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# Clinical code usage in UK general practice: a cohort study exploring 18 conditions over 14 years



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| Complete List of Authors: | Zghebi, Salwa; The University of Manchester, NIHR School for Primary Care Research, Centre for Primary Care and Health Services Research, Manchester Academic Health Science Centre (MAHSC); The University of Manchester, Division of Population Health, Health Services Research and Primary Care, School of Health Sciences, Faculty of Biology, Medicine and Health, Manchester Academic Health Science Centre (MAHSC)<br>Reeves, David; The University of Manchester, NIHR School for Primary Care Research, Centre for Primary Care and Health Services Research, Manchester Academic Health Science Centre (MAHSC); The University of Manchester, Centre for Biostatistics, School of Health Sciences, Faculty of Biology, Medicine and Health, Manchester Academic Health Science Centre (MAHSC)<br>Grigoroglou, Christos; The University of Manchester, Manchester Centre for Health Economics, Division of Population Health, Health Services Research and Primary Care, Manchester Academic Health Science Centre (MAHSC)<br>McMillan, Brian; The University of Manchester, NIHR School for Primary Care Research, Centre for Primary Care and Health Services Research, Manchester Academic Health Science Centre (MAHSC); The University of Manchester, Division of Population Health, Health Services Research and Primary Care, School of Health Sciences, Faculty of Biology, Medicine and Health, Manchester Academic Health Science Centre (MAHSC)<br>Ashcroft, Darren; The University of Manchester, NIHR School for Primary Care Research, Centre for Primary Care and Health Services Research, Manchester Academic Health Science Centre (MAHSC); The University of Manchester, Centre for Pharmacoepidemiology and Drug Safety, School of Health Sciences, Faculty of Biology, Medicine and Health, Manchester Academic Health Science Centre (MAHSC)<br>Parisi, Rosa; The University of Manchester, NIHR School for Primary Care Research, Centre for Primary Care and Health Services Research, Manchester Academic Health Science Centre (MAHSC); The University of Manchester, Division of Informatics, Imaging, and Data Sciences, School of Health Sciences, Faculty of Biology, Medicine and Health, Manchester Academic Health Science Centre (MAHSC)<br>Kontopantelis, Evangelos; The University of Manchester, NIHR School for Primary Care Research, Centre for Primary Care and Health Services Research, Manchester Academic Health Science Centre (MAHSC); The University of Manchester, Division of Informatics, Imaging, and Data Sciences, School of Health Sciences, Faculty of Biology, Medicine and Health, Manchester Academic Health Science Centre (MAHSC) |

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# Clinical code usage in UK general practice: a cohort study exploring 18 conditions over 14 years

Salwa S Zghebi,[1,2*] David Reeves,[1,2,3] Christos Grigoroglou,[4] Brian McMillan,[1,2] Darren M Ashcroft,[1,5] Rosa Parisi,[1,6] Evangelos Kontopantelis[1,2,6]

**1** NIHR School for Primary Care Research, Centre for Primary Care and Health Services Research, Manchester Academic Health Science Centre (MAHSC), The University of Manchester, Manchester, UK.

**2** Division of Population Health, Health Services Research and Primary Care, School of Health Sciences, Faculty of Biology, Medicine and Health, Manchester Academic Health Science Centre (MAHSC), The University of Manchester, Manchester, UK.

**3** Centre for Biostatistics, School of Health Sciences, Faculty of Biology, Medicine and Health, Manchester Academic Health Science Centre (MAHSC), The University of Manchester, Manchester, UK.

**4** Manchester Centre for Health Economics, Division of Population Health, Health Services Research and Primary Care, Manchester Academic Health Science Centre (MAHSC), The University of Manchester, Manchester, UK.

**5** Centre for Pharmacoepidemiology and Drug Safety , School of Health Sciences, Faculty of Biology, Medicine and Health, Manchester Academic Health Science Centre (MAHSC), The University of Manchester, Manchester, UK.

**6** Division of Informatics, Imaging, and Data Sciences, School of Health Sciences, Faculty of Biology, Medicine and Health, Manchester Academic Health Science Centre (MAHSC), The University of Manchester, Manchester, UK.

*Correspondence to:
Dr Salwa Zghebi, NIHR School for Primary Care Research, Centre for Primary Care and Health Services Research, Williamson Building, University of Manchester, Manchester M13 9PL, UK. E-mail: salwa.zghebi@manchester.ac.uk

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## Abstract

### Objectives
To assess the diagnostic Read code usage for 18 conditions by examining their frequency and diversity in UK primary care between 2000 and 2013.

### Design
Population-based cohort study

### Setting
684 UK general practices contributing data to the Clinical Practice Research Datalink (CPRD) GOLD.

### Participants
Patients with clinical codes for at least one of: asthma, chronic obstructive pulmonary disease (COPD), diabetes, hypertension, coronary heart disease, atrial fibrillation, heart failure, stroke, hypothyroidism, chronic kidney disease, learning disability (LD), depression, dementia, epilepsy, severe mental illness (SMI), osteoarthritis, osteoporosis, and cancer.

### Primary and secondary outcome measures
For the frequency ranking of clinical codes, canonical correlation analysis was applied to 1-, 3-, and 5-year correlations of clinical code usage. Three measures of diversity (Shannon entropy index of diversity, richness, and evenness) were used to quantify changes in incident and total clinical codes.

### Results
Overall, all examined conditions except LD, showed positive monotonic correlation. Hypertension, hypothyroidism, osteoarthritis, and SMI codes' usage had high 5-year correlation. The codes' usage diversity remained stable overall throughout the study period. Cancer, diabetes, and SMI had the highest richness (code lists need time to define) unlike atrial fibrillation, hypothyroidism, and LD. SMI and hypothyroidism (high vs. low richness, respectively) can last for 5 years, whereas, cancer/diabetes and LD (high vs. low richness) only last for 2 years.

### Conclusions
This is an underreported research area and the findings suggest the codes' usage diversity for most conditions remained overall stable throughout the study period. Generated mental health code lists can last for a long time unlike cardiometabolic conditions and cancer. Adopting more consistent and less diverse coding would help improve data quality in primary care. Future research is needed following the transfer to the Systematized Nomenclature of Medicine Clinical Terms (SNOMED CT) coding.



## Keywords

Primary care, clinical codes, electronic health records, QOF, Quality and Outcomes Framework.

## Strengths and limitations of this study

- Our study presents a contemporary longitudinal analysis of clinical code usage in UK primary care, addressing an underreported research area.
- Our findings are relevant to clinical practice as we examined 18 physical and mental conditions as recorded in primary care over 14 years, using data from a large nationally representative database.
- Given the design of the recorded electronic health records, we may have missed some patients with these 18 conditions (such as patients not registered with general practices) which may have affected the observed patterns of clinical code usage.
- Our analysis used CPRD GOLD data, which are obtained from clinical practices with the VISION clinical system, and EMIS and SystmOne practices will be using somewhat different diagnostic codes.

## Introduction

The use of electronic health records (EHRs) has increased rapidly over the last three decades.[1] This has enabled researchers from various disciplines to examine cross-sectional and longitudinal trends of large population medical records to address many clinical research questions. EHRs are increasingly used for clinical management, clinical audits and research with real-world data, applying cross-sectional to longitudinal study designs to address descriptive epidemiology, pharmacoepidemiology, interventions evaluation, and risk prediction modelling.[2,3] The available routinely collected data are far from perfect, but they provide a wealth of high-quality information on patients' clinical conditions, referrals, and medication usage,[4] informing important components of clinical practice such as clinical decision-making.

Since the beginning of medical computing systems usage from early 1970s,[5,6] the UK's primary care systems became fully computerised by 2003.[7,8] This transition was facilitated by Read codes, a comprehensive computerised semi-hierarchical clinical classification system designed for use in EHRs, which are still in use in the UK.[9] These were originally developed by a clinician, Dr James Read, in the early 1980's and became the main coding system for clinical data in the UK from the mid-1990s, succeeding the Oxford Medical Information System (OXMIS) codes that were the most widely used system throughout the 1980s.[10-12] However, the Systematized Nomenclature of Medicine Clinical Terms (SNOMED CT), a systematically organised collection of medical terms, is being rolled out in general practices in a phased approach from April 2018 to replace Read codes, and it includes symptoms, diagnoses, procedures, family history, allergies, and devices.[13,14] With evident increasing complexity of most healthcare disciplines,[15] such clinical terminologies make collated patient records more manageable in clinical practice settings.[16,17] To support users, national standards and guidelines are available on the use of clinical coding.[14,18] Several UK primary care electronic databases exist and are managed by different and varying computer software systems (EMIS, Vision and SystmOne), with Read codes still being the most common system through which to capture primary care clinical information. In the UK, the largest primary care databases available for research purposes include the Clinical Practice Research Datalink (CPRD), The Health Improvement Network (THIN), ResearchOne, and QResearch.[2,8]

In April 2004, the UK National Health Service (NHS) introduced the Quality and Outcomes Framework (QOF), a voluntary reward and incentive programme to reward UK general practices providing high-quality care based on a range of evidence-based clinical indicators, for example, management of common chronic conditions such as diabetes and asthma.[19,20,21]

Despite the fact that clinical coding is a key point in the daily functionality of routine clinical practice, studies investigating their usage in real-world electronic databases are limited, although the observed variation in coding practice between clinicians.[22] The use of codes is a fundamental aspect of analyses of EHRs, involving a considerable amount of work, through which researchers extract a final dataset to analyse. Clinical codes are commonly used and disseminated in the form of code lists which are compiled according to the purpose, such as diagnostic codes, or family history codes (Table S1). Accurate (high specificity and sensitivity) code lists are imperative in obtaining reliable data on exposures, covariates, and outcomes. Previous systematic reviews have reported overall high accuracy of discharge coding (completed by clinical and/or administrative staff) in UK EHRs data that is improving over time, where in one review accuracy was defined as the agreement between the codes allocated after independently assessing clinical notes (acting as a 'gold' standard) and those recorded on EHRs.[23,24] However, clinical practice changes over time, at varying degrees for different conditions, which is reflected in coding practice with new codes being introduced and others made redundant.

Thus, examining and quantifying the changes in clinical code usage over time is important, since alterations in usage that have not been considered, can have important implications for the analysis of EHRs, resource allocation and may inform public health policy. An example for EHR analysis implication, the use of a two-year old code-list for a given medical condition may or may not be a problem, depending on how much clinical practice has changed over time for that condition. This change in clinical practice may be driven by policy changes, such as better reimbursement for keeping a register of certain conditions. A study examining the variation in clinical code use in UK primary care using six clinical terms, found that searches for the same clinical term across four different computer systems resulted in different results e.g. the mean number of codes/list ranging between 12.7-35.2 codes.[25] This highlighted the need for a more consistent system of code usage, with a recommendation to replace primary care code lists with shorter lists and fewer number of coding choices.[25] In this study, we used data from

the UK CPRD GOLD database to examine the: 1) frequency ranking of diagnostic clinical codes for 18 physical and mental health conditions; 2) changes in the usage of individual clinical codes (incident vs. total codes) for these conditions between 2000-2013 covering the period before and after the launch of the QOF.

## Methods

### Data source and study design

We used data from the GOLD database of the UK Clinical Practice Research Datalink (CPRD), which comprises of data from contributing anonymised general practices using the VISION clinical computer system.[26] The CPRD is one of the world's largest longitudinal electronic medical databases providing anonymised data from primary care, and is broadly representative of the UK population.[8,27] The CPRD is structured to provide data on clinical information, referrals, consultations, immunisation, tests and prescribed therapies. Up to July 2013, the CPRD held data for 11.3 million patients registered in 674 general practices. Of these, 4.4 million were active patients (representing 6.9% of the total UK population), and 6.9 million records represent inactive patients (people who have died or are no longer registered with a participating general practice).[27]

Using financial year intervals between 01/04/2000-31/03/2013, we examined the changes in the use of diagnostic clinical codes for 18 exemplar medical conditions in UK practices: asthma, chronic obstructive pulmonary disease (COPD), diabetes (DM) both types, hypertension (HT), coronary heart disease (CHD), atrial fibrillation (AF), heart failure (HF), stroke, hypothyroidism, chronic kidney disease (CKD), learning disability (LD), depression, dementia, epilepsy, severe mental illness (SMI), osteoarthritis, osteoporosis, and cancer. The diabetes codes included those with complications if clearly linked to diabetes, such as 'type 2 diabetes mellitus with nephropathy' (Table S1). The selected conditions, apart from osteoarthritis, were included in the QOF scheme from 2004, whereas AF, CKD, dementia, depression, and LD were incentivised from 2006, and osteoporosis incentivised from 2012. This allowed us to examine and compare QOF conditions (incentivised at different stages) plus a condition not part of the QOF (osteoarthritis).

The clinical codes used to define the examined conditions are listed in the Clinical Codes online repository.[28] Each condition was examined as an incident code (using codes to identify new cases) and total codes (incident and prevalent cases) for each year during the study period.

## Data analysis

To examine the consistency of clinical code use across time, we applied canonical correlation analysis (CAA) to estimate 1-year (e.g. 2006 to 2007), 3-year (e.g. 2006 to 2009), and 5-yearly canonical correlations (e.g. 2006 to 2011) for clinical code usage. CCA is a descriptive multivariable method that provides a measure of the canonical correlation (CC) between two groups of variables. CCA finds the best linear combinations maximizing the correlation ($\gamma_1$) between $p$ variables in group 1 and $q$ variables in group 2, where the variables are measured across a common set of units (e.g. general practices): [29]

$$Y^1 = (Y_1^1, \cdots, Y_p^1) \quad (1)$$

$$Y^2 = (Y_1^2, \cdots, Y_q^2) \quad (2)$$

Where $Y^1$ represents the set of $p$ outcomes in group 1, and $Y^2$ the set of $q$ outcomes in group 2. Consider the two linear combinations $\alpha' Y^1$ and $b' Y^2$, where $\alpha'$ is a $p\ x\ 1$ vector of weighting coefficients and $b'$ is likewise a $q\ x\ 1$ vector; the CC ($\gamma_1$) is given by the choice of $\alpha'$ and $b'$ that maximises the correlation between $\alpha' Y^1$ and $b' Y^2$: [29]

$$\gamma_1 = \max_{a,b} Corr(a' Y^1, b' Y^2) = \max_{a,b} \frac{a' \Sigma_{12} b}{\sqrt{a' \Sigma_{11} a b' \Sigma_{22} b}} \quad (3)$$

Where $\Sigma_{11} = Cov(Y^{(1)}, Y^{(1)})$; $\Sigma_{12} = Cov(Y^{(1)}, Y^{(2)})$; $\Sigma_{21} = \Sigma_{12}'$; and $\Sigma_{22} = Cov(Y^{(2)}, Y^{(2)})$.

In the present study, for a given practice the Y's represent the relative use of each clinical codes for a specific disease condition, expressed as a percentage of the total use across all codes for that condition. For example, for the 2006-2007 year-on-year diabetes correlation, group 1 would be the percentage frequency use of each clinical code for diabetes recorded in year 2006 and group 2 would be the corresponding percentage frequencies for each corresponding code recorded in year 2007, at the general practice level. The same applies for the 3-year and 5-year correlations.

We analysed percentage frequencies rather than frequency counts so as to remove any effects of variations in practice size or disease prevalence from the estimated CCs. CCs were calculated using the R statistical software ccaPP package[30] with the "Spearman" method, by which the weighted linear combinations $\alpha' Y^1$ and $b' Y^2$ for each year are ranked across practices prior to computation of the correlation. This method produces estimates that are more robust against model misspecification.[31]

Numbers of incident clinical codes could be small for some conditions and practices, which can lead to biased estimates of the CCs. To adjust for this, we applied the jackknife bias correction to the estimation of CCs for the incidence of clinical codes.[29]

For each of the 18 conditions, we also quantified changes in incident and total clinical code usage applying three measures of diversity. First, the Shannon entropy index of diversity ($H$), an equitability index which takes into account two dimensions of diversity (richness and evenness). The Shannon entropy index ($H$) was calculated as:

$$H = -\sum_i (p_i \, ln \, p_i)$$

Where $p_i$ is the proportion of a clinical code *i* usage in a given year.

Second, we examined the richness ($S$) of clinical code usage by calculating the annual total number of incident and all codes used in a given year. Third, we estimated the evenness ($J$) of incident and total codes' usage, a measure of the relative usage of codes within a given year, i.e. evenness will be high if all codes have a similar distribution. $J$ ranges between zero and one, with $J = 0$ indicating no evenness, and $J = 1$ indicating complete evenness. Evenness was calculated annually by dividing Shannon index ($H$) over the natural logarithm of richness ($S$).

$$J = \frac{H}{\ln(S)}$$

To simplify what these diversity measures imply, for example, if diabetes was represented using three diagnostic codes: code A (used 100 times), code B (used 175 times), and code C (used 350 times), then the proportions of codes would be 0.16, 0.28, and 0.56, respectively.

Shannon's entropy index ($H$) will be = -1*((0.16*ln0.16) + (0.28*ln0.28) + (0.56*ln0.56)) = 0.97; richness ($S$) = 3; and evenness ($J$) = 0.97/ln (3) = 0.88. All analyses were conducted using R software,[32] and were visualised using the ggplots2 package.

