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Leveraging free-text diagnoses to identify patients with diabetes mellitus, obesity or dyslipidaemia – a cross-sectional study in a large Swiss primary care database

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Summary

BACKGROUND: Electronic medical records (EMRs) in general practice provide various methods for identifying patients with specific diagnoses. While several studies have focused on case identification via structured EMR components, diagnoses in general practice are frequently documented as unstructured free-text entries, making their use for research challenging. Furthermore, diagnoses may remain undocumented even when evidence of the underlying disease exists within structured EMR data.

OBJECTIVE: This study aimed to quantify the extent to which free-text diagnoses contribute to identifying additional cases of diabetes mellitus, obesity and dyslipidaemia (target diseases) and assess the cases missed when relying exclusively on free-text entries.

METHODS: This cross-sectional study utilised EMR data from all consultations up to 2019 for 6,000 patients across 10 general practices in Switzerland. Diagnoses documented in a free-text entry field for diagnoses were manually coded for target diseases. Cases were defined as patients with a corresponding coded free-text diagnosis or meeting predefined criteria in structured EMR components (medication data or clinical and laboratory parameters). For each target disease, prevalence was calculated along with the proportion of cases identified exclusively via free-text diagnoses and the proportion missed when using free-text diagnoses alone.

RESULTS: The prevalence estimates for diabetes mellitus, obesity and dyslipidaemia were 8.8%, 16.2% and 38.9%, respectively. Few cases relied exclusively on free-text diagnoses for identification, but a substantial proportion of cases were missed when relying solely on free-text diagnoses, particularly for obesity (19.5% exclusively identified; 50.7% missed) and dyslipidaemia (8.7% exclusively identified; 53.3% missed).

CONCLUSION: Free-text diagnoses were of limited utility for case identification of diabetes mellitus, obesity or dyslipidaemia, suggesting that manual coding of free-text diagnoses may not always be justified. Relying solely on free-text diagnoses for case identification is not recommended, as substantial proportions of cases may remain undetected, leading to biased prevalence estimates.

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Introduction

The prevalence of chronic diseases is increasing globally, making epidemiological research essential for surveillance and for designing targeted interventions [1]. In Switzerland, primary healthcare services are predominantly provided by general practitioners, who are highly accessible across most regions. Patient billing follows a nationally standardised fee-for-service tariff system, with costs beyond the deductible covered by compulsory general health insurance. Chronic disease management is typically conducted within this primary care setting [2, 3], making primary care data critical for chronic disease epidemiology [4, 5]. By 2019, approximately 70% of Swiss general practitioners were storing medical records electronically, a figure that increased to 82% by 2023 [6]. With their growing adoption in Swiss general practice [7, 8], electronic medical records (EMRs) from primary care databases have become an increasingly important resource for estimating the prevalence of chronic diseases. Utilising EMR data for epidemiological research is both time- and cost-efficient [7] as maintaining EMRs is already an integral part of the general practitioners' daily routine [9].

Data in EMRs are either structured (i.e., in a standardised format suitable for both electronic processing and human interpretation) or unstructured (typically human-generated

ABBREVIATIONS

ATC	Anatomical Therapeutic Chemical Classification System
BMI	Body Mass Index
EMR	Electronic Medical Record
FIRE	Family Medicine Research using Electronic Medical Records
HbA1c	Glycated haemoglobin
ICPC-2	International Classification of Primary Care, 2nd edition

free-text) [10]. Structured data in EMRs may include medication records or standardised measures of clinical and laboratory parameters. Notably, for this work, certain drugs and standardised measures within structured routine data can be sufficiently specific to identify certain chronic diseases with reasonable certainty [11]. Common chronic diseases identifiable through structured routine data include diabetes mellitus, which can be recognised by the use of antidiabetic drugs or glycated haemoglobin (HbA1c) values [12]; obesity, identified through anti-obesity medications or body mass index (BMI) [13]; and dyslipidaemia, detected via lipid-modifying agents or serum lipid levels [14, 15]. Unsurprisingly, standardised measures within structured data have frequently been employed to identify these diagnoses [16–21].

