9	13.2	37	7.0	0.07	99	7.3	0.07	0.84
Sleep apnea	19	27.9	153	29.1	0.84	316	23.3	0.38	0.009
Osteoarthritis	18	26.5	122	23.2	0.56	335	24.7	0.75	0.50
Gallbladder disease	1	1.5	13	2.5	0.61	13	1.0	0.68	**0.01**
Cerebrovascular disease	0	0.0	0	0.0	–	0	0.0	–	–
Back pain/disorders	19	27.9	109	20.8	0.18	330	24.4	0.51	0.10
Non-alcoholic steatohepatitis	0	0.0	8	1.5	0.31	16	1.2	0.37	0.55
Post-index medication use									
Antidepressants	51	75.0	288	54.9	**0.002**	926	68.4	0.25	**<0.001**
Antipsychotics	12	17.6	75	14.3	0.46	265	19.6	0.70	**0.008**
Anxiolytics	22	32.4	121	23.0	0.09	433	32.0	0.95	**<0.001**
Antihypertensives	40	58.8	346	65.9	0.25	802	59.2	0.95	**0.008**
Anti-diabetics	24	35.3	176	33.5	0.77	451	33.3	0.74	0.93
Antihyperlipidemics	31	45.6	251	47.8	0.73	592	43.7	0.76	0.11
Weight loss agents	6	8.8	23	4.4	0.11	66	4.9	0.15	0.65
Opioids	32	47.1	198	37.7	0.14	548	40.5	0.28	0.27

p Values in bold indicate significance.
*p Value for comparison to BED+EDNOS group.
†p Value for comparison to BED-only group.
BED, binge eating disorder; BMI, body mass index; EDNOS, eating disorder not otherwise specified; NLP, natural language processing.

sex, race, BMI), comorbidities (identified in 1-year post-index period by ICD-9 code), and medication use (identified in 1-year post-index period by prescription fill records). Pair-wise t tests and χ^2 tests were used to compare characteristics between groups with a p value less than 0.05 considered significant.

RESULTS

Approximately 10.9 million patients (comprising >1.7 billion clinical notes) had a medical encounter in the VA during the study period. Over 193 000 clinical notes contained instances of the initial terms and phrases. Manual review of 1000 instances from the NLP output revealed the NLP tool was able to classify BED diagnoses correctly in clinical notes in 82.4% of instances in the first iteration, which improved to 91.8% in the final iteration. In addition, in the final iteration, the NLP system correctly identified patients as having BED in 90.7% of instances, as not having BED in 96.6% of instances, and as having a possible BED diagnosis, including differential diagnosis, in 91.3% of instances (table 1). Review of patient records found the NLP tool to be 96.2% sensitive in identifying and correctly classifying patients with BED, 99.5% sensitive for patient records containing any of the initial terms and phrases and 94.7% sensitive for patients with EDNOS diagnosis codes (table 1). The NLP tool found 1487 unique patients with a confirmed BED diagnosis. After applying study eligibility criteria, there were 525 BED-only, 1354 EDNOS-only, and 68 BED+EDNOS patients (figure 3).

Patient characteristics were similar between the groups (table 2). There were no significant differences between the BED+EDNOS group and the other groups with regard to demographics and only a few with regard to comorbidities and medication use. However, the BED-only and EDNOS-only groups were significantly different in terms of demographics as well as several comorbidities and medication classes.

DISCUSSION

This study demonstrated the ability to apply NLP to narrative clinical notes within the EHR of the VA to identify patients with a diagnosis of BED with greater than 90% classification accuracy and sensitivity. In addition, this study showed that BED is not commonly coded using the EDNOS ICD-9 code in the VA population. Given the differences in the characteristics between the BED-only and EDNOS-only populations and the lack of overlap between the populations, this study highlights the need for a specific identifier of BED in structured data, such as an ICD-9 code. The lack of a specific BED diagnosis code limits epidemiological study and hinders retrospective analyses of BED. The use of NLP may help to provide useful insights into the BED population, when suitable physician notes are available, and may be used to identify other conditions that do not have a specific ICD-9 code.

The study was conducted exclusively within the VA system and, therefore, represents veterans with BED and EDNOS, but may not necessarily represent the general population of patients with these diseases. Other institutions may possibly use different language to denote a BED diagnosis that was not considered in this study. However, VA physicians often work in healthcare centers outside of the VA system, thus institutional bias pertaining to diagnostic diction may be minimal. In addition, clinician diagnosis of BED was identified using only variations of a single concept: 'BED'. This limited lexicon and the set of terms and phrases that filtered the initial documents for processing could have potentially reduced the number of patients identified and may not have the same results in other institutions. However, the NLP tool benefitted from the frequent use of semistructured data and was able to identify and classify patients with BED with a high sensitivity using a limited lexicon. Despite these limitations, these methods have provided the only existing automated means by which to capture information on this population and enable a platform for future work.

CONCLUSION

As there is no ICD-9 diagnosis code for BED, before this study there was no applicable method of automating a specific search for patients diagnosed with BED. In this study patients with BED were identified in the VA system using NLP with greater than 90% accuracy and sensitivity. After inclusion criteria, only 68 patients identified by NLP also had a diagnosis of EDNOS. While there were few differences between the BED+EDNOS group and the other two groups, BED-only patients were younger, more obese, and more were men than the EDNOS-only patients. These differences, combined with the lack of overlap between BED and EDNOS, highlight the need for a specific identifier of BED in structured data. However, NLP provides a new method for better identifying patients diagnosed with BED from unstructured EHR data.