## Patient and Public Involvement

No patients or members of the public were involved in this study.

## Results

### Clinical code frequency ranking

Correlation of code usage over a 3-year period showed a positive association for most conditions (Figure 1). Strong, overall positive, and monotonic correlation (CC >0.7) was observed for depression, hypertension, hypothyroidism, osteoarthritis, SMI, and stroke. Positive, monotonic but weaker associations were observed for CKD, epilepsy, and osteoporosis. Learning disability (LD) showed a non-monotonic function with fluctuations ranging between 0.4-1.0, and a notable decline after 2004 before increasing again from 2007. The 1-year and 5-year windows correlations showed similar overall trends, but the association was slightly decreasing as the window increases. Clinical conditions with the highest correlation levels were asthma, AF, cancer, CHD, depression, diabetes, hypertension, hypothyroidism, osteoarthritis, SMI, and stroke for the 1-year window (Figure S1). For the 5-year window, hypertension, hypothyroidism, osteoarthritis, and SMI codes' usage was overall highly correlated mainly in recent years (Figure S2). On the other hand, conditions with the lowest correlations (CC ≤0.6) were CKD and LD (for most years) for the 1-year window; and cancer, CHD, CKD, COPD, dementia, diabetes, epilepsy, HF, LD, and osteoporosis for the 5-year window.

Over a 3-year window, strong correlation for incident code usage (Jackknife bias corrected CC≥0.6) were observed for all examined conditions except CKD, epilepsy, and osteoporosis (Figure 2). Similarly, the 1-year and 5-year windows correlations showed similar trends but lower coefficients with longer windows (Figures S3 and S4, respectively).

### Clinical code usage diversity

Data from 684 UK general practices contributing to the Clinical Practice Research Datalink (CPRD) GOLD were used. Overall, the diversity indices of code usage were stable over the study period for most conditions, but with wide confidence intervals. Higher entropy ($H$) indices were observed with cancer, diabetes, and SMI ($H$ between 2-4), while the lowest levels were observed with LD and osteoporosis ($H$ between 0-2) (Figure 3). Over time, the entropy index of code usage remained stable for most conditions, but increased gradually for asthma, COPD, diabetes, heart failure, and osteoporosis (primarily incident codes). Fluctuations and/or a separation between the incident and total codes trends were observed around 2006, mainly for AF, dementia, depression, CKD, and LD. The Shannon index ($H$) for incident codes had a similar trend to that for total codes for most conditions over time, except for cardiovascular disease (CVD) and diabetes where it exceeded total codes.

Across the examined conditions, the richness ($S$) of incident and total code usage (number of codes used) was the highest for cancer (>500 codes), diabetes and SMI (≥250 codes each) and the lowest for AF, hypothyroidism, and LD ($S$ <100) (Figure 4). The trends however remained stable throughout the study period, except a small decrease for SMI codes and a decrease in cancer after a brief rise between 2000-2005. The difference between the number of incident and total codes for SMI, diabetes and cancer were evident (total codes more than incident codes), unlike in the other conditions where the $S$ index was similar for both code categories.

The evenness ($J$) of both incident and total codes was overall stable and almost identical at least up to 2006, before total codes surpassed incident codes for most conditions except for depression and dementia where the $J$ index for incident codes exceeded that of total codes (Figure 5). The two exceptions to this observation were LD and CKD. For LD, evenness was stable ~0.75 between 2000-2003, declined in 2004 before re-increasing from 2007 and returning to pre-2004 levels from 2011 onwards. For CKD, evenness dipped briefly around 2006-2007 and started to increase again from 2008 until the end of the study period (2013). Given the calculation formula, it is worth noting that the trends of entropy were similar to that of evenness for conditions with low richness, namely for AF, dementia, heart failure, hypertension, hypothyroidism, LD, osteoarthritis, and osteoporosis.

## Discussion

### Main findings

We assessed the clinical code usage for 18 conditions recorded in a large nationally representative UK EHR between 2000-2013. The results show overall strong positive monotonic correlation for all examined conditions except LD, that showed a fluctuating pattern during the study period. The CCs diminished over longer windows (5-year vs. 1-year window). Hypertension, hypothyroidism, osteoarthritis, and SMI had the highest 5-year correlation, mainly in later years of the study period.

The codes' usage entropy and evenness diversity measures remained overall stable throughout the study period for most conditions, except gradual increases over time for respiratory conditions, diabetes, HF, and osteoporosis. This increase in diversity may be partially due to the regular addition of new diagnostic codes and domains over time. For example, major revisions were introduced to the QOF in April 2006 resulting in the addition of new clinical areas and indicators.[33] As a consequence, CKD is among the conditions that it has been acknowledged to have benefited from these revisions as the CKD domain was added in 2006 reflected in improved recording in primary care from that year onwards.[34] For most conditions (except LD), evenness (indicating the abundance of codes in a sample) was overall ≥0.5 suggesting a uniform distribution of the codes. Cancer, diabetes, and SMI had the highest richness indices among all examined conditions.

### Comparison with previous studies

Observational studies examining variations in clinical code usage are limited. A recent study examined the code usage of CVD between 2001-2015 in primary and secondary care records in England.[35] The study aimed to examine if temporal variability methods can identify changes in CVD recording by quantifying the differences of monthly distributions of the variables of interest: CVD status and sociodemographic variables. The study found variability in the frequency of CVD codes across time, potentially due to non-medical causes such as changes in coding used and coding guidelines e.g. changes in ICD (international classification of disease) coding in hospital records. Despite relevance, their approach (examining the

prevalence of CVD stratified by patient demographic variables) differs from our methods and hence the results are not directly comparable. In addition, we examined code usage for 18 conditions, including CVD, from UK general practices.

A study by Tai et al. examined the diversity of data entry screens in four clinical computer systems available in UK general practices and assessed its impact on the variation and quality of recorded clinical data for six exemplar conditions.[25] These were sore throat, tired all the time, depression, cystitis, type 2 diabetes, and myocardial infarction. The study concluded that the systems may contribute towards a diverse coding in primary care, suggesting the need to standardise clinical coding across systems and to adopt shorter and more restricted code lists to help improve data quality. This is an important issue for UK primary care, since the semi-structured and dynamic nature of Read codes often results in diverse and long clinical code lists. Additionally, some GP systems use CTV3 clinical codes and not Read codes resulting in the availability of two versions of clinical codes. SNOMED CT system, which is gradually being implemented across UK primary care from 2018, aimed to provide a single clinical terminology for effective and consistent exchange of clinical data across all NHS settings to help improve patient care and data analysis.[36] Being an international clinical terminology, SNOMED will allow the UK to participate in global health care research.

Our results showed that diabetes codes usage (types 1 and 2) had one of the highest richness index levels (number of codes used), while the diversity entropy index was steadily increasing over the study period, highlighting the increasing variety of diabetes codes used in primary care over time. This observation agrees with a previous study that examined the Read codes used to identify diabetes management in people with diabetes registered with 17 general practices in one locality in London.[11] That study concluded that a wide range of diabetes codes were used and that the number of people assigned each code differed across practices. This again indicates that an approach is required to standardise clinical code lists and thereby coding usage as much as possible, minimise clinical recording errors, and improve research robustness.

### Implication of findings

Our findings shed additional light on the use of clinical codes in research. We found that hypertension, hypothyroidism, osteoarthritis, and SMI codes' usage are highly correlated over the 5-year window (i.e. the codes' usage was similar across years), whereas cancer, CHD, CKD, COPD, dementia, diabetes, epilepsy, HF, LD, and osteoporosis had lowest correlation over the same window. In terms of clinical code lists' size required to define a condition (richness), we found that conditions with the highest richness across the study period were cancer, diabetes, and SMI (between 250-875 codes), whereas AF, hypothyroidism, and LD had the lowest richness (<100 codes). Collectively, these findings indicate that diabetes, cancer, and SMI codes have high richness and need to be defined carefully and then they can either last for 5 years (SMI), or only to 2 years (diabetes and cancer). Whereas hypothyroidism has low code usage richness and can last for 5 years. This might be due to that diabetes is often a target of government initiatives, unlike hypothyroidism which is rarely a focus of such interventions.

The results suggest that defining cohorts of people with mental health conditions (SMI, depression) over time was less sensitive to the changes of code usage (up to 5 years old) compared with most cardiometabolic conditions and cancer.

The observed findings also suggest the need to adopt a more consistent and less diverse coding in primary care, as this will help improve data quality. Inconsistent use of clinical coding may result in people with the same condition not being flagged as having the condition,[22] which may have implications on searching and identifying these people for clinical and research purposes, or to identify people for shielding measures or those who are a priority for a vaccination as in the current COVID-19 pandemic. While acknowledging that SNOMED CT is gradually replacing Read codes in general practice care since April 2018, our findings are still relevant in documenting the clinical code usage over a long period where Read codes were the main UK coding system.

Also, the rapidly increasing complexity of healthcare systems[15] might play a role on the observed trends in code usage over time. In other words, code usage practices (e.g. the tendency of data enterer to use easily accessed and well-known codes) may be partially driven by personal and work factors in the complex healthcare systems such as limited time and organisational factors.

### Strengths and limitations of the study

Our study has several strengths. Using a range of frequency and diversity measures, we present a contemporary longitudinal analysis of clinical code usage in UK primary care, while only a few existing studies have addressed this research area. We used data from a large nationally representative database, where the validity of recorded diagnostic coding has been acknowledged previously.[37] Additionally, the data quality is assumed to be high, as it is based on QOF clinical codes lists (except osteoarthritis). Our findings are relevant to clinical practice as we examined a broad range of prevalent physical and mental illnesses as recorded in primary care and considered the clinical implications of variations in clinical coding over 14 years.

Our study has also several limitations. Given the design of the recorded EHRs, we may have missed some patients with the examined conditions due to some unusual circumstances or settings, such as patients not registered with general practices (e.g. homeless people), which may have affected the observed patterns of clinical code usage. Also, analyses were not extended to examine ICD-10 clinical codes in secondary care setting (only available in England), as our aim was to focus on the usage of Read codes recorded in UK primary care visits as the main point of clinical care. CCA provides a single multivariate measure of correlation, thus simplifying interpretation compared to analysing each clinical code separately. However, the measure represents the maximum possible correlation between code use at two different time points and does not account for the code set being the same at both times, hence may over-represent actual agreement to some degree. Finally, we used CPRD GOLD which collects data from general practices using the VISION clinical system, and code usage will vary to some extent in general practices using EMIS or SystmOne. However, we would expect such variation to be low in chronic conditions incentivised through the QOF, with specific common code lists used by practices to ensure remuneration eligibility.

## Conclusions

The code usage in UK primary care was overall stable for most of the examined chronic conditions managed in general practice between 2000-2013, but the changes were higher over longer time windows. Diabetes, cancer, and SMI codes need to be defined carefully but

SMI codes can last up to 5 years, whereas hypothyroidism has low richness and can last up for 5 years. Our study addresses an underreported research area and the findings suggest the need to adopt a more consistent and less diverse coding in primary care to help improve data quality and the use of recent codes for cardiometabolic conditions and cancer. More research is needed in this area following the full transfer to the SNOMED CT coding and to examine the code usage in secondary care settings.

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## Competing interests

DMA reports research grants from Abbvie, Almirall, Celgene, Eli Lilly, Novartis, UCB and the Leo Foundation. Other co-authors declare no competing interests.

## Author contribution

EK and DAS designed the study. DAS extracted the data from all sources and performed the initial analyses. RP and SSZ validated and expanded the analyses. SSZ wrote the manuscript and EK, RP, DR, and CG critically edited the initial drafts. All authors contributed to interpretation of data and revised the paper for important intellectual content and agreed on the final version of the paper before submission. SSZ is the guarantor of this work and, as such, had full access to all the data in the study and takes responsibility for the integrity of the data and the accuracy of the data analysis.

## Patient consent

Not applicable.

## Data sharing

Clinical code lists are available from clinicalcodes.org. Electronic health records are, by definition, considered sensitive data in the UK by the Data Protection Act and cannot be shared via public deposition because of information governance restriction in place to protect patient confidentiality. Access to data is available only once approval has been obtained through the individual constituent entities controlling access to the data. The data can be requested via application to the Clinical Practice Research Datalink.

## Transparency declaration

SSZ affirms that the manuscript is an honest, accurate, and transparent account of the study being reported; that no important aspects of the study have been omitted; and that any discrepancies from the study as planned (and, if relevant, registered) have been explained.

## Ethical approval

This study is based on data from Clinical Practice Research Datalink (CPRD) obtained under licence from the UK Medicines and Healthcare products Regulatory Agency. The study was approved by the Independent Scientific Advisory Committee (ISAC) for MHRA Database Research (protocol number: 16_115). The data are provided by patients and collected by the NHS as part of their care and support. Generic ethical approval for observational research using CPRD with approval from ISAC has been granted by a Health Research Authority (HRA) Research Ethics Committee (East Midlands—Derby, REC reference number 05/MRE04/87).

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## Figure legends

### Figure 1 Canonical correlations using 3-year window of clinical code usage for 18 mental and physical conditions

CHD, coronary heart disease; CKD, chronic kidney disease; COPD, chronic obstructive pulmonary disease; DM, diabetes mellitus; HF, heart failure; HT, hypertension; SMI, severe mental illness.

### Figure 2 Bias-corrected canonical correlations (95%CI) using 3-year window (incident codes) for 18 mental and physical conditions

CHD, coronary heart disease; CKD, chronic kidney disease; COPD, chronic obstructive pulmonary disease; DM, diabetes mellitus; HF, heart failure; HT, hypertension; SMI, severe mental illness.
Incident code: a clinical code indicating new (incident) cases.

### Figure 3 Entropy (95% CI) of incident and all clinical codes usage for 18 mental and physical conditions

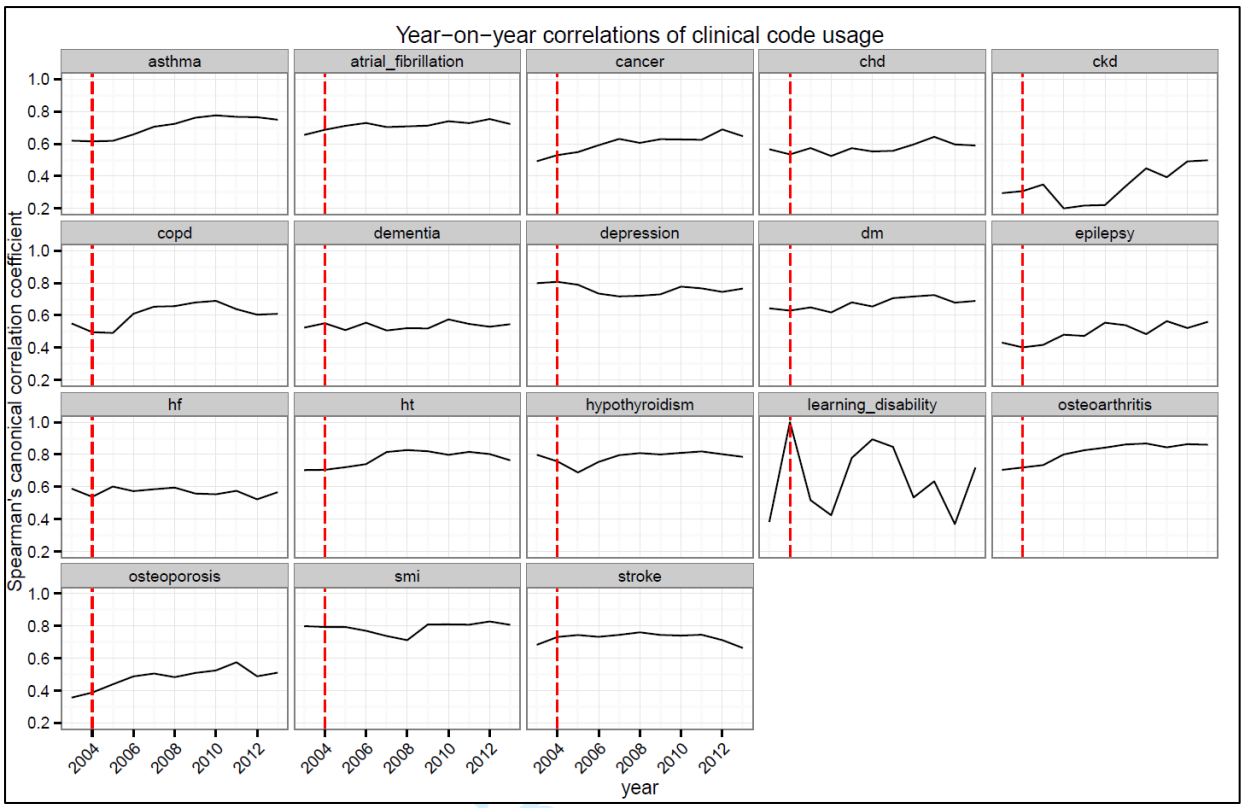
CHD, coronary heart disease; CKD, chronic kidney disease; COPD, chronic obstructive pulmonary disease; DM, diabetes mellitus; HF, heart failure; HT, hypertension; SMI, severe mental illness.
Incident code: a clinical code indicating new (incident) cases. All codes: any diagnostic clinical code for the condition incident and prevalent cases).