In addition to structured components, EMRs frequently contain substantial amounts of free-text data, including clinical notes entered by physicians to document reasons for encounters, diagnostic considerations, confirmed diagnoses, and other relevant information. Many practice software systems provide dedicated fields for recording diagnoses and problems in free-text form (free-text diagnoses) as part of patients' EMRs [10]. Analysing such free-text data may uncover additional cases of chronic diseases that are not identifiable from structured EMR data alone [22, 23]. Moreover, with recent advancements in artificial intelligence and natural language processing, free-text data are increasingly recognised as valuable sources for identifying specific diseases within EMRs [24]. However, to evaluate the additional utility of these approaches, it is essential to determine the proportion of cases identified through free-text diagnoses that would otherwise remain undetected using only structured data. Conversely, free-text diagnoses may present significant limitations in chronic disease identification compared to structured data. For instance, the documentation of diagnoses in free-text form may be incomplete, inconsistent, or influenced by disease severity [25], potentially introducing bias into case identification efforts.

The objectives of this study were threefold. First, it aimed to evaluate the extent to which analysing free-text diagnoses from dedicated entry fields for diagnoses and problems enhances case identification for three target diseases – diabetes mellitus, obesity and dyslipidaemia – beyond what is achievable using structured data alone (i.e., specific drugs, HbA1c values, BMI and serum lipid levels). Second, the study sought to determine whether analysing free-text diagnoses alone provides prevalence estimates comparable to those derived from combining structured and free-text data. Finally, the third objective was to investigate whether case identification through free-text diagnoses is associated with disease severity.

Methods

Study design and data source

This cross-sectional study utilised anonymised patient data from the "Family Medicine Research using Electronic Medical Records" (FIRE) database, hosted by the Institute of Primary Care at the University Hospital Zurich. Since its establishment in 2009, the FIRE database has collected anonymised data from the EMRs of over 700 Swiss general practitioners [26].

Initially, the FIRE database had only integrated data from structured EMR components, such as administrative details, medication records, clinical and laboratory parameters and International Classification of Primary Care, 2nd edition (ICPC-2) coded reasons for encounters [27]. Recently, however, an increasing number of practices have begun contributing unstructured free-text from their patients' EMRs to the FIRE database.

For this study, we included all ten practices that had contributed their EMR data, including unstructured free-text entries for diagnoses and problems, to the FIRE database for the full year of 2019 at the study's commencement. From each practice, 600 patients of any age with at least one consultation in 2019 were randomly selected.

Database query and data preparation

Demographic data, including birth year and sex, were retrieved for all selected general practitioners and patients.

Diagnoses that could be derived from the unstructured free-text diagnoses corresponding to blocks/categories E10-14, E65-68 or E78 of the 10th Revision of the International Statistical Classification of Diseases and Related Health Problems (ICD-10) were manually identified and coded (i.e., labelled as diabetes mellitus, obesity or dyslipidaemia, respectively). The coding process followed a multi-stage procedure involving independent coders, third-party arbitration for resolving disagreements, and monitoring interrater reliability, resulting in a dataset of coded free-text diagnoses (see appendix for details). No additional information from unstructured EMR data was used.

From the structured EMR components, we extracted medication data (MED) and clinical and laboratory parameters (CLPs). MED were queried using Anatomical Therapeutic Chemical (ATC) classification codes to identify drugs for diabetes, peripherally acting anti-obesity products and lipid-modifying agents [28]. CLP data included BMI, HbA1c values and serum lipid levels (high-density lipoprotein, low-density lipoprotein, total cholesterol and triglycerides).

Coded free-text diagnoses, MED, and CLPs were considered up to the date of the patients' last consultations in 2019.

Criteria for case identification using structured EMR components

We used the following criteria for case identification based on the structured EMR components documenting medication data or clinical and laboratory parameters.

Diabetes mellitus

At least one drug used to treat diabetes mellitus (excluding GLP-1 analogues, which are not specific for diabetes mellitus due to their use for obesity treatment), or at least two consecutive HbA1c values at or above the cut point stipulated by the American Diabetes Association [12]:

$\geq$1 drug with {ATC $\in$ A10 and ATC $\notin$ A10BJ} (MED criterion) or

$\geq$2 consecutive HbA1c $\geq$6.5 mmol/l (CLPs criterion)

Obesity

At least one prescription of a peripherally acting anti-obesity drug, or a recent BMI that falls within the World Health Organization's "obese" BMI category [13]:

≥1 drug with ATC ∈ A08AB (MED criterion) or

last measurement of BMI >30 kg/m^2 (CLPs criterion)