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REFERENCES

1 American Psychiatric Association. *Diagnostic and statistical maual of mental disorders*. 5th edn. Washington, DC: American Psychiatric Press, 2013.
2 Hudson JI, Hiripi E, Pope HG Jr, *et al*. The prevalence and correlates of eating disorders in the National Comorbidity Survey Replication. *Biol Psychiatry* 2007;61:348–58.
3 Kessler RC, Berglund PA, Chiu WT, *et al*. The prevalence and correlates of binge eating disorder in the World Health Organization World Mental Health Surveys. *Biol Psychiatry* 2013;73:904–14.
4 Smink FR, van Hoeken D, Hoek HW. Epidemiology of eating disorders: incidence, prevalence and mortality rates. *Curr Psychiatry Rep* 2012;14:406–14.
5 Safran C. Electronic medical records: a decade of experience. *JAMA* 2001;285:1766.
6 Tang P, Hammond W. A progress report on computer-based patient records in the United States. In: Dick RS, Detmer DE, eds. *The computer-based patient record: an essential technology for health care*. Washington, DC: National Academies Press, 1997:1–20.
7 Gunter TD, Terry NP. The emergence of national electronic health record architectures in the United States and Australia: models, costs, and questions. *J Med Internet Res* 2005;7:e3.
8 Hippisley-Cox J, Pringle M, Cater R, *et al*. The electronic patient record in primary care—regression or progression? A cross sectional study. *BMJ* 2003;326:1439–43.
9 Hogan WR, Wagner MM. Accuracy of data in computer-based patient records. *J Am Med Inform Assoc* 1997;4:342–55.
10 Pakhomov S, Weston SA, Jacobsen SJ, *et al*. Electronic medical records for clinical research: application to the identification of heart failure. *Am J Manag Care* 2007;13:281–8.
11 American Psychiatric Association. *Diagnostic and statistical manual of mental disorders*. 4th edn Text Revision. Washington, DC: American Psychiatric Press, 2000.

12 Fontenelle LF, Mendlowicz MV, Moreira RO, *et al*. An empirical comparison of atypical bulimia nervosa and binge eating disorder. *Braz J Med Biol Res* 2005;38:1663–7.
13 von Lojewski A, Boyd C, Abraham S, *et al*. Lifetime and recent DSM and ICD psychiatric comorbidity of inpatients engaging in different eating disorder behaviours. *Eat Weight Disord* 2012;17:e185–93.
14 Guisado JA, Vaz FJ, Lopez-Ibor JJ Jr, *et al*. Eating behavior in morbidly obese patients undergoing gastric surgery: differences between obese people with and without psychiatric disorders. *Obes Surg* 2001;11:576–80.
15 Ricca V, Mannucci E, Moretti S, *et al*. Screening for binge eating disorder in obese outpatients. *Compr Psychiatry* 2000;41:111–15.
16 Grilo CM, Masheb RM, Wilson GT. Different methods for assessing the features of eating disorders in patients with binge eating disorder: a replication. *Obes Res* 2001;9:418–22.
17 Grilo CM, Masheb RM, Wilson GT. A comparison of different methods for assessing the features of eating disorders in patients with binge eating disorder. *J Consult Clin Psychol* 2001;69:317–22.
18 Larranaga A, Docet MF, Garcia-Mayor RV. High prevalence of eating disorders not otherwise specified in northwestern Spain: population-based study. *Soc Psychiatry Psychiatr Epidemiol* 2012;47:1669–73.
19 Mitchison D, Hay P, Slewa-Younan S, *et al*. Time trends in population prevalence of eating disorder behaviors and their relationship to quality of life. *PLoS ONE* 2012;7:e48450.
20 Birgegard A, Norring C, Clinton D. DSM-IV versus DSM-5: implementation of proposed DSM-5 criteria in a large naturalistic database. *Int J Eat Disord* 2012;45:353–61.
21 Trace SE, Thornton LM, Root TL, *et al*. Effects of reducing the frequency and duration criteria for binge eating on lifetime prevalence of bulimia nervosa and binge eating disorder: implications for DSM-5. *Int J Eat Disord* 2012;45:531–6.
22 Meystre SM, Savova GK, Kipper-Schuler KC, *et al*. Extracting information from textual documents in the electronic health record: a review of recent research. *Yearb Med Inform* 2008;47(Suppl 1):128–44.
23 Hripcsak G, Friedman C, Alderson PO, *et al*. Unlocking clinical data from narrative reports: a study of natural language processing. *Ann Intern Med* 1995;122:681–8.
24 Jones M, DuVall SL, Spuhl J, *et al*. Identification of methicillin-resistant *Staphylococcus aureus* within the nation's Veterans Affairs medical centers using natural language processing. *BMC Med Inform Decis Mak* 2012;12:34.
25 Garvin JH, DuVall SL, South BR, *et al*. Automated extraction of ejection fraction for quality measurement using regular expressions in unstructured information management architecture (UIMA) for heart failure. *J Am Med Inform Assoc* 2012;19:859–66.
26 Dickerson JF, DeBar L, Perrin NA, *et al*. Health-service use in women with binge eating disorders. *Int J Eat Disord* 2011;44:524–30.
27 Simon J, Schmidt U, Pilling S. The health service use and cost of eating disorders. *Psychol Med* 2005;35:1543–51.
28 Harkema H, Dowling JN, Thornblade T, *et al*. ConText: an algorithm for determining negation, experiencer, and temporal status from clinical reports. *J Biomed Inform* 2009;42:839–51.