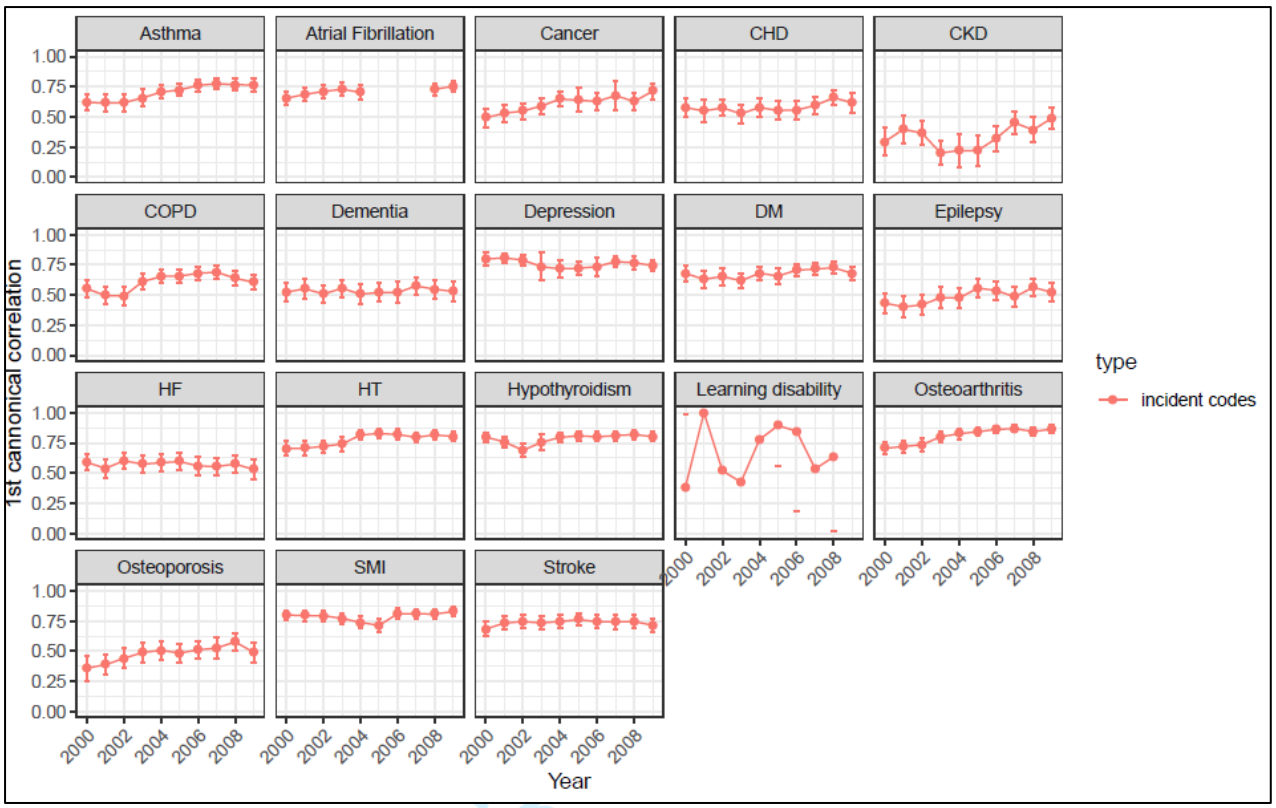
### Figure 4 Richness of incident and all clinical codes usage for 18 mental and physical conditions

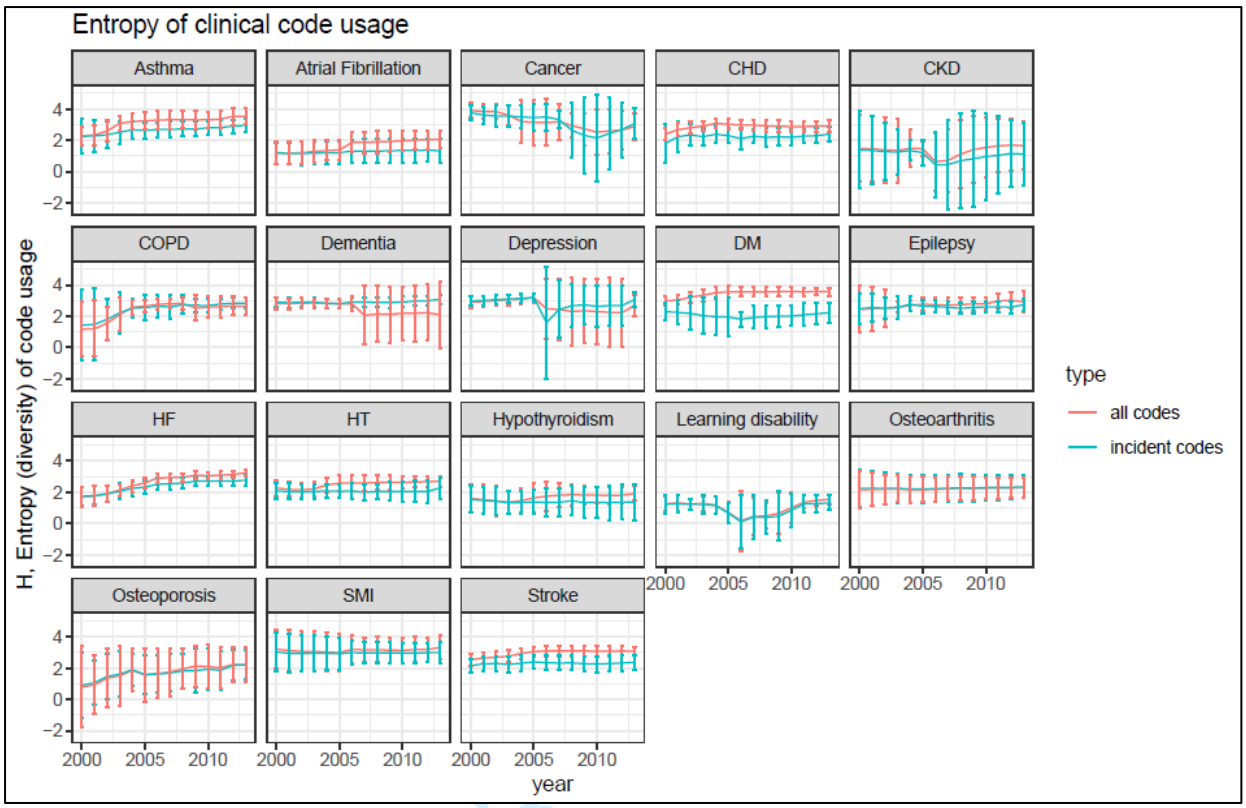
CHD, coronary heart disease; CKD, chronic kidney disease; COPD, chronic obstructive pulmonary disease; DM, diabetes mellitus; HF, heart failure; HT, hypertension; SMI, severe mental illness.
Incident code: a clinical code indicating new (incident) cases. All codes: any diagnostic clinical code for the condition incident and prevalent cases).

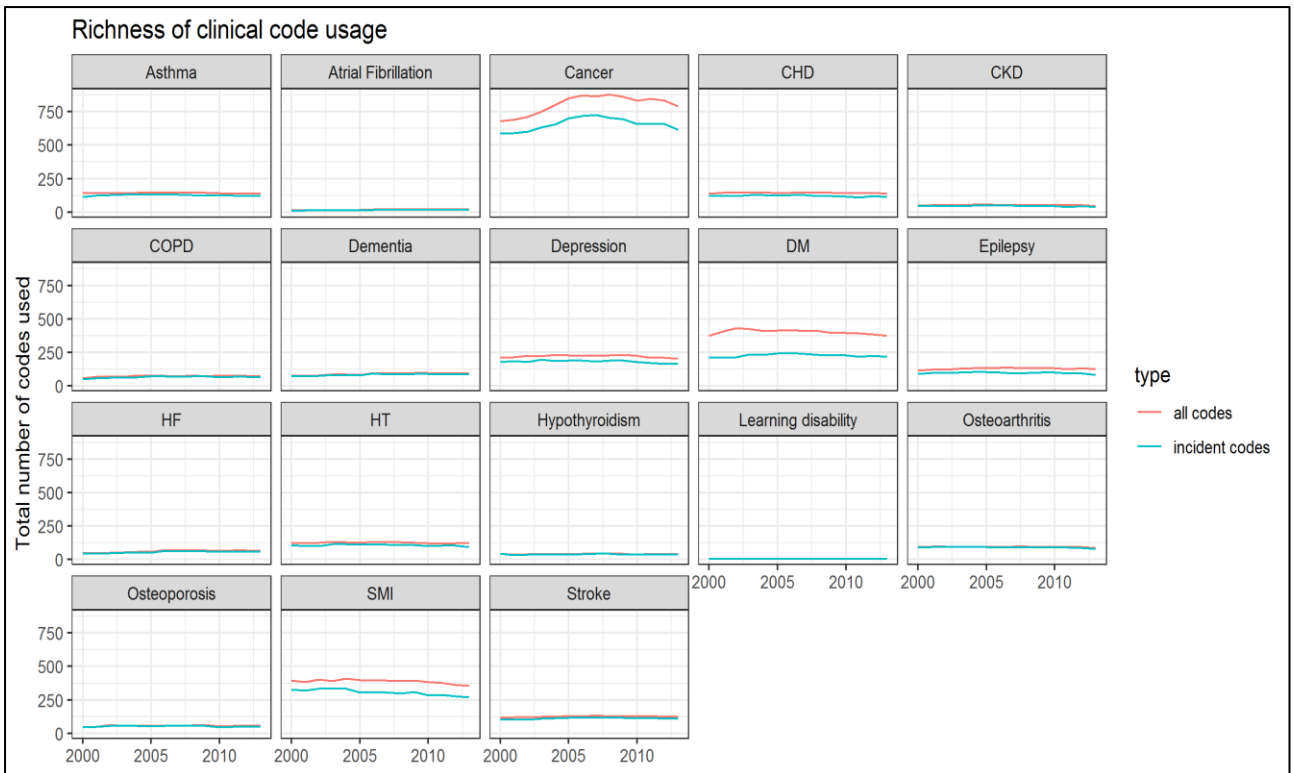
### Figure 5 Evenness (95% CI) of incident and all clinical codes usage for 18 mental and physical conditions

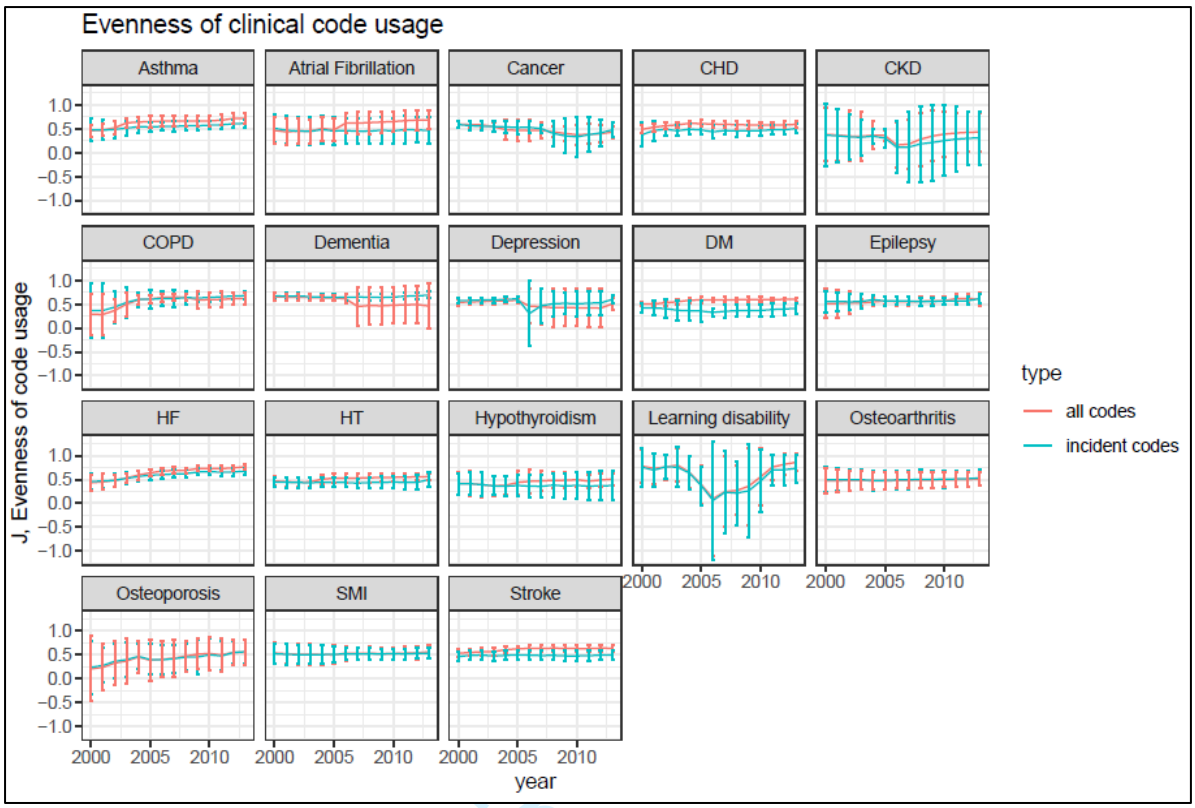
CHD, coronary heart disease; CKD, chronic kidney disease; COPD, chronic obstructive pulmonary disease; DM, diabetes mellitus; HF, heart failure; HT, hypertension; SMI, severe mental illness.
Incident code: a clinical code indicating new (incident) cases. All codes: any diagnostic clinical code for the condition incident and prevalent cases).











Supplementary data to "Clinical code usage in UK general practice: a cohort study exploring 18 conditions over 14 years", Zghebi et al. 2021.

# Supplementary data

Supplementary data to "Clinical code usage in UK general practice: a cohort study exploring 18 conditions over 14 years", Zghebi et al. 2021.

## Table S1 Diabetes Read code list

| | Code | Coding system | Description |
|---|---|---|---|
| 1. | 66A3.00 | Read | Diabetic on diet only |
| 2. | 66A4.00 | Read | Diabetic on oral treatment |
| 3. | 66A5.00 | Read | Diabetic on insulin |
| 4. | 66AI.00 | Read | Diabetic - good control |
| 5. | 66AJ.00 | Read | Diabetic - poor control |
| 6. | 66AJ100 | Read | Brittle diabetes |
| 7. | 66AJ.11 | Read | Unstable diabetes |
| 8. | 66AJz00 | Read | Diabetic - poor control NOS |
| 9. | 66AK.00 | Read | Diabetic - cooperative patient |
| 10. | 66AL.00 | Read | Diabetic-uncooperative patient |
| 11. | 66AV.00 | Read | Diabetic on insulin and oral treatment |
| 12. | C10..00 | Read | Diabetes mellitus |
| 13. | C100.00 | Read | Diabetes mellitus with no mention of complication |
| 14. | C100000 | Read | Diabetes mellitus; juvenile type; no mention of complication |
| 15. | C100011 | Read | Insulin dependent diabetes mellitus |
| 16. | C100100 | Read | Diabetes mellitus; adult onset; no mention of complication |
| 17. | C100111 | Read | Maturity onset diabetes |
| 18. | C100112 | Read | Non-insulin dependent diabetes mellitus |
| 19. | C100z00 | Read | Diabetes mellitus NOS with no mention of complication |
| 20. | C101.00 | Read | Diabetes mellitus with ketoacidosis |
| 21. | C101000 | Read | Diabetes mellitus; juvenile type; with ketoacidosis |
| 22. | C101100 | Read | Diabetes mellitus; adult onset; with ketoacidosis |
| 23. | C101y00 | Read | Other specified diabetes mellitus with ketoacidosis |
| 24. | C101z00 | Read | Diabetes mellitus NOS with ketoacidosis |
| 25. | C102.00 | Read | Diabetes mellitus with hyperosmolar coma |
| 26. | C102000 | Read | Diabetes mellitus; juvenile type; with hyperosmolar coma |
| 27. | C102100 | Read | Diabetes mellitus; adult onset; with hyperosmolar coma |
| 28. | C102z00 | Read | Diabetes mellitus NOS with hyperosmolar coma |
| 29. | C103.00 | Read | Diabetes mellitus with ketoacidotic coma |
| 30. | C103000 | Read | Diabetes mellitus; juvenile type; with ketoacidotic coma |
| 31. | C103100 | Read | Diabetes mellitus; adult onset; with ketoacidotic coma |
| 32. | C103y00 | Read | Other specified diabetes mellitus with coma |
| 33. | C103z00 | Read | Diabetes mellitus NOS with ketoacidotic coma |
| 34. | C104.00 | Read | Diabetes mellitus with renal manifestation |
| 35. | C104000 | Read | Diabetes mellitus; juvenile type; with renal manifestation |
| 36. | C104100 | Read | Diabetes mellitus; adult onset; with renal manifestation |
| 37. | C104y00 | Read | Other specified diabetes mellitus with renal complications |
| 38. | C104z00 | Read | Diabetes mellitis with nephropathy NOS |
| 39. | C105.00 | Read | Diabetes mellitus with ophthalmic manifestation |
| 40. | C105000 | Read | Diabetes mellitus; juvenile type; + ophthalmic manifestation |
| 41. | C105100 | Read | Diabetes mellitus; adult onset; + ophthalmic manifestation |
| 42. | C105y00 | Read | Other specified diabetes mellitus with ophthalmic complicatn |
| 43. | C105z00 | Read | Diabetes mellitus NOS with ophthalmic manifestation |
| 44. | C106.00 | Read | Diabetes mellitus with neurological manifestation |
| 45. | C106000 | Read | Diabetes mellitus; juvenile; + neurological manifestation |
| 46. | C106100 | Read | Diabetes mellitus; adult onset; + neurological manifestation |
| 47. | C106.12 | Read | Diabetes mellitus with neuropathy |