Dyslipidaemia

At least one prescription of a lipid-modifying agent, or serum lipid levels repeatedly exceeding the thresholds specified in the European Society of Cardiology (ESC) guidelines on cardiovascular disease prevention in clinical practice [15] or the consensus statement from the European Atherosclerosis Society and the European Federation of Clinical Chemistry and Laboratory Medicine [14]:

≥1 drug with ATC ∈ C10 (MED criterion) or

{≥2 triglyceride >1.7 mmol/l

or ≥2 cholesterol$_{Total}$ >4.9 mmol/l

or ≥2 cholesterol$_{LDL}$ >3.0 mmol/l

or (sex = female and ≥2 cholesterol$_{HDL}$ ≤1.2 mmol/l)

or (sex = male and ≥2 cholesterol$_{HDL}$ ≤1.0 mmol/l)} (CLPs criterion)

Quantities of interest and statistical analysis

To describe the study population, counts and proportions (*n* and %) were reported alongside medians and interquartile ranges (IQR).

In this study, a *case* of a target disease was defined as a patient with the relevant coded free-text diagnosis *or* meeting the MED or CLPs criteria for the diagnosis. Period prevalence estimates for the year 2019 were calculated by dividing the number of cases for each target disease by the total study population size (n_{cases} = 6,000).

The key quantities of interest included, for each target disease, the proportion of cases identified exclusively through coded free-text diagnoses (denoted as *e*, the "exclusive" proportion) and the proportion of cases missed by coded free-text diagnoses (denoted as *m*, the "missed" proportion). These proportions were calculated relative to all cases identifiable via coded free-text diagnoses or the structured EMR components (medication data and clinical and laboratory parameters), representing the estimated prevalence of the disease. Analogous metrics were also determined for both structured EMR components (MED and CLPs).

To assess whether the probability of a diagnosis being recorded in free-text depended on disease severity, we determined the proportions of cases with coded free-text diagnoses across different BMI, HbA1c and LDL classes and compared them using Fisher's exact test.

All analyses were performed using R software (version 4.2.0) [29]. Figure 1 was created using the R package *eulerr* [30].

Ethics

This study, part of the fully anonymised FIRE project, was exempt from ethics approval under the Human Research Act, confirmed by the Ethics Committee of the Canton of Zurich (BASEC No. Req-2017-00797). Accordingly, no ethics application or formal protocol was prepared.

Results

Sample characteristics and disease prevalence estimates

The ten selected practices were staffed by a median of 3 general practitioners (IQR 2–3). Of the 27 general practitioners, 15 (55.6%) were female, with a median age of 51 years (IQR 45–54). The median number of patients registered per practice was 7,381 (IQR 5,336–11,530). Table 1 presents the demographic characteristics of the randomly selected patients (n_{cases} = 6,000).

Using coded free-text diagnoses or structured EMR components (MED or CLPs), 527 cases of diabetes mellitus (prevalence 8.8%), 971 cases of obesity (prevalence 16.2%), and 2,334 cases of dyslipidaemia (prevalence 38.9%) were identified. Among the 2,725 patients identified with at least one target disease, 1,816 (66.6%) were identified with only one disease, 711 (26.1%) with two diseases, and 198 (7.3%) with all three target diseases.

Exclusive and missed identification by coded free-text diagnoses

Figure 1 illustrates the overlap in case identification among the three EMR components. Greater overlap between the ovals indicates that the components identify the same cases, while smaller overlaps suggest that a substantial proportion of cases are identified exclusively by specific EMR components and would be missed by others. For coded free-text diagnoses, this overlap is quantified using the previously defined proportions *e* ("exclusive" proportion) and *m* ("missed" proportion) as follows:

For diabetes mellitus, coded free-text diagnoses identified 469 cases (89.0% of all cases of this disease), MED identified 400 cases (75.9%), and CLPs identified 336 cases

Table 1:
Patient characteristics (available for all patients with no missing values) by target disease.