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| | | | |
|---|---|---|---|
| 48. | C106.13 | Read | Diabetes mellitus with polyneuropathy |
| 49. | C106y00 | Read | Other specified diabetes mellitus with neurological comps |
| 50. | C106z00 | Read | Diabetes mellitus NOS with neurological manifestation |
| 51. | C107.00 | Read | Diabetes mellitus with peripheral circulatory disorder |
| 52. | C107000 | Read | Diabetes mellitus; juvenile +peripheral circulatory disorder |
| 53. | C107100 | Read | Diabetes mellitus; adult; + peripheral circulatory disorder |
| 54. | C107.11 | Read | Diabetes mellitus with gangrene |
| 55. | C107.12 | Read | Diabetes with gangrene |
| 56. | C107200 | Read | Diabetes mellitus; adult with gangrene |
| 57. | C107300 | Read | IDDM with peripheral circulatory disorder |
| 58. | C107400 | Read | NIDDM with peripheral circulatory disorder |
| 59. | C107z00 | Read | Diabetes mellitus NOS with peripheral circulatory disorder |
| 60. | C108.00 | Read | Insulin dependent diabetes mellitus |
| 61. | C108000 | Read | Insulin-dependent diabetes mellitus with renal complications |
| 62. | C108011 | Read | Type I diabetes mellitus with renal complications |
| 63. | C108012 | Read | Type 1 diabetes mellitus with renal complications |
| 64. | C108100 | Read | Insulin-dependent diabetes mellitus with ophthalmic comps |
| 65. | C108.11 | Read | IDDM-Insulin dependent diabetes mellitus |
| 66. | C108.12 | Read | Type 1 diabetes mellitus |
| 67. | C108.13 | Read | Type I diabetes mellitus |
| 68. | C108200 | Read | Insulin-dependent diabetes mellitus with neurological comps |
| 69. | C108211 | Read | Type I diabetes mellitus with neurological complications |
| 70. | C108212 | Read | Type 1 diabetes mellitus with neurological complications |
| 71. | C108300 | Read | Insulin dependent diabetes mellitus with multiple complicatn |
| 72. | C108400 | Read | Unstable insulin dependent diabetes mellitus |
| 73. | C108411 | Read | Unstable type I diabetes mellitus |
| 74. | C108500 | Read | Insulin dependent diabetes mellitus with ulcer |
| 75. | C108511 | Read | Type I diabetes mellitus with ulcer |
| 76. | C108600 | Read | Insulin dependent diabetes mellitus with gangrene |
| 77. | C108700 | Read | Insulin dependent diabetes mellitus with retinopathy |
| 78. | C108711 | Read | Type I diabetes mellitus with retinopathy |
| 79. | C108712 | Read | Type 1 diabetes mellitus with retinopathy |
| 80. | C108800 | Read | Insulin dependent diabetes mellitus - poor control |
| 81. | C108811 | Read | Type I diabetes mellitus - poor control |
| 82. | C108812 | Read | Type 1 diabetes mellitus - poor control |
| 83. | C108900 | Read | Insulin dependent diabetes maturity onset |
| 84. | C108911 | Read | Type I diabetes mellitus maturity onset |
| 85. | C108A00 | Read | Insulin-dependent diabetes without complication |
| 86. | C108B00 | Read | Insulin dependent diabetes mellitus with mononeuropathy |
| 87. | C108B11 | Read | Type I diabetes mellitus with mononeuropathy |
| 88. | C108C00 | Read | Insulin dependent diabetes mellitus with polyneuropathy |
| 89. | C108D00 | Read | Insulin dependent diabetes mellitus with nephropathy |
| 90. | C108D11 | Read | Type I diabetes mellitus with nephropathy |
| 91. | C108E00 | Read | Insulin dependent diabetes mellitus with hypoglycaemic coma |
| 92. | C108E11 | Read | Type I diabetes mellitus with hypoglycaemic coma |
| 93. | C108E12 | Read | Type 1 diabetes mellitus with hypoglycaemic coma |
| 94. | C108F00 | Read | Insulin dependent diabetes mellitus with diabetic cataract |
| 95. | C108F11 | Read | Type I diabetes mellitus with diabetic cataract |
| 96. | C108G00 | Read | Insulin dependent diab mell with peripheral angiopathy |
| 97. | C108H00 | Read | Insulin dependent diabetes mellitus with arthropathy |

Supplementary data to "Clinical code usage in UK general practice: a cohort study exploring 18 conditions over 14 years", Zghebi et al. 2021.

| | | | |
|---|---|---|---|
| 98. | C108H11 | Read | Type I diabetes mellitus with arthropathy |
| 99. | C108J00 | Read | Insulin dependent diab mell with neuropathic arthropathy |
| 100. | C108J12 | Read | Type 1 diabetes mellitus with neuropathic arthropathy |
| 101. | C108y00 | Read | Other specified diabetes mellitus with multiple comps |
| 102. | C108z00 | Read | Unspecified diabetes mellitus with multiple complications |
| 103. | C109.00 | Read | Non-insulin-dependent diabetes mellitus |
| 104. | C109000 | Read | Non-insulin-dependent diabetes mellitus with renal comps |
| 105. | C109011 | Read | Type II diabetes mellitus with renal complications |
| 106. | C109012 | Read | Type 2 diabetes mellitus with renal complications |
| 107. | C109100 | Read | Non-insulin-dependent diabetes mellitus with ophthalm comps |
| 108. | C109.11 | Read | NIDDM - Non-insulin dependent diabetes mellitus |
| 109. | C109111 | Read | Type II diabetes mellitus with ophthalmic complications |
| 110. | C109112 | Read | Type 2 diabetes mellitus with ophthalmic complications |
| 111. | C109.12 | Read | Type 2 diabetes mellitus |
| 112. | C109.13 | Read | Type II diabetes mellitus |
| 113. | C109200 | Read | Non-insulin-dependent diabetes mellitus with neuro comps |
| 114. | C109211 | Read | Type II diabetes mellitus with neurological complications |
| 115. | C109212 | Read | Type 2 diabetes mellitus with neurological complications |
| 116. | C109300 | Read | Non-insulin-dependent diabetes mellitus with multiple comps |
| 117. | C109400 | Read | Non-insulin dependent diabetes mellitus with ulcer |
| 118. | C109411 | Read | Type II diabetes mellitus with ulcer |
| 119. | C109412 | Read | Type 2 diabetes mellitus with ulcer |
| 120. | C109500 | Read | Non-insulin dependent diabetes mellitus with gangrene |
| 121. | C109511 | Read | Type II diabetes mellitus with gangrene |
| 122. | C109600 | Read | Non-insulin-dependent diabetes mellitus with retinopathy |
| 123. | C109611 | Read | Type II diabetes mellitus with retinopathy |
| 124. | C109612 | Read | Type 2 diabetes mellitus with retinopathy |
| 125. | C109700 | Read | Non-insulin dependant diabetes mellitus - poor control |
| 126. | C109711 | Read | Type II diabetes mellitus - poor control |
| 127. | C109712 | Read | Type 2 diabetes mellitus - poor control |
| 128. | C109900 | Read | Non-insulin-dependent diabetes mellitus without complication |
| 129. | C109A00 | Read | Non-insulin dependent diabetes mellitus with mononeuropathy |
| 130. | C109A11 | Read | Type II diabetes mellitus with mononeuropathy |
| 131. | C109B00 | Read | Non-insulin dependent diabetes mellitus with polyneuropathy |
| 132. | C109B11 | Read | Type II diabetes mellitus with polyneuropathy |
| 133. | C109C00 | Read | Non-insulin dependent diabetes mellitus with nephropathy |
| 134. | C109C11 | Read | Type II diabetes mellitus with nephropathy |
| 135. | C109C12 | Read | Type 2 diabetes mellitus with nephropathy |
| 136. | C109D00 | Read | Non-insulin dependent diabetes mellitus with hypoglyca coma |
| 137. | C109D11 | Read | Type II diabetes mellitus with hypoglycaemic coma |
| 138. | C109D12 | Read | Type 2 diabetes mellitus with hypoglycaemic coma |
| 139. | C109E00 | Read | Non-insulin depend diabetes mellitus with diabetic cataract |
| 140. | C109E11 | Read | Type II diabetes mellitus with diabetic cataract |
| 141. | C109E12 | Read | Type 2 diabetes mellitus with diabetic cataract |
| 142. | C109F00 | Read | Non-insulin-dependent d m with peripheral angiopath |
| 143. | C109F11 | Read | Type II diabetes mellitus with peripheral angiopathy |
| 144. | C109F12 | Read | Type 2 diabetes mellitus with peripheral angiopathy |
| 145. | C109G00 | Read | Non-insulin dependent diabetes mellitus with arthropathy |
| 146. | C109G11 | Read | Type II diabetes mellitus with arthropathy |
| 147. | C109G12 | Read | Type 2 diabetes mellitus with arthropathy |

Supplementary data to "Clinical code usage in UK general practice: a cohort study exploring 18 conditions over 14 years", Zghebi et al. 2021.

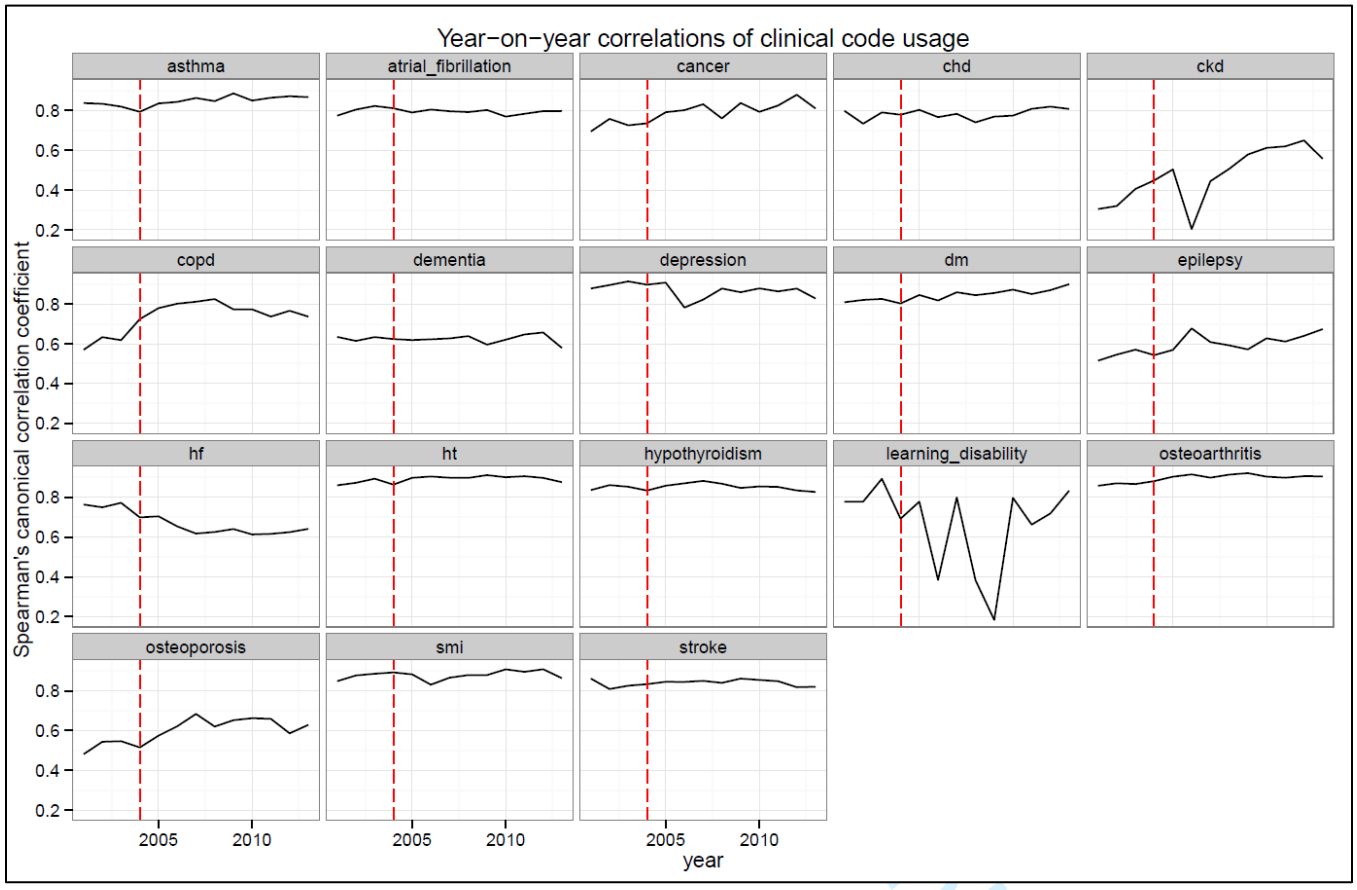
| | | | |
|---|---|---|---|
| 148. | C109H00 | Read | Non-insulin dependent d m with neuropathic arthropathy |
| 149. | C109H11 | Read | Type II diabetes mellitus with neuropathic arthropathy |
| 150. | C109H12 | Read | Type 2 diabetes mellitus with neuropathic arthropathy |
| 151. | C109J00 | Read | Insulin treated Type 2 diabetes mellitus |
| 152. | C109J11 | Read | Insulin treated non-insulin dependent diabetes mellitus |
| 153. | C109J12 | Read | Insulin treated Type II diabetes mellitus |
| 154. | C109K00 | Read | Hyperosmolar non-ketotic state in type 2 diabetes mellitus |
| 155. | C10C.00 | Read | Diabetes mellitus autosomal dominant |
| 156. | C10C.11 | Read | Maturity onset diabetes in youth |
| 157. | C10D.00 | Read | Diabetes mellitus autosomal dominant type 2 |
| 158. | C10D.11 | Read | Maturity onset diabetes in youth type 2 |
| 159. | C10E.00 | Read | Type 1 diabetes mellitus |
| 160. | C10E000 | Read | Type 1 diabetes mellitus with renal complications |
| 161. | C10E100 | Read | Type 1 diabetes mellitus with ophthalmic complications |
| 162. | C10E.11 | Read | Type I diabetes mellitus |
| 163. | C10E.12 | Read | Insulin dependent diabetes mellitus |
| 164. | C10E200 | Read | Type 1 diabetes mellitus with neurological complications |
| 165. | C10E300 | Read | Type 1 diabetes mellitus with multiple complications |
| 166. | C10E312 | Read | Insulin dependent diabetes mellitus with multiple complicat |
| 167. | C10E400 | Read | Unstable type 1 diabetes mellitus |
| 168. | C10E411 | Read | Unstable type I diabetes mellitus |
| 169. | C10E412 | Read | Unstable insulin dependent diabetes mellitus |
| 170. | C10E500 | Read | Type 1 diabetes mellitus with ulcer |
| 171. | C10E600 | Read | Type 1 diabetes mellitus with gangrene |
| 172. | C10E700 | Read | Type 1 diabetes mellitus with retinopathy |
| 173. | C10E800 | Read | Type 1 diabetes mellitus - poor control |
| 174. | C10E812 | Read | Insulin dependent diabetes mellitus - poor control |
| 175. | C10E900 | Read | Type 1 diabetes mellitus maturity onset |
| 176. | C10EA00 | Read | Type 1 diabetes mellitus without complication |
| 177. | C10EA11 | Read | Type I diabetes mellitus without complication |
| 178. | C10EB00 | Read | Type 1 diabetes mellitus with mononeuropathy |
| 179. | C10EC00 | Read | Type 1 diabetes mellitus with polyneuropathy |
| 180. | C10ED00 | Read | Type 1 diabetes mellitus with nephropathy |
| 181. | C10EE00 | Read | Type 1 diabetes mellitus with hypoglycaemic coma |
| 182. | C10EF00 | Read | Type 1 diabetes mellitus with diabetic cataract |
| 183. | C10EG00 | Read | Type 1 diabetes mellitus with peripheral angiopathy |
| 184. | C10EH00 | Read | Type 1 diabetes mellitus with arthropathy |
| 185. | C10EJ00 | Read | Type 1 diabetes mellitus with neuropathic arthropathy |
| 186. | C10EK00 | Read | Type 1 diabetes mellitus with persistent proteinuria |
| 187. | C10EL00 | Read | Type 1 diabetes mellitus with persistent microalbuminuria |
| 188. | C10EM00 | Read | Type 1 diabetes mellitus with ketoacidosis |
| 189. | C10EM11 | Read | Type I diabetes mellitus with ketoacidosis |
| 190. | C10EN00 | Read | Type 1 diabetes mellitus with ketoacidotic coma |
| 191. | C10EN11 | Read | Type I diabetes mellitus with ketoacidotic coma |
| 192. | C10EP00 | Read | Type 1 diabetes mellitus with exudative maculopathy |
| 193. | C10EQ00 | Read | Type 1 diabetes mellitus with gastroparesis |
| 194. | C10F.00 | Read | Type 2 diabetes mellitus |
| 195. | C10F000 | Read | Type 2 diabetes mellitus with renal complications |
| 196. | C10F011 | Read | Type II diabetes mellitus with renal complications |
| 197. | C10F100 | Read | Type 2 diabetes mellitus with ophthalmic complications |

Supplementary data to "Clinical code usage in UK general practice: a cohort study exploring 18 conditions over 14 years", Zghebi et al. 2021.

| | | | |
|---|---|---|---|
| 198. | C10F.11 | Read | Type II diabetes mellitus |
| 199. | C10F200 | Read | Type 2 diabetes mellitus with neurological complications |
| 200. | C10F300 | Read | Type 2 diabetes mellitus with multiple complications |
| 201. | C10F311 | Read | Type II diabetes mellitus with multiple complications |
| 202. | C10F400 | Read | Type 2 diabetes mellitus with ulcer |
| 203. | C10F500 | Read | Type 2 diabetes mellitus with gangrene |
| 204. | C10F511 | Read | Type II diabetes mellitus with gangrene |
| 205. | C10F600 | Read | Type 2 diabetes mellitus with retinopathy |
| 206. | C10F611 | Read | Type II diabetes mellitus with retinopathy |
| 207. | C10F700 | Read | Type 2 diabetes mellitus - poor control |
| 208. | C10F711 | Read | Type II diabetes mellitus - poor control |
| 209. | C10F900 | Read | Type 2 diabetes mellitus without complication |
| 210. | C10F911 | Read | Type II diabetes mellitus without complication |
| 211. | C10FA00 | Read | Type 2 diabetes mellitus with mononeuropathy |
| 212. | C10FB00 | Read | Type 2 diabetes mellitus with polyneuropathy |
| 213. | C10FB11 | Read | Type II diabetes mellitus with polyneuropathy |
| 214. | C10FC00 | Read | Type 2 diabetes mellitus with nephropathy |
| 215. | C10FC11 | Read | Type II diabetes mellitus with nephropathy |
| 216. | C10FD00 | Read | Type 2 diabetes mellitus with hypoglycaemic coma |
| 217. | C10FE00 | Read | Type 2 diabetes mellitus with diabetic cataract |
| 218. | C10FF00 | Read | Type 2 diabetes mellitus with peripheral angiopathy |
| 219. | C10FG00 | Read | Type 2 diabetes mellitus with arthropathy |
| 220. | C10FH00 | Read | Type 2 diabetes mellitus with neuropathic arthropathy |
| 221. | C10FJ00 | Read | Insulin treated Type 2 diabetes mellitus |
| 222. | C10FJ11 | Read | Insulin treated Type II diabetes mellitus |
| 223. | C10FK00 | Read | Hyperosmolar non-ketotic state in type 2 diabetes mellitus |
| 224. | C10FL00 | Read | Type 2 diabetes mellitus with persistent proteinuria |
| 225. | C10FL11 | Read | Type II diabetes mellitus with persistent proteinuria |
| 226. | C10FM00 | Read | Type 2 diabetes mellitus with persistent microalbuminuria |
| 227. | C10FN00 | Read | Type 2 diabetes mellitus with ketoacidosis |
| 228. | C10FP00 | Read | Type 2 diabetes mellitus with ketoacidotic coma |
| 229. | C10FQ00 | Read | Type 2 diabetes mellitus with exudative maculopathy |
| 230. | C10FR00 | Read | Type 2 diabetes mellitus with gastroparesis |
| 231. | C10G.00 | Read | Secondary pancreatic diabetes mellitus |
| 232. | C10G000 | Read | Secondary pancreatic diabetes mellitus without complication |
| 233. | C10y.00 | Read | Diabetes mellitus with other specified manifestation |
| 234. | C10y100 | Read | Diabetes mellitus; adult; + other specified manifestation |
| 235. | C10yy00 | Read | Other specified diabetes mellitus with other spec comps |
| 236. | C10yz00 | Read | Diabetes mellitus NOS with other specified manifestation |
| 237. | C10z.00 | Read | Diabetes mellitus with unspecified complication |
| 238. | C10z000 | Read | Diabetes mellitus; juvenile type; + unspecified complication |
| 239. | C10z100 | Read | Diabetes mellitus; adult onset; + unspecified complication |
| 240. | C10zy00 | Read | Other specified diabetes mellitus with unspecified comps |
| 241. | C10zz00 | Read | Diabetes mellitus NOS with unspecified complication |
| 242. | Cyu2.00 | Read | [X]Diabetes mellitus |
| 243. | Cyu2000 | Read | [X]Other specified diabetes mellitus |
| 244. | Cyu2300 | Read | [X]Unspecified diabetes mellitus with renal complications |
| 245. | L180500 | Read | Pre-existing diabetes mellitus; insulin-dependent |
| 246. | L180600 | Read | Pre-existing diabetes mellitus; non-insulin-dependent |
| 247. | L180X00 | Read | Pre-existing diabetes mellitus; unspecified |

Supplementary data to "Clinical code usage in UK general practice: a cohort study exploring 18 conditions over 14 years", Zghebi et al. 2021.

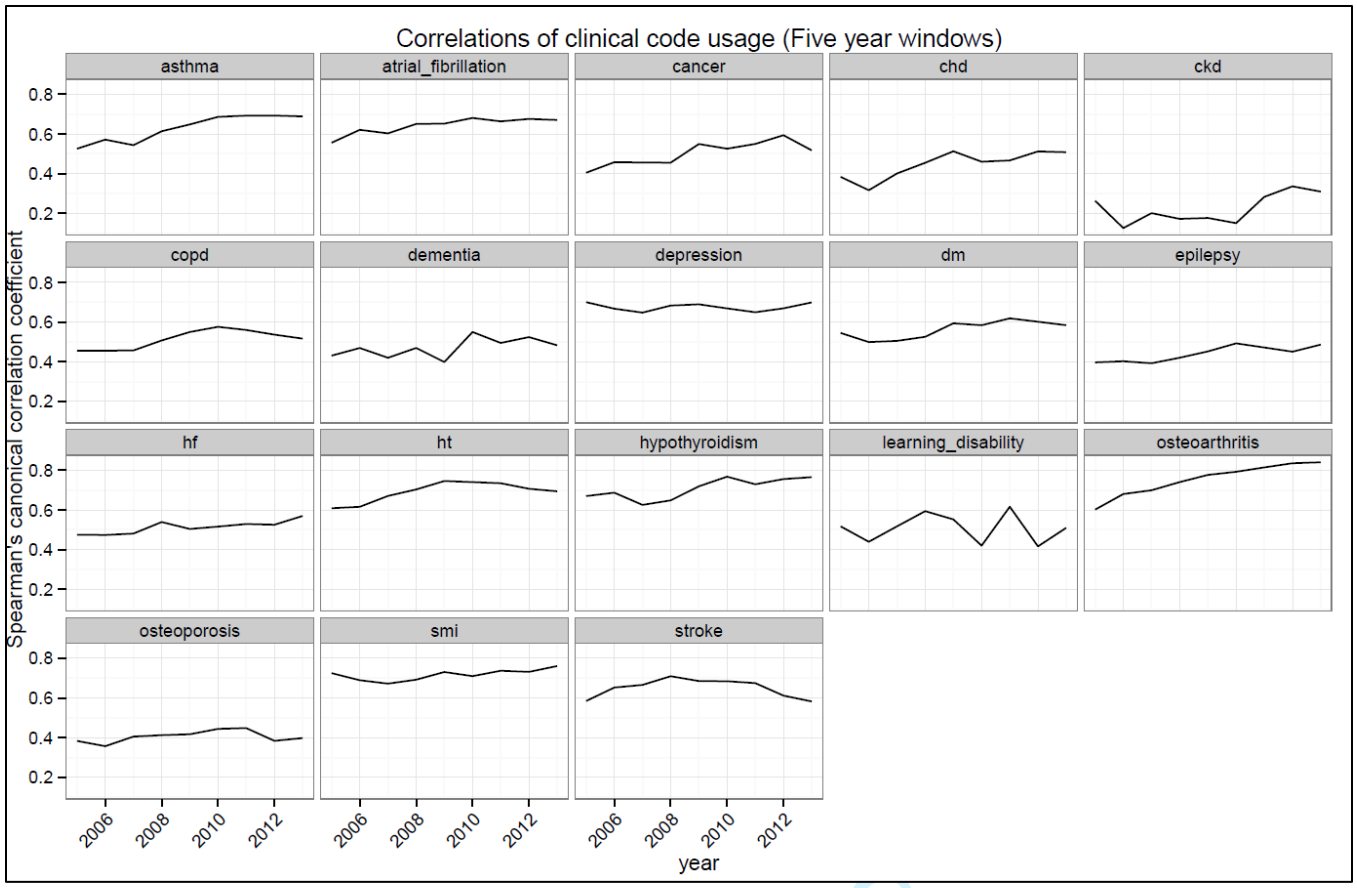
**Figure S1 Canonical correlation using 1-year window of clinical code usage for 18 mental and physical conditions**




AF, atrial fibrillation; CHD, coronary heart disease; CKD, chronic kidney disease; COPD, chronic obstructive pulmonary disease; DM, diabetes mellitus; HF, heart failure; HT, hypertension; SMI, severe mental illness.

Supplementary data to "Clinical code usage in UK general practice: a cohort study exploring 18 conditions over 14 years", Zghebi et al. 2021.

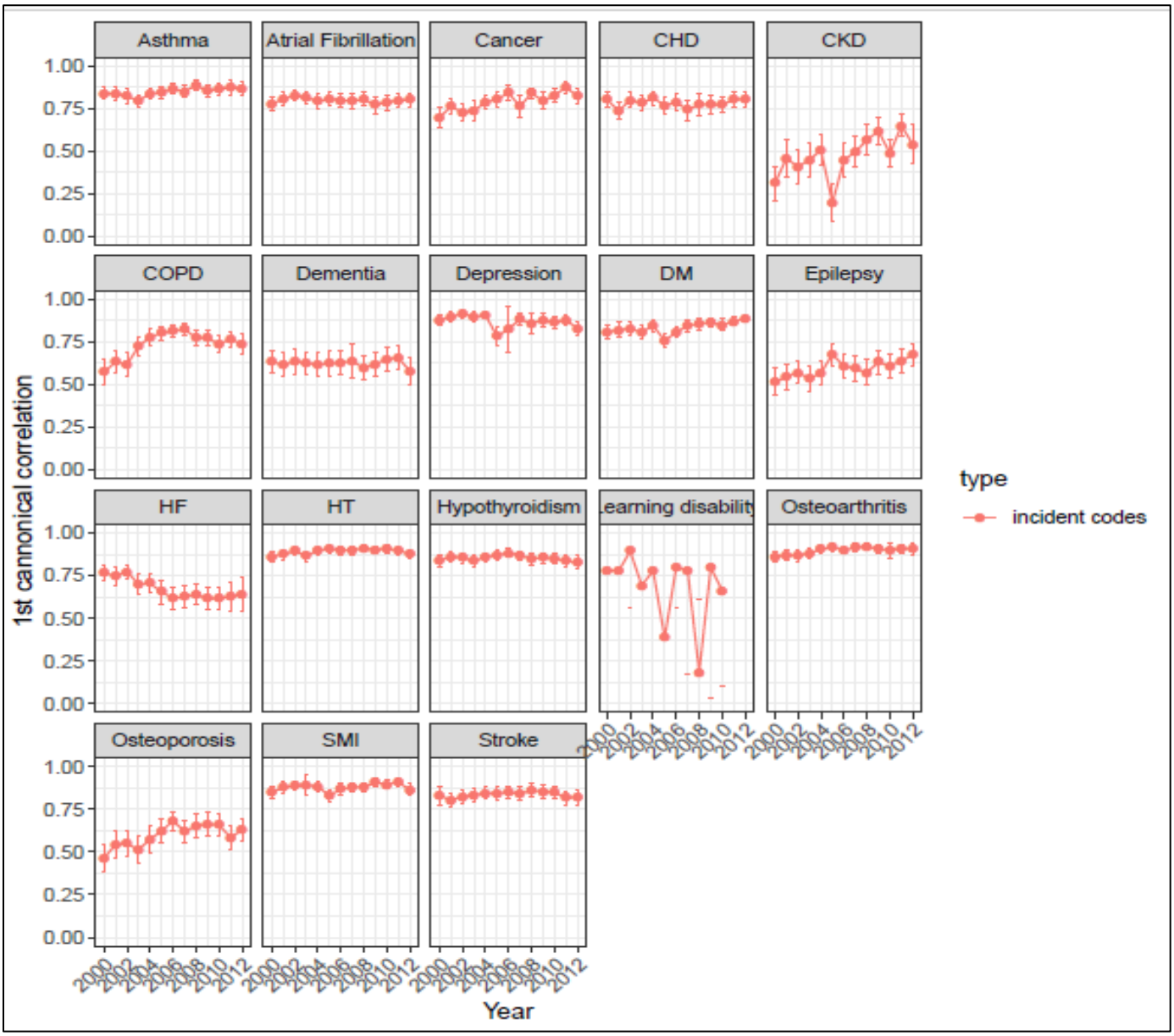
**Figure S2 Canonical correlation using 5-year window of clinical code usage for 18 mental and physical conditions**




CHD, coronary heart disease; CKD, chronic kidney disease; COPD, chronic obstructive pulmonary disease; DM, diabetes mellitus; HF, heart failure; HT, hypertension; SMI, severe mental illness.

Supplementary data to "Clinical code usage in UK general practice: a cohort study exploring 18 conditions over 14 years", Zghebi et al. 2021.

**Figure S3 Jackknife correlation using 1-year window (incident codes) for 18 mental and physical conditions**

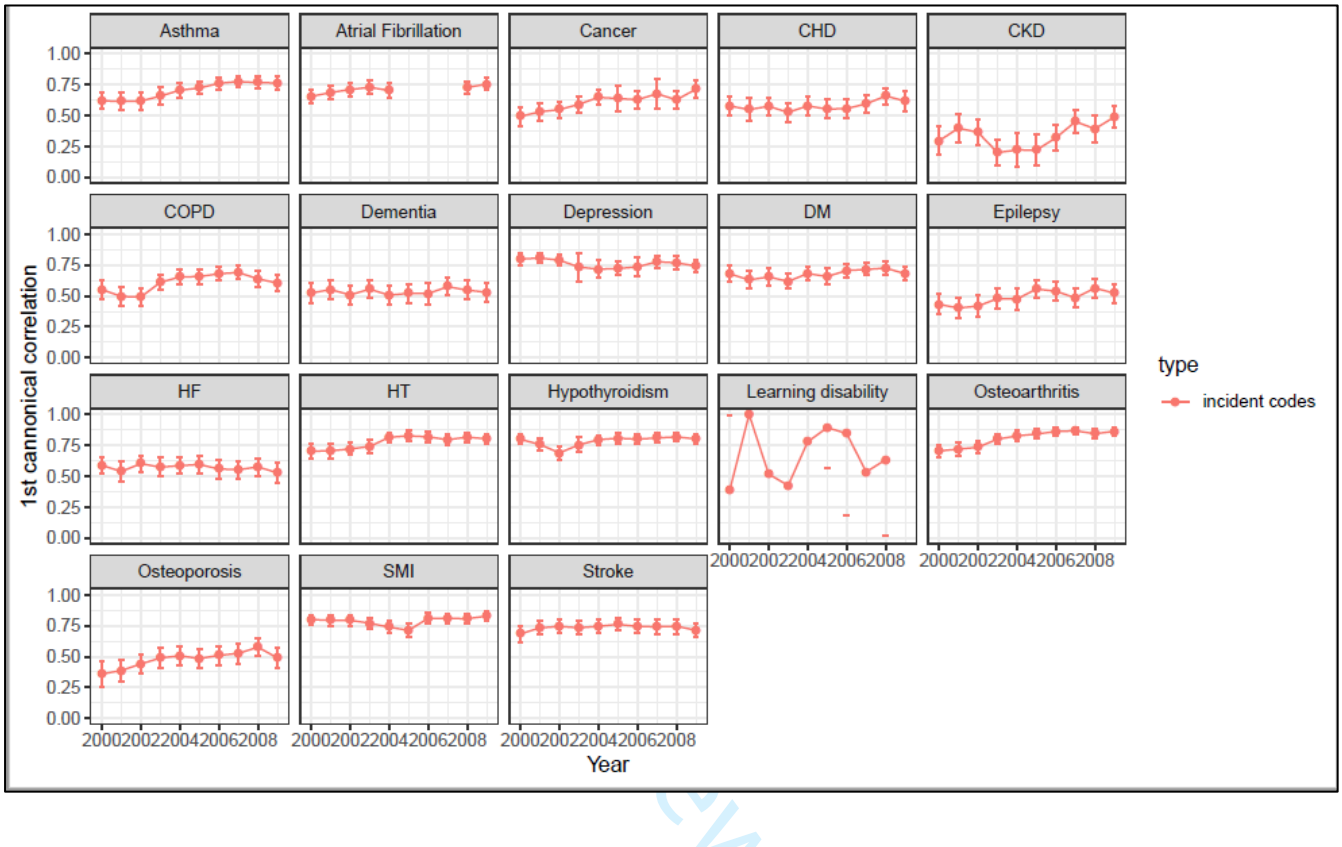



CHD, coronary heart disease; CKD, chronic kidney disease; COPD, chronic obstructive pulmonary disease; DM, diabetes mellitus; HF, heart failure; HT, hypertension; SMI, severe mental illness.