		Total	Diabetes mellitus	Obesity	Dyslipidaemia
n_{cases}		6,000	527	971	2,334
Female sex, *n* (%)		3,314 (55.2%)	241 (45.7%)	520 (53.6%)	1,235 (52.9%)
Age, median (IQR)		55 (37–70)	71 (60–79)	62 (50–73)	68 (57–77)
Age groups, *n* (%)	0–40 years	1,786 (29.8%)	20 (3.8%)	141 (14.5%)	83 (3.6%)
	41–64 years	2,179 (36.3%)	159 (30.2%)	391 (40.3%)	903 (38.7%)
	65–80 years	1,394 (23.2%)	239 (45.4%)	330 (34.0%)	959 (41.1%)
	>80 years	641 (10.7%)	109 (20.7%)	109 (11.2%)	389 (16.7%)

IQR, interquartile range

(63.8%). The proportion of cases identified exclusively by coded free-text diagnoses was *e* = 14.0%, while the proportion of cases missed by coded free-text diagnoses was *m* = 11.0%.

For obesity, coded free-text diagnoses identified 479 cases (49.3% of all cases of this disease), MED identified 18 cases (1.9%), and CLPs identified 776 cases (79.9%). The proportion of cases identified exclusively by coded free-text diagnoses was *e* = 19.5%, and the proportion of cases missed by coded free-text diagnoses was *m* = 50.7%.

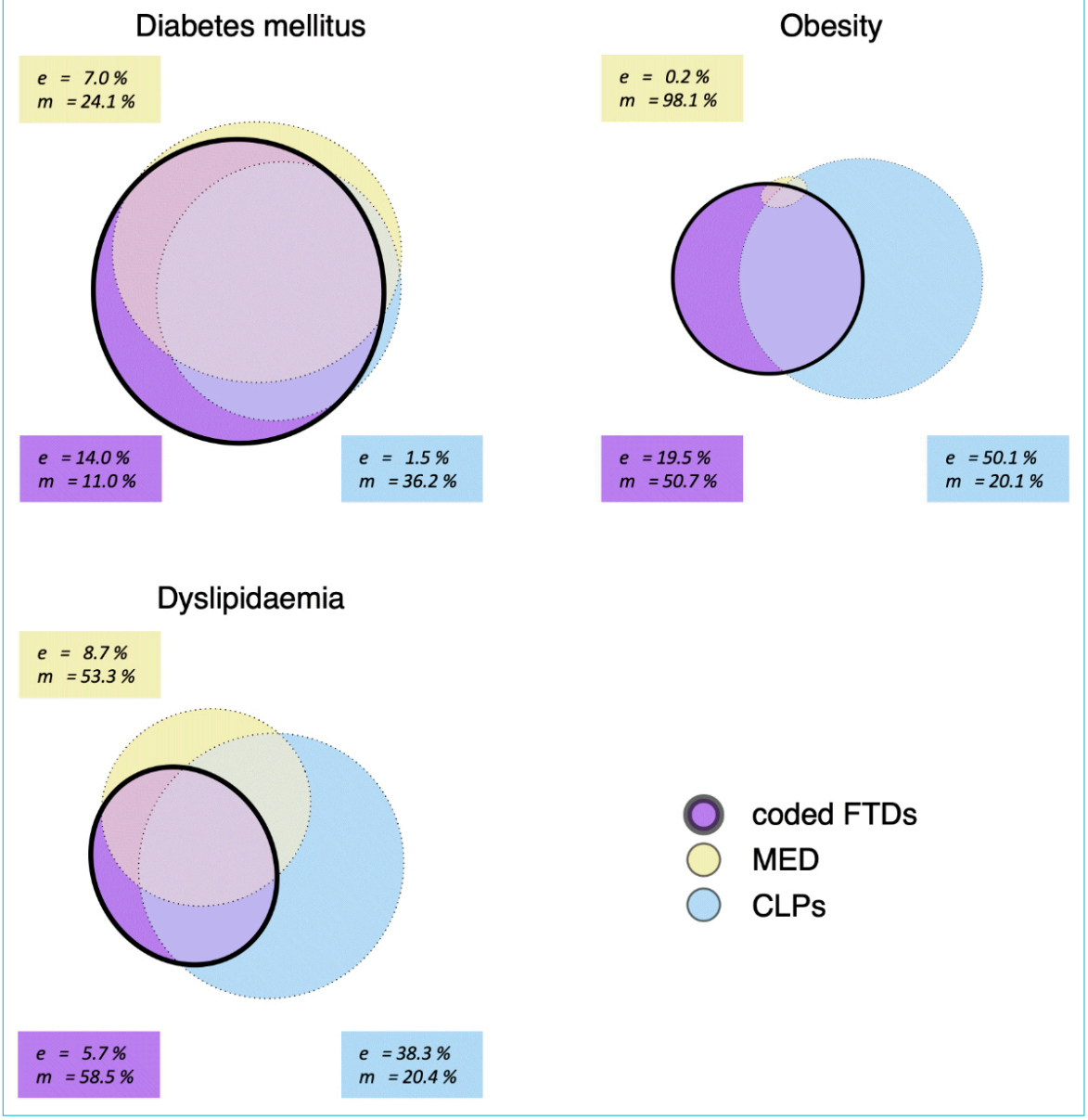
For dyslipidaemia, coded free-text diagnoses identified 968 cases (41.5% of all cases of this disease), MED identified 1,090 cases (46.7%), and CLPs identified 1,858 cases (79.6%). The proportion of cases identified exclusively by coded free-text diagnoses was *e* = 5.7%, and the proportion of cases missed by coded free-text diagnoses was *m* = 58.5 %.