Incident code: a clinical code indicating new (incident) cases.

Supplementary data to "Clinical code usage in UK general practice: a cohort study exploring 18 conditions over 14 years", Zghebi et al. 2021.

**Figure S4 Jackknife correlation using 5-year window (incident codes) for 18 mental and physical conditions**




CHD, coronary heart disease; CKD, chronic kidney disease; COPD, chronic obstructive pulmonary disease; DM, diabetes mellitus; HF, heart failure; HT, hypertension; SMI, severe mental illness.

Incident code: a clinical code indicating new (incident) cases.

**The RECORD statement – checklist of items, extended from the STROBE statement, that should be reported in observational studies using routinely collected health data.**

| | Item No. | STROBE items | Location in manuscript where items are reported | RECORD items | Location in manuscript where items are reported |
|---|---|---|---|---|---|
| **Title and abstract** | | | | | |
| | 1 | (a) Indicate the study's design with a commonly used term in the title or the abstract (b) Provide in the abstract an informative and balanced summary of what was done and what was found | **Title and Abstract** | RECORD 1.1: The type of data used should be specified in the title or abstract. When possible, the name of the databases used should be included.<br><br>RECORD 1.2: If applicable, the geographic region and timeframe within which the study took place should be reported in the title or abstract.<br><br>RECORD 1.3: If linkage between databases was conducted for the study, this should be clearly stated in the title or abstract. | **Abstract**<br><br>**Title and Abstract**<br><br>**Not applicable** |
| **Introduction** | | | | | |
| Background rationale | 2 | Explain the scientific background and rationale for the investigation being reported | **Introduction** | | |
| Objectives | 3 | State specific objectives, including any prespecified hypotheses | **Abstract, Introduction** | | |
| **Methods** | | | | | |
| Study Design | 4 | Present key elements of study design early in the paper | **Methods** | | |
| Setting | 5 | Describe the setting, locations, and relevant dates, including | **Abstract, Methods** | | |

| | | | | | |
|---|---|---|---|---|---|
| | | periods of recruitment, exposure, follow-up, and data collection | | | |
| Participants | 6 | *(a)* ***Cohort study*** - Give the eligibility criteria, and the sources and methods of selection of participants. Describe methods of follow-up<br><br>*(b)* ***Cohort study*** - For matched studies, give matching criteria and number of exposed and unexposed<br>*Case-control study* - For matched studies, give matching criteria and the number of controls per case | **Methods**<br><br>**Not applicable** | RECORD 6.1: The methods of study population selection (such as codes or algorithms used to identify subjects) should be listed in detail. If this is not possible, an explanation should be provided.<br><br>RECORD 6.2: Any validation studies of the codes or algorithms used to select the population should be referenced. If validation was conducted for this study and not published elsewhere, detailed methods and results should be provided.<br><br>RECORD 6.3: If the study involved linkage of databases, consider use of a flow diagram or other graphical display to demonstrate the data linkage process, including the number of individuals with linked data at each stage. | **Methods**<br><br>**Not applicable**<br><br>**Not applicable** |
| Variables | 7 | Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable. | **Methods** | RECORD 7.1: A complete list of codes and algorithms used to classify exposures, outcomes, confounders, and effect modifiers should be provided. If these cannot be reported, an explanation should be provided. | **Methods** (codes available from online repository: clinicalcodes.org) |
| Data sources/ measurement | 8 | For each variable of interest, give sources of data and details of methods of assessment (measurement). | **Methods** | | |

| | | | | | |
|---|---|---|---|---|---|
| | | Describe comparability of assessment methods if there is more than one group | | | |
| Bias | 9 | Describe any efforts to address potential sources of bias | **Methods**<br>Also, the used population (CPRD) is representative of the UK population | | |
| Study size | 10 | Explain how the study size was arrived at | **Methods** | | |
| Quantitative variables | 11 | Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen, and why | **Methods** | | |
| Statistical methods | 12 | (a) Describe all statistical methods, including those used to control for confounding<br>(b) Describe any methods used to examine subgroups and interactions<br>(c) Explain how missing data were addressed<br>(d) ***Cohort study*** - If applicable, explain how loss to follow-up was addressed<br>(e) Describe any sensitivity analyses | **Methods** | | |
| Data access and cleaning methods | | .. | | RECORD 12.1: Authors should describe the extent to which the investigators had access to the database population used to create the study population.<br><br>RECORD 12.2: Authors should provide information on the data cleaning methods used in the study. | **Methods**<br><br>**Not applicable** |

| | | | | | |
|---|---|---|---|---|---|
| Linkage | | .. | | RECORD 12.3: State whether the study included person-level, institutional-level, or other data linkage across two or more databases. The methods of linkage and methods of linkage quality evaluation should be provided. | **Not applicable** |
| **Results** | | | | | |
| Participants | 13 | (a) Report the numbers of individuals at each stage of the study (*e.g.*, numbers potentially eligible, examined for eligibility, confirmed eligible, included in the study, completing follow-up, and analysed)<br>(b) Give reasons for non-participation at each stage.<br>(c) Consider use of a flow diagram | **Not applicable** | RECORD 13.1: Describe in detail the selection of the persons included in the study (*i.e.,* study population selection) including filtering based on data quality, data availability and linkage. The selection of included persons can be described in the text and/or by means of the study flow diagram. | **Methods, Results** |
| Descriptive data | 14 | (a) Give characteristics of study participants (*e.g.*, demographic, clinical, social) and information on exposures and potential confounders<br>(b) Indicate the number of participants with missing data for each variable of interest<br>(c) ***Cohort study*** - summarise follow-up time (*e.g.*, average and total amount) | **Not applicable** | | |
| Outcome data | 15 | ***Cohort study*** - Report numbers of outcome events or summary measures over time | **Results** | | |
| Main results | 16 | (a) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision (e.g., 95% confidence | **Results, Figures 1-5, Figures S1 – S4.** | | |

| | | | | | |
|---|---|---|---|---|---|
| | | interval). Make clear which confounders were adjusted for and why they were included<br>(b) Report category boundaries when continuous variables were categorized<br>(c) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period | | | |
| Other analyses | 17 | Report other analyses done—e.g., analyses of subgroups and interactions, and sensitivity analyses | **Not applicable** | | |
| **Discussion** | | | | | |
| Key results | 18 | Summarise key results with reference to study objectives | **Discussion** | | |
| Limitations | 19 | Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias | **Discussion** | RECORD 19.1: Discuss the implications of using data that were not created or collected to answer the specific research question(s). Include discussion of misclassification bias, unmeasured confounding, missing data, and changing eligibility over time, as they pertain to the study being reported. | **Discussion / Conclusion** |
| Interpretation | 20 | Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence | **Discussion** | | |
| Generalisability | 21 | Discuss the generalisability (external validity) of the study results | **Not applicable** | | |

| **Other Information** | | | | | |
|---|---|---|---|---|---|
| Funding | 22 | Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based | **Funding** | | |
| Accessibility of protocol, raw data, and programming code | | .. | | RECORD 22.1: Authors should provide information on how to access any supplemental information such as the study protocol, raw data, or programming code. | **Methods** (raw data can only by accessed via the CPRD) |

*Reference: Benchimol EI, Smeeth L, Guttmann A, Harron K, Moher D, Petersen I, Sørensen HT, von Elm E, Langan SM, the RECORD Working Committee. The REporting of studies Conducted using Observational Routinely-collected health Data (RECORD) Statement. *PLoS Medicine* 2015; in press.

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# Clinical code usage in UK general practice: a cohort study exploring 18 conditions over 14 years

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# Clinical code usage in UK general practice: a cohort study exploring 18 conditions over 14 years

Salwa S Zghebi,[1,2*] David Reeves,[1,2,3] Christos Grigoroglou,[4] Brian McMillan,[1,2] Darren M Ashcroft,[1,5] Rosa Parisi,[1,6] Evangelos Kontopantelis[1,2,6]

**1** NIHR School for Primary Care Research, Centre for Primary Care and Health Services Research, Manchester Academic Health Science Centre (MAHSC), The University of Manchester, Manchester, UK.

**2** Division of Population Health, Health Services Research and Primary Care, School of Health Sciences, Faculty of Biology, Medicine and Health, Manchester Academic Health Science Centre (MAHSC), The University of Manchester, Manchester, UK.

**3** Centre for Biostatistics, School of Health Sciences, Faculty of Biology, Medicine and Health, Manchester Academic Health Science Centre (MAHSC), The University of Manchester, Manchester, UK.

**4** Manchester Centre for Health Economics, Division of Population Health, Health Services Research and Primary Care, Manchester Academic Health Science Centre (MAHSC), The University of Manchester, Manchester, UK.

**5** Centre for Pharmacoepidemiology and Drug Safety , School of Health Sciences, Faculty of Biology, Medicine and Health, Manchester Academic Health Science Centre (MAHSC), The University of Manchester, Manchester, UK.

**6** Division of Informatics, Imaging, and Data Sciences, School of Health Sciences, Faculty of Biology, Medicine and Health, Manchester Academic Health Science Centre (MAHSC), The University of Manchester, Manchester, UK.

*Correspondence to:
Dr Salwa Zghebi, NIHR School for Primary Care Research, Centre for Primary Care and Health Services Research, Williamson Building, University of Manchester, Manchester M13 9PL, UK. E-mail: salwa.zghebi@manchester.ac.uk

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Number of Figures: 5

## Abstract

### Objectives
To assess the diagnostic Read code usage for 18 conditions by examining their frequency and diversity in UK primary care between 2000 and 2013.

### Design
Population-based cohort study

### Setting
684 UK general practices contributing data to the Clinical Practice Research Datalink (CPRD) GOLD.

### Participants
Patients with clinical codes for at least one of: asthma, chronic obstructive pulmonary disease (COPD), diabetes, hypertension, coronary heart disease, atrial fibrillation, heart failure, stroke, hypothyroidism, chronic kidney disease, learning disability (LD), depression, dementia, epilepsy, severe mental illness (SMI), osteoarthritis, osteoporosis, and cancer.

### Primary and secondary outcome measures
For the frequency ranking of clinical codes, canonical correlation analysis was applied to 1-, 3-, and 5-year correlations of clinical code usage. Three measures of diversity (Shannon entropy index of diversity, richness, and evenness) were used to quantify changes in incident and total clinical codes.

### Results
Overall, all examined conditions except LD, showed positive monotonic correlation. Hypertension, hypothyroidism, osteoarthritis, and SMI codes' usage had high 5-year correlation. The codes' usage diversity remained stable overall throughout the study period. Cancer, diabetes, and SMI had the highest richness (code lists need time to define) unlike atrial fibrillation, hypothyroidism, and LD. SMI (high richness) and hypothyroidism (low richness) can last for 5 years, whereas, cancer and diabetes (high richness) and LD (low richness) only last for 2 years.

### Conclusions
This is an underreported research area and the findings suggest the codes' usage diversity for most conditions remained overall stable throughout the study period. Generated mental health code lists can last for a long time unlike cardiometabolic conditions and cancer. Adopting more consistent and less diverse coding would help improve data quality in primary care. Future research is needed following the transfer to the Systematized Nomenclature of Medicine Clinical Terms (SNOMED CT) coding.



## Keywords

Primary care, clinical codes, electronic health records, QOF, Quality and Outcomes Framework.

## Strengths and limitations of this study

- Our study presents a contemporary longitudinal analysis of clinical code usage in UK primary care, addressing an underreported research area.
- Our findings are relevant to clinical practice as we examined 18 physical and mental conditions as recorded in primary care over 14 years, using data from a large nationally representative database.
- Given the design of the recorded electronic health records, we may have missed some patients with these 18 conditions (such as patients not registered with general practices) which may have affected the observed patterns of clinical code usage.
- Our analysis used CPRD GOLD data, which are obtained from clinical practices with the VISION clinical system, and EMIS and SystmOne practices will be using somewhat different diagnostic codes.

## Introduction

The use of electronic health records (EHRs) has increased rapidly over the last three decades.[1] This has enabled researchers from various disciplines to examine cross-sectional and longitudinal trends of large population medical records to address many clinical research questions. EHRs are increasingly used for clinical management, clinical audits and research with real-world data, applying cross-sectional to longitudinal study designs to address descriptive epidemiology, pharmacoepidemiology, interventions evaluation, and risk prediction modelling.[2,3] The available routinely collected data are far from perfect, but they provide a wealth of high-quality information on patients' clinical conditions, referrals, and medication usage,[4] informing important components of clinical practice such as clinical decision-making.

Since the beginning of medical computing systems usage from early 1970s,[5,6] the UK's primary care systems became fully computerised by 2003.[7,8] This transition was facilitated by Read codes, a comprehensive computerised semi-hierarchical clinical classification system designed for use in EHRs, which are still in use in the UK.[9] These were originally developed by a clinician, Dr James Read, in the early 1980's and became the main coding system for clinical data in the UK from the mid-1990s, succeeding the Oxford Medical Information System (OXMIS) codes that were the most widely used system throughout the 1980s.[10-12] However, the Systematized Nomenclature of Medicine Clinical Terms (SNOMED CT), a systematically organised collection of medical terms, is being rolled out in general practices in a phased approach from April 2018 to replace Read codes, and it includes symptoms, diagnoses, procedures, family history, allergies, and devices.[13,14] With evident increasing complexity of most healthcare disciplines,[15] such clinical terminologies make collated patient records more manageable in clinical practice settings.[16,17] To support users, national standards and guidelines are available on the use of clinical coding.[14,18] Several UK primary care electronic databases exist and are managed by different and varying computer software systems (EMIS, Vision and SystmOne), with Read codes still being the most common system through which to capture primary care clinical information. In the UK, the largest primary care databases available for research purposes include the Clinical Practice Research Datalink (CPRD), The Health Improvement Network (THIN), ResearchOne, and QResearch.[2,8]

Despite the fact that clinical coding is a key point in the daily functionality of routine clinical practice, studies investigating their usage in real-world electronic databases are limited, although the observed variation in coding practice between clinicians.[19] The use of codes is a fundamental aspect of analyses of EHRs, involving a considerable amount of work, through which researchers extract a final dataset to analyse. Clinical codes are commonly used and disseminated in the form of code lists which are compiled according to the purpose, such as diagnostic codes, or family history codes (Table S1). Accurate (high specificity and sensitivity) code lists are imperative in obtaining reliable data on exposures, covariates, and outcomes. Previous systematic reviews have reported overall high accuracy of discharge coding (completed by clinical and/or administrative staff) in UK EHRs data that is improving over time, where in one review accuracy was defined as the agreement between the codes allocated after independently assessing clinical notes (acting as a 'gold' standard) and those recorded on EHRs.[20,21] However, clinical practice changes over time, at varying degrees for different conditions, which is reflected in coding practice with new codes being introduced and others made redundant.

Thus, examining and quantifying the changes in clinical code usage over time is important, since alterations in usage that have not been considered, can have important implications for the analysis of EHRs, resource allocation and may inform public health policy. An example for EHR analysis implication, the use of a two-year old code-list for a given medical condition may or may not be a problem, depending on how much clinical practice has changed over time for that condition. This change in clinical practice may be driven by policy changes, such as better reimbursement for keeping a register of certain conditions. A study examining the variation in clinical code use in UK primary care using six clinical terms, found that searches for the same clinical term across four different computer systems resulted in different results e.g. the mean number of codes per list ranging between 12.7-35.2 codes.[22] This highlighted the need for a more consistent system of code usage, with a recommendation to replace primary care code lists with shorter lists and fewer number of coding choices.[22] Importantly, the UK National Health Service (NHS) introduced the Quality and Outcomes Framework (QOF) in April 2004, a voluntary reward and incentive programme to reward UK general practices providing high-quality care based on a range of evidence-based clinical indicators, for example, management of common chronic conditions such as diabetes and asthma.[23,24,25] Furthermore,

Important revisions were introduced to QOF in April 2006 (covering up to March 2007)[26,27] including adding new indicators for diabetes, amending diabetes clinical indicator sets, and redefining the diabetes register so general practitioners required to identify patients with diabetes as either having type 1 or type 2 diabetes, which have potentially increased the capture of diabetes cases on that period. In this study, we used data from the UK CPRD GOLD database to examine the: 1) frequency ranking of diagnostic clinical codes for 18 physical and mental health conditions; 2) changes in the usage of individual clinical codes (incident vs. total codes) for these conditions between 2000-2013 covering the period before and after the launch of the QOF.

## Methods

### Data source and study design

We used data from the GOLD database of the UK Clinical Practice Research Datalink (CPRD), which comprises of data from contributing anonymised general practices using the VISION clinical computer system.[28] The CPRD is one of the world's largest longitudinal electronic medical databases providing anonymised data from primary care, and is broadly representative of the UK population.[8,29] The CPRD is structured to provide data on clinical information, referrals, consultations, immunisation, tests and prescribed therapies. Up to July 2013, the CPRD held data for 11.3 million patients registered in 674 general practices. Of these, 4.4 million were active patients (representing 6.9% of the total UK population), and 6.9 million records represent inactive patients (people who have died or are no longer registered with a participating general practice).[29]

Using financial year intervals between 01/04/2000-31/03/2013, we examined the changes in the use of diagnostic clinical codes for 18 exemplar medical conditions in UK practices: asthma, chronic obstructive pulmonary disease (COPD), diabetes (DM) both types, hypertension (HT), coronary heart disease (CHD), atrial fibrillation (AF), heart failure (HF), stroke, hypothyroidism, chronic kidney disease (CKD), learning disability (LD), depression, dementia, epilepsy, severe mental illness (SMI), osteoarthritis, osteoporosis, and cancer. The diabetes codes included those with complications if clearly linked to diabetes, such as 'type 2

diabetes mellitus with nephropathy' (Table S1). The selected conditions, apart from osteoarthritis, were included in the QOF scheme from 2004, whereas AF, CKD, dementia, depression, and LD were incentivised from 2006, and osteoporosis incentivised from 2012. This allowed us to examine and compare QOF conditions (incentivised at different stages) plus a condition not part of the QOF (osteoarthritis).

The clinical codes used to define the examined conditions are listed in the Clinical Codes online repository.[30] Each condition was examined as an incident code (using codes to identify new cases) and total codes (incident and prevalent cases) for each year during the study period.

## Data analysis

To examine the consistency of clinical code use across time, we applied canonical correlation analysis (CAA)[31,32] to estimate 1-year (e.g. 2006 to 2007), 3-year (e.g. 2006 to 2009), and 5-yearly canonical correlations (e.g. 2006 to 2011) for code usage for each of the 18 conditions based on ranking the percentage frequency use of codes. CCA is a descriptive multivariable method that provides a measure of the canonical correlation (CC) between two groups of variables or two data matrices that should be numerically complete and non-missing. CCA finds the best linear combinations maximizing the correlation ($\gamma_1$) between $p$ variables in group 1 and $q$ variables in group 2, where the variables are measured across a common set of units (e.g. general practices): [33]

$$Y^1 = (Y_1^1, \cdots, Y_p^1) \text{ (1)}$$

$$Y^2 = (Y_1^2, \cdots, Y_q^2) \text{ (2)}$$

Where $Y^1$ represents the set of $p$ outcomes in group 1, and $Y^2$ the set of $q$ outcomes in group 2. Consider the two linear combinations $\alpha' Y^1$ and $b' Y^2$, where $\alpha'$ is a $p\ x\ 1$ vector of weighting coefficients and $b'$ is likewise a $q\ x\ 1$ vector; the CC ($\gamma_1$) is given by the choice of $\alpha'$ and $b'$ that maximises the correlation between $\alpha' Y^1$ and $b' Y^2$: [33]

$$\gamma_1 = \max_{a,b} Corr(a' Y^1, b' Y^2) = \max_{a,b} \frac{a' \Sigma_{12} b}{\sqrt{a' \Sigma_{11} a b' \Sigma_{22} b}} \text{ (3)}$$

Where $\Sigma_{11} = Cov(Y^{(1)}, Y^{(1)})$; $\Sigma_{12} = Cov(Y^{(1)}, Y^{(2)})$; and $\Sigma_{22} = Cov(Y^{(2)}, Y^{(2)})$. (4)

In the present study, for a given practice the Y's represent the relative use of each clinical code for a particular condition, expressed as a percentage of the total use across all codes for that condition. For example, for the 2006-2007 year-on-year diabetes correlation, the Y's represents the relative use of each diabetes code expressed as a percentage of the total use across all diabetes codes, where group 1 (represented by $Y^1$) would be the percentage frequency use of each clinical code for diabetes recorded in year 2006; whereas group 2 (represented by $Y^2$) would be the corresponding percentage frequency use for each corresponding diabetes code recorded in year 2007, at the general practice level. The same applies for the 3-year and 5-year correlations.

We analysed percentage frequencies rather than frequency counts so as to remove any effects of variations in practice size or disease prevalence from the estimated CCs. CCs were calculated using the R statistical software ccaPP package[34] with the "Spearman" method, by which the weighted linear combinations $\alpha' Y^1$ and $b' Y^2$ for each year are ranked across practices prior to computation of the correlation. This method produces estimates that are more robust against model misspecification.[35]

Numbers of incident clinical codes could be small for some conditions and practices, which can lead to biased estimates of the CCs. To adjust for this, we applied the Jackknife bias correction to the estimation of CCs for the incidence of clinical codes.[33]

For each of the 18 conditions, we also quantified changes in incident and total clinical code usage applying three measures of diversity. First, the Shannon entropy ($H$), an equitability and popular index of diversity. The index is interchangeably referred to as Shannon entropy or Shannon index where the term 'entropy' indicates the uncertainty or variability of information in a variable whose diversity is assessed by the Shannon index. The Shannon entropy index ($H$) was calculated as:

$$H = -\sum_i (p_i \ln p_i)$$

Where $p_i$ is the proportion of a clinical code *i* usage in a given year.

Second, we examined the richness ($S$) of clinical code usage by calculating the annual total number of incident and all codes used in a given year. Third, we estimated the evenness ($J$)

of incident and total codes' usage, a measure of the relative usage of codes within a given year, in other words evenness will be high if all codes have a similar distribution (e.g. 100 diabetes records based on using 4 different diabetes codes, 25 times each) whereas it will be low if a few codes dominate the code usage (e.g. 100 diabetes records based on using one code 70 times and another code 30 times). $J$ ranges between zero and one, with $J = 0$ indicating no evenness, and $J = 1$ indicating complete evenness. Evenness was calculated annually by dividing Shannon index ($H$) over the natural logarithm of richness ($S$).

$$J = \frac{H}{\ln(S)}$$

To simplify what these diversity measures imply, we describe a hypothetical example: if diabetes was represented using three diagnostic codes: code A (used 100 times), code B (used 175 times), and code C (used 350 times), then the proportions of codes would be 0.16, 0.28, and 0.56, respectively. Shannon's entropy index ($H$) will be = -1*((0.16*ln0.16) + (0.28*In0.28) + (0.56*In0.56)) = 0.97; richness ($S$) = 3; and evenness ($J$) = 0.97/ln (3) = 0.88. All analyses were conducted using R software,[36] and were visualised using the ggplots2 package. A copy of the R code is presented in Table S2.

## Patient and Public Involvement

No patients or members of the public were involved in this study.

## Results

### Clinical code frequency ranking

Correlation of code usage over a 3-year period showed a positive association for most conditions (Figure 1). Strong, overall positive, and monotonic correlation (CC >0.7) was observed for depression, hypertension, hypothyroidism, osteoarthritis, SMI, and stroke. Positive, monotonic but weaker associations were observed for CKD, epilepsy, and osteoporosis. Learning disability (LD) showed a non-monotonic function with fluctuations ranging between 0.4-1.0, and a notable decline after 2004 before increasing again from 2007.

The 1-year and 5-year windows correlations showed similar overall trends, but the association was slightly decreasing as the window increases. Clinical conditions with the highest correlation levels were asthma, AF, cancer, CHD, depression, diabetes, hypertension, hypothyroidism, osteoarthritis, SMI, and stroke for the 1-year window (Figure S1). For the 5-year window, hypertension, hypothyroidism, osteoarthritis, and SMI codes' usage was overall highly correlated mainly in recent years (Figure S2). On the other hand, conditions with the lowest correlations (CC ≤0.6) were CKD and LD (for most years) for the 1-year window; and cancer, CHD, CKD, COPD, dementia, diabetes, epilepsy, HF, LD, and osteoporosis for the 5-year window.

Over a 3-year window, strong correlation for incident code usage (Jackknife bias corrected CC≥0.6) were observed for all examined conditions except CKD, epilepsy, and osteoporosis (Figure 2). Similarly, the 1-year and 5-year windows correlations showed similar trends but lower coefficients with longer windows (Figures S3 and S4, respectively).

### Clinical code usage diversity

Data from 684 UK general practices contributing to the Clinical Practice Research Datalink (CPRD) GOLD were used. Overall, the diversity indices of code usage were stable over the study period for most conditions, but with wide confidence intervals. Higher entropy ($H$) indices were observed with cancer, diabetes, and SMI ($H$ between 2-4), while the lowest levels were observed with LD and osteoporosis ($H$ between 0-2) (Figure 3). Over time, the entropy index of code usage remained stable for most conditions, but increased gradually for asthma, COPD, diabetes, heart failure, and osteoporosis (primarily incident codes). Fluctuations and/or a separation between the incident and total codes trends were observed around 2006, mainly for AF, dementia, depression, CKD, and LD. The Shannon index ($H$) for incident codes had a similar trend to that for total codes for most conditions over time, except for cardiovascular disease (CVD) and diabetes where it exceeded total codes.

Across the examined conditions, the richness ($S$) of incident and total code usage (number of codes used) was the highest for cancer (>500 codes), diabetes and SMI (≥250 codes each) and the lowest for AF, hypothyroidism, and LD ($S$ <100) (Figure 4). The trends however remained stable throughout the study period, except a small decrease for SMI codes and a decrease in

cancer after a brief rise between 2000-2005. The difference between the number of incident and total codes for SMI, diabetes and cancer were evident (total codes more than incident codes), unlike in the other conditions where the $S$ index was similar for both code categories.

The evenness ($J$) of both incident and total codes was overall stable and almost identical at least up to 2006, before total codes surpassed incident codes for most conditions except for depression and dementia where the $J$ index for incident codes exceeded that of total codes (Figure 5). The two exceptions to this observation were LD and CKD. For LD, evenness was stable ~0.75 between 2000-2003, declined in 2004 before re-increasing from 2007 and returning to pre-2004 levels from 2011 onwards. For CKD, evenness dipped briefly around 2006-2007 and started to increase again from 2008 until the end of the study period (2013). Given the calculation formula, it is worth noting that the trends of entropy were similar to that of evenness for conditions with low richness, namely for AF, dementia, heart failure, hypertension, hypothyroidism, LD, osteoarthritis, and osteoporosis.

## Discussion

### Main findings

We assessed the clinical code usage for 18 conditions recorded in a large nationally representative UK EHR between 2000 and 2013. The results show overall strong positive monotonic correlation for all examined conditions except LD, that showed a fluctuating pattern during the study period. The CCs diminished over longer windows (5-year vs. 1-year window). Hypertension, hypothyroidism, osteoarthritis, and SMI had the highest 5-year correlation, mainly in later years of the study period.

The codes' usage entropy and evenness diversity measures remained overall stable throughout the study period for most conditions, except gradual increases over time for respiratory conditions, diabetes, HF, and osteoporosis. This increase in diversity may be partially due to the regular addition of new diagnostic codes and domains over time. For example, major revisions were introduced to the QOF in April 2006 resulting in the addition of new clinical areas and indicators.[27] As a consequence, CKD is among the conditions that it has been acknowledged to have benefited from these revisions as the CKD domain was added in 2006 reflected in improved recording in primary care from that year onwards.[37] For most

conditions (except LD), evenness (indicating the abundance of codes in a sample) was overall ≥0.5 suggesting a uniform distribution of the codes. Cancer, diabetes, and SMI had the highest richness indices among all examined conditions.

### Comparison with previous studies

Observational studies examining variations in clinical code usage are limited. A recent study examined the code usage of CVD between 2001-2015 in primary and secondary care records in England.[38] The study aimed to examine if temporal variability methods can identify changes in CVD recording by quantifying the differences of monthly distributions of the variables of interest: CVD status and sociodemographic variables. The study found variability in the frequency of CVD codes across time, potentially due to non-medical causes such as changes in coding used and coding guidelines e.g. changes in ICD (international classification of disease) coding in hospital records. Despite relevance, their approach (examining the prevalence of CVD stratified by patient demographic variables) differs from our methods and hence the results are not directly comparable. In addition, we examined code usage for 18 conditions, including CVD, from UK general practices.

A study by Tai et al. (2007) examined the diversity of data entry screens in four clinical computer systems available in UK general practices and assessed its impact on the variation and quality of recorded clinical data for six exemplar conditions (sore throat, tired all the time, depression, cystitis, type 2 diabetes, and myocardial infarction).[22] In agreement with what we report on the large number of available codes for some conditions (high richness), Tai and colleagues found that searches for the same clinical term across the systems resulted in different results and found long code lists where the mean number of codes ranged between 12.7 and 35.2 codes per list.[22] Their study concluded that the systems may contribute towards a diverse coding in primary care, suggesting the need to standardise clinical coding across systems and to adopt shorter and more restricted code lists to help improve data quality. This is an important issue for UK primary care, since the semi-structured and dynamic nature of Read codes often results in diverse and long clinical code lists. Their findings highlight the need for analyses as ours, which are lacking in current literature, investigating the real-world abundance and trends of code usage over time derived from routine clinical data. Additionally, some general practice systems use CTV3 clinical codes and not Read codes

resulting in the availability of two versions of clinical codes. SNOMED CT system, which is gradually being implemented across UK primary care from 2018, aimed to provide a single clinical terminology for effective and consistent exchange of clinical data across all NHS settings to help improve patient care and data analysis.[39] Being an international clinical terminology, SNOMED will allow the UK to participate in global health care research.

Our results showed that diabetes codes usage (types 1 and 2) had one of the highest richness index levels (number of codes used), while the diversity entropy index was steadily increasing over the study period, highlighting the increasing variety of diabetes codes used in primary care over time. This observation agrees with a previous study that examined the Read codes used to identify diabetes management in people with diabetes registered with 17 general practices in one locality in London.[11] That study concluded that a wide range of diabetes codes were used and that the number of people assigned each code differed across practices. This again indicates that an approach is required to standardise clinical code lists and thereby coding usage as much as possible, minimise clinical recording errors, and improve research robustness.

### Implication of findings

Our findings shed additional light on the use of clinical codes in research. We found that hypertension, hypothyroidism, osteoarthritis, and SMI codes' usage are highly correlated over the 5-year window (i.e. the codes' usage was similar across years), whereas cancer, CHD, CKD, COPD, dementia, diabetes, epilepsy, HF, LD, and osteoporosis had lowest correlation over the same window. In terms of clinical code lists' size required to define a condition (richness), we found that conditions with the highest richness across the study period were cancer, diabetes, and SMI (between 250-875 codes), whereas AF, hypothyroidism, and LD had the lowest richness (<100 codes). Collectively, these findings indicate that diabetes, cancer, and SMI codes have high richness and need to be defined carefully and then they can either last for 5 years (SMI), or only to 2 years (diabetes and cancer). Whereas hypothyroidism has low code usage richness and can last for 5 years. This might be due to that diabetes is often a target of government initiatives, unlike hypothyroidism which is rarely a focus of such interventions.

The results suggest that defining cohorts of people with mental health conditions (SMI, depression) over time was less sensitive to the changes of code usage (up to 5 years old) compared with most cardiometabolic conditions and cancer.

The observed findings also suggest the need to adopt a more consistent and less diverse coding in primary care, as this will help improve data quality. Inconsistent use of clinical coding may result in people with the same condition not being flagged as having the condition,[19] which may have implications on searching and identifying these people for clinical and research purposes, or to identify people for shielding measures or those who are a priority for a vaccination as in the current COVID-19 pandemic. While acknowledging that SNOMED CT is gradually replacing Read codes in general practice care since April 2018, our findings are still relevant in documenting the clinical code usage over a long period where Read codes were the main UK coding system. There is potential for SNOMED CT terminology to improve coding consistency, mainly through the plan to implement it in both primary care and secondary care systems.[40] However, a possible issue with SNOMED terminology is the need for specialist browser and reference sets, such as the general practice reference set to handle the long hierarchies of SNOMED system.[40] A reference set is a mechanism that can be employed to represent value sets of SNOMED CT components.[41]

Also, the rapidly increasing complexity of healthcare systems[15] might play a role on the observed trends in code usage over time. In other words, code usage practices (e.g. the tendency of data enterer to use easily accessed and well-known codes) may be partially driven by personal and work factors in the complex healthcare systems such as limited time and organisational factors. A possible relationship between clinical code selection and epidemiology of chronic conditions has been reported previously, for example, for diabetes.[19,42] From general practitioners (GPs) stance, one thing that may have changed in recent years is the coding of people being at "High risk of diabetes mellitus" and it is something that GPs are increasingly aware of (i.e. people with $HbA_{1c}$ 42-47 mmol/mol).

### Strengths and limitations of the study

Our study has several strengths. Using a range of frequency and diversity measures, we present a contemporary longitudinal analysis of clinical code usage in UK primary care, while only a few existing studies have addressed this research area. We used data from a large nationally representative database, where the validity of recorded diagnostic coding has been

acknowledged previously.[43] Additionally, the data quality is assumed to be high, as it is based on QOF clinical codes lists (except osteoarthritis). Our findings are relevant to clinical practice as we examined a broad range of prevalent physical and mental illnesses as recorded in primary care and considered the clinical implications of variations in clinical coding over 14 years.