Metrics analogous to *e* and *m* were calculated for the structured EMR components MED and CLPs and are presented in figure 1.

Case identification via coded free-text diagnoses by disease severity

Table 2 demonstrates that the frequency of coded free-text diagnoses for diabetes mellitus remained consistent across all HbA1c classes, with no significant variation ($p = 0.72$). In contrast, coded free-text diagnoses for obesity and dyslipidaemia were increasingly frequent in higher BMI and LDL classes, indicating an association with greater disease severity ($p < 0.001$ for both BMI and LDL).

Figure 1: Exclusive and missed cases identified by individual EMR components for each target disease, displayed as approximately area-proportional Euler diagrams. The areas represent the number of cases identified by each EMR component. Abbreviations: coded FTDs, coded free-text diagnoses; MED, medication data; CLPs, clinical and laboratory parameters; *e*, proportion of total disease prevalence identified exclusively by the respective EMR component; *m*, proportion of total disease prevalence missed by the respective EMR component.



Discussion

In general practice, diagnoses are often documented as free-text entries in designated fields of practice software and stored as unstructured data within patients' EMRs [24, 31]. However, diagnoses may be absent from these unstructured EMR data, despite being evident from information in structured EMR components [32]. This EMR-based study investigated the potential of diagnostic coding of free-text from entry fields intended for diagnoses and problems for identifying cases and estimating the prevalence of three common chronic diseases – diabetes mellitus, obesity and dyslipidaemia – compared with identification based solely on medication data and clinical and laboratory parameters. We found limited additional benefit in using free-text diagnoses for prevalence estimation of the three target diseases, and many cases were overlooked when structured EMR components were ignored.

For diabetes mellitus, incorporating free-text diagnoses for case identification increased the prevalence estimate from 7.6% to 8.8%, a value approaching the confidence interval for diabetes mellitus prevalence in Swiss general practice (9.0–11.9%) as reported in a recent study by Excoffier et al. [4]. Excoffier's study, which used prospective epidemiological monitoring in Swiss general practices, provides a valuable comparator. The 1.2% increase in prevalence shows that one in seven cases of diabetes mellitus was identified exclusively via free-text diagnoses and would have been missed using structured EMR components alone. This contribution may be relevant depending on the specific objectives of a study or project. However, most cases could still be identified using medication data and clinical and laboratory parameters alone. Conversely, the risk of overlooking cases when relying exclusively on free-text diagnoses was similarly low: only one in nine cases would have been missed if only free-text diagnoses were considered for case identification.

For obesity, the inclusion of all EMR components yielded a prevalence estimate of 16.2%, which aligns with Excoffier's confidence interval (13.3–17.9%). Compared to diabetes mellitus, free-text diagnoses had a greater role in identifying cases of obesity, with one in five cases identified exclusively via coded free-text diagnoses. However, in contrast to diabetes mellitus, the implications of excluding structured EMR components in the identification of obesity were substantial: more than half of all cases would have been missed depending exclusively on free-text diagnoses.

For dyslipidaemia, the prevalence estimate was 38.9% when all EMR components were considered. While comparable references from Swiss general practice are lacking, a Canadian study that inferred dyslipidaemia prevalence from lipid laboratory test results in general practice reported a prevalence of 35.8%, which closely aligns with our findings [16]. We found that the additional contribution of free-text diagnoses to dyslipidaemia case identification was minimal, with only one in 18 cases identified exclusively through coded free-text diagnoses. Conversely, as with obesity, relying on free-text diagnoses alone would have resulted in a substantial proportion of missed cases: slightly more than half of all dyslipidaemia cases would have been overlooked without the inclusion of structured EMR components.

The proportions of cases exclusively identified or missed by free-text diagnoses varied considerably across the target diseases. Free-text diagnoses appeared to be more important for the identification of obesity compared to diabetes mellitus and dyslipidaemia and were a more effective sole detector for diabetes mellitus than for obesity or dyslipidaemia.

This likely reflects differences in how general practitioners document these conditions. Diabetes mellitus is more likely to be thoroughly documented due to its pressing therapeutic implications and the frequent follow-up visits recommended by current guidelines [33, 34]. As a result, patients with diabetes mellitus likely generate more free-text diagnoses, increasing the likelihood of case identification through this component. In contrast, general practitioners may perceive obesity and dyslipidaemia more as risk factors than as diseases requiring consistent documentation, leading to fewer free-text diagnoses. Moreover, disease severity or stage might influence whether a condition is documented. The higher frequency of free-text diagnoses for obesity and hyperlipidaemia observed at elevated BMI and LDL levels suggests a degree of perceptual salience for these conditions. For obesity, this aligns with earlier findings that patients with more severe obesity are more likely to be identified as cases compared to those with less severe forms [25]. Additionally, the substantial proportion of nearly 20% of obese patients identified exclusively via free-text diagnoses can likely be attributed to the limited informative value of the medication data component for obesity, due to the low number and infrequent use of specific anti-obesity medications in clinical practice.

Strengths and limitations

While extensive research has explored case identification using structured EMR data, few studies have considered free-text diagnoses from dedicated entry fields [35]. There are also several studies that have investigated whether extracting information from unstructured EMR data can improve diagnosis recognition, although most focus on hospital settings, where the case mix differs significantly [32]. To our knowledge, this study is the first to examine and quantify the contribution of unstructured free-text data to case identification of chronic diseases in general practice.

Our findings offer insights into the potential for case identification using artificial intelligence and enable an in-

Table 2:
Proportions of cases with coded free-text diagnoses across different BMI, HbA1c and LDL classes.

Diabetes mellitus		Obesity		Dyslipidaemia	
HbA1c (%)	**Coded FTDs** $n_{FTDs}/size_{class}$ (%)	**BMI (kg/m^2)**	**Coded FTDs** $n_{FTDs}/size_{class}$ (%)	**LDL (mmol/l)**	**Coded FTDs** $n_{FTDs}/size_{class}$ (%)
[6.5, 7.0)	110/115 (95.7%)	(30, 35]	139/529 (26.3%)	(3, 4]	245/695 (35.3%)
[7.0, 7.5)	63/67 (94.0%)	(35, 40]	84/170 (49.4%)	(4, 5]	134/303 (44.2%)
≥7.5	93/100 (93.0%)	>40	63/77 (81.8%)	>5	47/75 (62.7%)

Coded FTDs, coded free-text diagnoses; HbA1c, glycated haemoglobin; BMI, body mass index; LDL, low-density lipoprotein; [*a*, *b*), values ≥*a* and <*b*; (*a*, *b*], values >*a* and ≤*b*.

formed evaluation of the expected cost-benefit ratio, both for research purposes and for clinical practitioners who depend on problem lists to review patients' diagnoses and health issues. These lists are often subjective and therefore unreliable when shared among practitioners [36], and incorporating diagnoses inferred from all available EMR components into the problem list could enhance its completeness, currency, reliability, and structure. This approach would preserve the narrative and clinical reasoning embedded in free-text, which is essential for effective communication, while simultaneously providing the structured data required for billing and quality monitoring [37]. More comprehensive, reliable and well-structured problem lists have the potential to improve the accuracy and efficiency of clinical decision-making while streamlining administrative processes [38, 39].

The limitations of this study stem from its use of routine general practice data rather than data collected through epidemiological studies with standardised patient sampling and diagnostic criteria. Moreover, we observed missing diagnoses in the free-text entries as well as missing information required to infer diagnoses from medication data and from clinical and laboratory parameters data. Our results are therefore likely biased by the included patients' propensity to seek medical care, heterogeneous diagnostic practices, and incomplete documentation in general practice. While computerised approaches to improving the maintenance of free-text problem lists – such as automatic prompts for associated indication or diagnosis when prescribing medication – are expected to improve the accuracy of problem lists [40-42], current evidence suggests that our study likely underestimates true prevalence rates.

Although medication data have demonstrated value in chronic disease identification in previous studies [43, 44], relatively few cases of the target diseases were identified through medication data in this study. This may be attributed to the focus on lifestyle modifications as a primary therapeutic approach at the onset of these diseases [13, 15, 33]. Furthermore, the results of this study, which examined the role of free-text diagnoses in identifying diabetes mellitus, obesity and dyslipidaemia, may not be generalised to the identification of other conditions. As shown in a previous study, the traces left by specific diseases in EMR data vary depending on physicians' documentation practices, prescribing habits and the extent to which these diseases can be measured using anthropometric or biochemical tests [21]. The diseases targeted in this study had significant potential to be identified through from clinical and laboratory parameters data. In contrast, other prevalent conditions, such as chronic back pain or chronic fatigue, lack specific clinical or laboratory parameters measurements or associated medications and may therefore rely more heavily on free-text diagnoses for identification.

Conclusion

This study demonstrated that free-text diagnoses provided limited utility for identifying cases of diabetes mellitus, obesity or dyslipidaemia, suggesting that manual coding of free-text diagnoses may not always justify the effort. Furthermore, using free-text diagnoses as the sole method of case identification for these diseases should be discouraged, as large portions of cases may remain undetected, which could substantially bias prevalence estimates.

Availability of data and materials

Data and materials are available from the corresponding author upon reasonable request.

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Authors' contributions: DB, SM and JB conceived and designed the study; DB and TG analysed the data; DB, TG and SM drafted the manuscript, and all authors participated in revision; KW supervised diagnostic coding; OS and TR contributed resources and project administration. All authors approved the final manuscript for publication.

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Potential competing interests

All authors have completed and submitted the International Committee of Medical Journal Editors form for disclosure of potential conflicts of interest. No potential conflict of interest related to the content of this manuscript was disclosed.

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Appendix: Approach to diagnostic free-text coding

The following procedure was used to identify and code target diagnoses in the unstructured free-text from the diagnosis and problem entry fields.

As its input unit, the procedure processed the entire contents of the entry field from an individual documentation occasion for an individual patient, i.e. one FTD ("free-text diagnosis"). To each such unit, the procedure assigned appropriate disease labels if the free-text allowed for the conclusion that the patient had chronic conditions classifiable under the International Statistical Classification of Diseases and Related Health Problems 10th revision (ICD-10) blocks/categories "E10-E14" (diabetes mellitus), "E65-E68" (obesity) or "E78" (dyslipidaemia). The outputs of the procedure, i.e., the disease labels reflecting the specified ICD-10 blocks/categories, are referred to as "*coded* FTDs" in the following and in the article's main text.

A pilot phase involved four coders (medical doctor candidates DB, AW, AK and GB) without specific training in coding. Two coders (DB and AW) first piloted coding of FTDs independently on a random sample of 381 patients and jointly developed a coding instruction to be used by the other coders (AK and GB) who then, again independently, verified coding according to this instruction on the FTDs of 143 patients already coded by DB and AW. Cohen's Kappa was calculated for each pair of coders to assess interrater-reliability of coding with excellent results (Kappa range for diabetes 0.92 to 1, and perfect concordance with Kappa = 1 for both obesity and dyslipidaemia).

Following the pilot phase, DB and AW independently coded all FTDs of another 2,619 patients, and interrater-reliability was assessed again showing almost perfect agreement (Kappa for diabetes 0.91, obesity 0.96, dyslipidaemia 0.99). Discrepancies were resolved by arbitration by a third party (KW, a trained medical doctor with three years working experience). In view of the very high interrater-reliability evident after a total of 3,000 free-texts that were double-coded by DB and AW, we considered it justifiable to continue coding by a single coder without introducing a significant risk of bias. Consecutively, AK coded the FTDs of another 3,000 patients without subsequent independent verification, resulting in a final dataset containing coded FTDs from 6,000 patients.