Our study has also several limitations. Given the design of the recorded EHRs, we may have missed some patients with the examined conditions due to some unusual circumstances or settings, such as patients not registered with general practices (e.g. homeless people), which may have affected the observed patterns of clinical code usage. Also, analyses were not extended to examine ICD-10 clinical codes in secondary care setting (only available in England), as our aim was to focus on the usage of Read codes recorded in UK primary care visits as the main point of clinical care. CCA provides a single multivariate measure of correlation, thus simplifying interpretation compared to analysing each clinical code separately. However, the measure represents the maximum possible correlation between frequencies of code use at two different time points and does not account for the code set being the same at both times, hence may over-represent actual agreement to a degree. This is an intrinsic limitation of CCA is that it does not consider the 'code' per se but its frequency, so it would return high correlation for possible scenarios such as if a code merges at a time point with another code into a single code, or if, hypothetically, all practices transition from one code to another at the same time. As CCA is based on the correlation of two positive-definite matrices of data that should be numerically complete, problematic quality and levels of recording as observed with AF and LD recording on some time points results in missing values as observed in e.g. Figures 1, 2 and S4. In addition, although the clinical relevance of the examined conditions which are also prevalent outside UK, such as diabetes, CVD, and cancer, and that our findings highlight the need of consistent coding lists applies for non-UK national health system with established or aiming to develop electronic clinical coding, our study may have limited generalisability to non-UK systems. Finally, we used CPRD GOLD which collects data from general practices using the VISION clinical system, and code usage will vary to some extent in general practices using EMIS or SystmOne. However, we would expect such variation to be low in chronic conditions incentivised through the QOF, with specific common code lists used by practices to ensure remuneration eligibility.

## Conclusions

The code usage in UK primary care was overall stable for most of the examined chronic conditions managed in general practice between 2000 and 2013, but, as would be expected, the changes were higher over longer time windows. Diabetes, cancer, and SMI code lists have high richness and need to be defined carefully by researchers and/or clinicians which might be considerably time-consuming, but once defined SMI codes can last up to 5 years, while diabetes and cancer codes only for 2 years. On the other hand, hypothyroidism has low richness but also can last up for 5 years. Our study addresses an underreported research area and the findings suggest the need to adopt a more consistent and less diverse coding in primary care to help improve data quality and the use of recent codes for cardiometabolic conditions and cancer. More research is needed in this area following the full transfer to the SNOMED CT coding and to examine the code usage in secondary care settings.

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## Competing interests

DMA reports research grants from Abbvie, Almirall, Celgene, Eli Lilly, Novartis, UCB and the Leo Foundation. Other co-authors declare no competing interests.

## Author contribution

EK and DAS designed the study. DAS extracted the data from all sources and performed the initial analyses. RP and SSZ validated the analyses; RP developed the final figures. SSZ wrote the manuscript and EK, RP, DR, and CG critically edited the initial drafts; DMA and BM contributed to interpretation of data and revised the paper for important intellectual content. All authors agreed on the final version of the paper before submission. SSZ is the guarantor of this work and, as such, had full access to all the data in the study and takes responsibility for the integrity of the data and the accuracy of the data analysis.

## Patient consent

Not applicable.

## Data sharing

Clinical code lists are available from clinicalcodes.org. Electronic health records are, by definition, considered sensitive data in the UK by the Data Protection Act and cannot be shared via public deposition because of information governance restriction in place to protect patient confidentiality. Access to data is available only once approval has been obtained through the individual constituent entities controlling access to the data. The data can be requested via application to the Clinical Practice Research Datalink.

## Transparency declaration

SSZ affirms that the manuscript is an honest, accurate, and transparent account of the study being reported; that no important aspects of the study have been omitted; and that any discrepancies from the study as planned (and, if relevant, registered) have been explained.

## Ethical approval

This study is based on data from Clinical Practice Research Datalink (CPRD) obtained under licence from the UK Medicines and Healthcare products Regulatory Agency. The study was approved by the Independent Scientific Advisory Committee (ISAC) for MHRA Database Research (protocol number: 16_115). The data are provided by patients and collected by the NHS as part of their care and support. Generic ethical approval for observational research

using CPRD with approval from ISAC has been granted by a Health Research Authority (HRA) Research Ethics Committee (East Midlands—Derby, REC reference number 05/MRE04/87).

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## Figure legends

### Figure 1 Canonical correlations using 3-year window of clinical code usage for 18 mental and physical conditions

CHD, coronary heart disease; CKD, chronic kidney disease; COPD, chronic obstructive pulmonary disease; DM, diabetes mellitus; HF, heart failure; HT, hypertension; SMI, severe mental illness. The red line represents the launching year of the QOF in 2004.

### Figure 2 Bias-corrected canonical correlations (95%CI) using 3-year window for incident clinical code usage for 18 mental and physical conditions

CHD, coronary heart disease; CKD, chronic kidney disease; COPD, chronic obstructive pulmonary disease; DM, diabetes mellitus; HF, heart failure; HT, hypertension; SMI, severe mental illness.
Incident code: a clinical code indicating new (incident) cases. The red line represents the launching year of the QOF in 2004.

### Figure 3 Entropy (95% CI) of incident and all clinical code usage for 18 mental and physical conditions

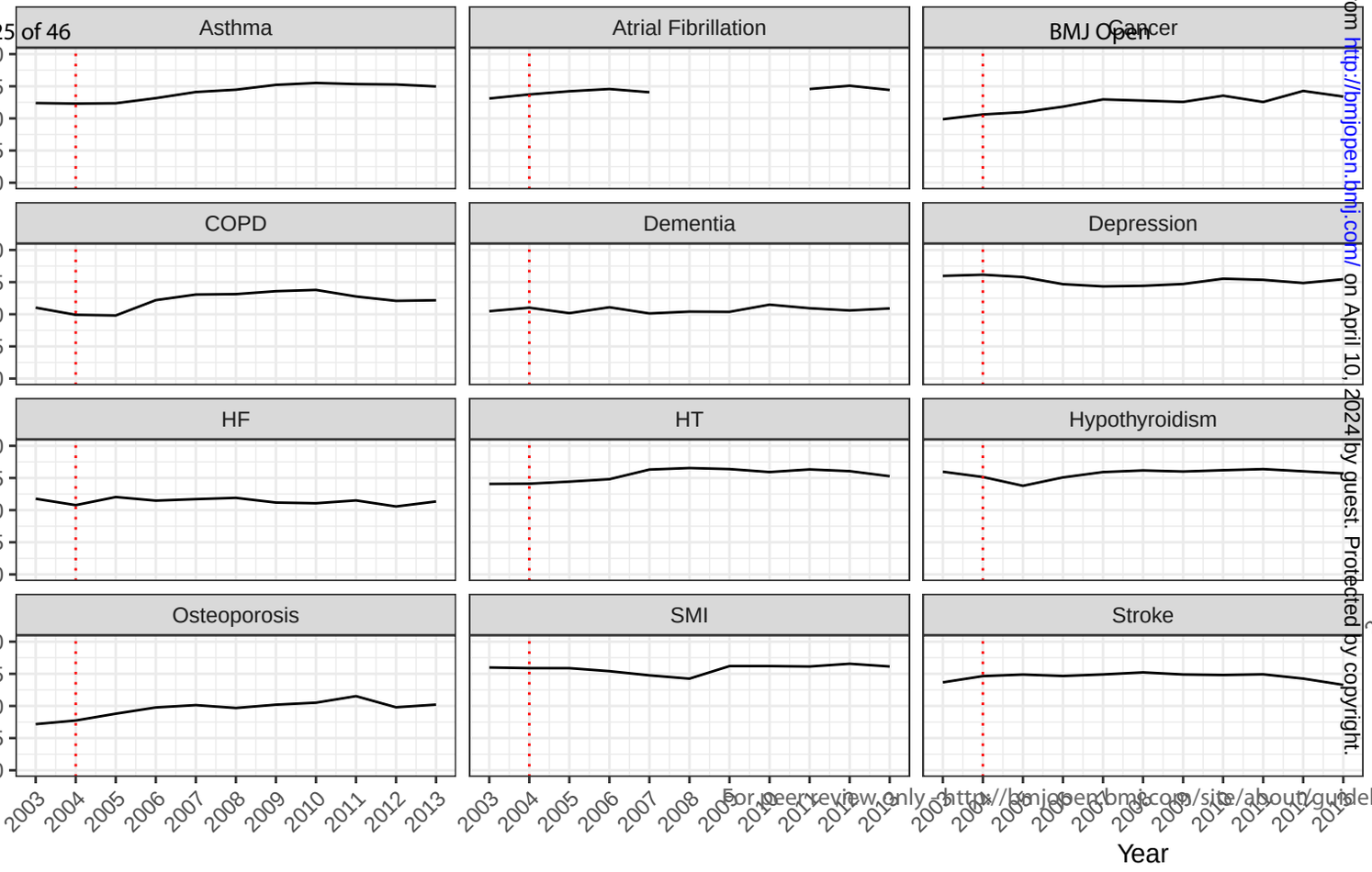
CHD, coronary heart disease; CKD, chronic kidney disease; COPD, chronic obstructive pulmonary disease; DM, diabetes mellitus; HF, heart failure; HT, hypertension; SMI, severe mental illness.
Incident code: a clinical code indicating new (incident) cases. All codes: any diagnostic clinical code for the condition incident and prevalent cases). The red line represents the launching year of the QOF in 2004. The 95% CIs were calculated as the mean +/- 1.96*SE (SE has been estimated using Jackknife approach).

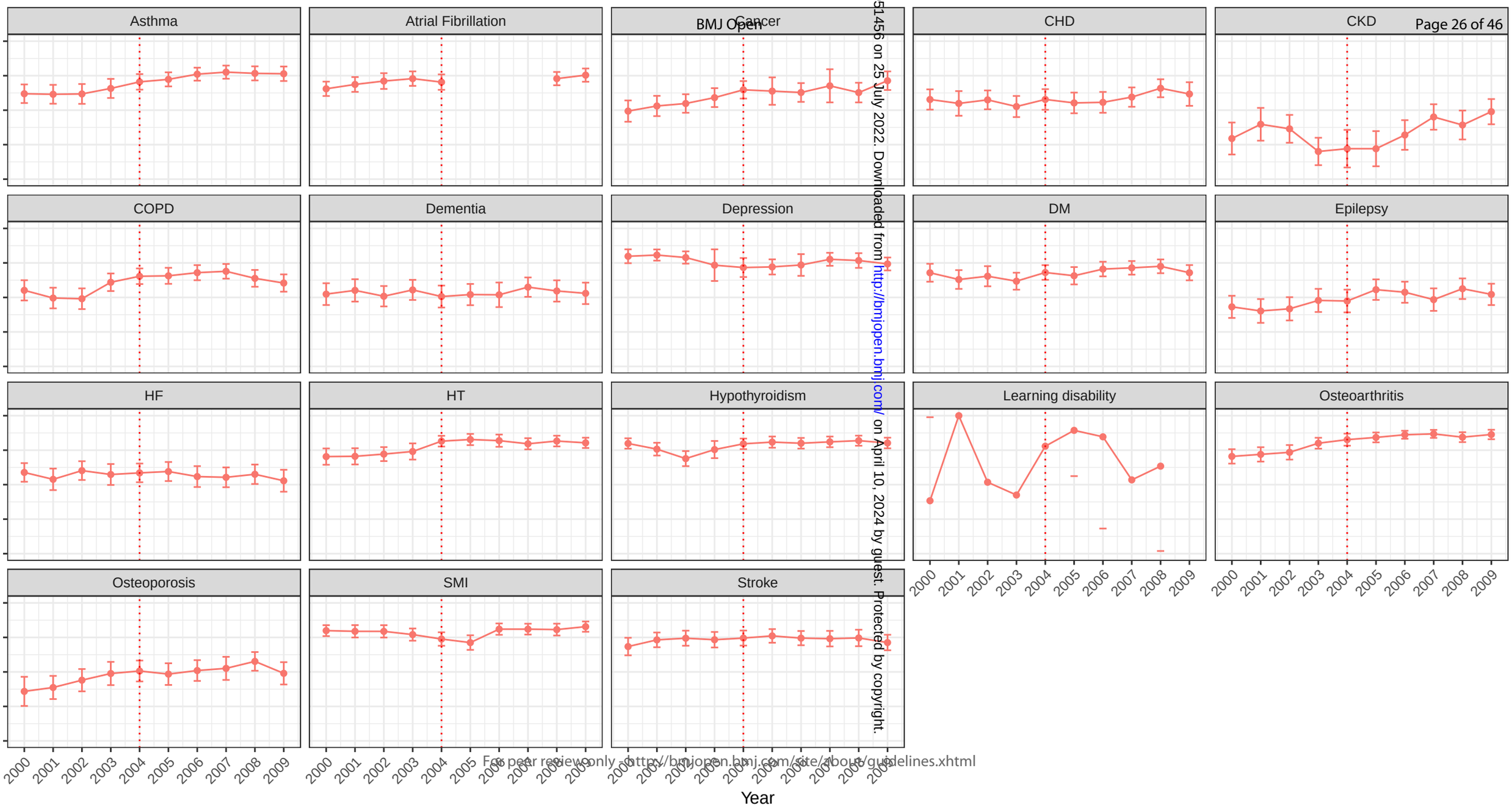
### Figure 4 Richness of incident and all clinical code usage for 18 mental and physical conditions

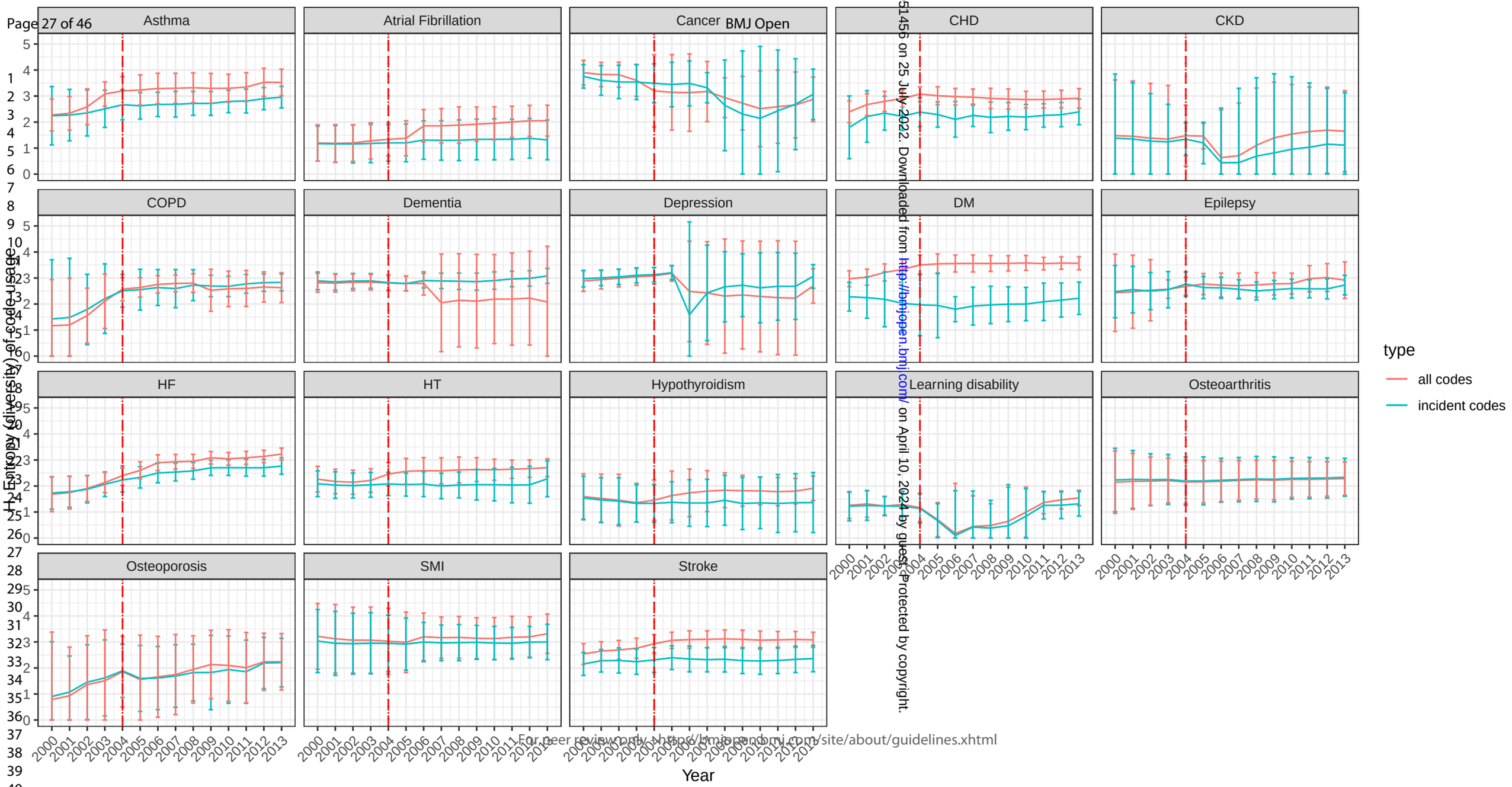
CHD, coronary heart disease; CKD, chronic kidney disease; COPD, chronic obstructive pulmonary disease; DM, diabetes mellitus; HF, heart failure; HT, hypertension; SMI, severe mental illness.
Incident code: a clinical code indicating new (incident) cases. All codes: any diagnostic clinical code for the condition incident and prevalent cases). The red line represents the launching year of the QOF in 2004.

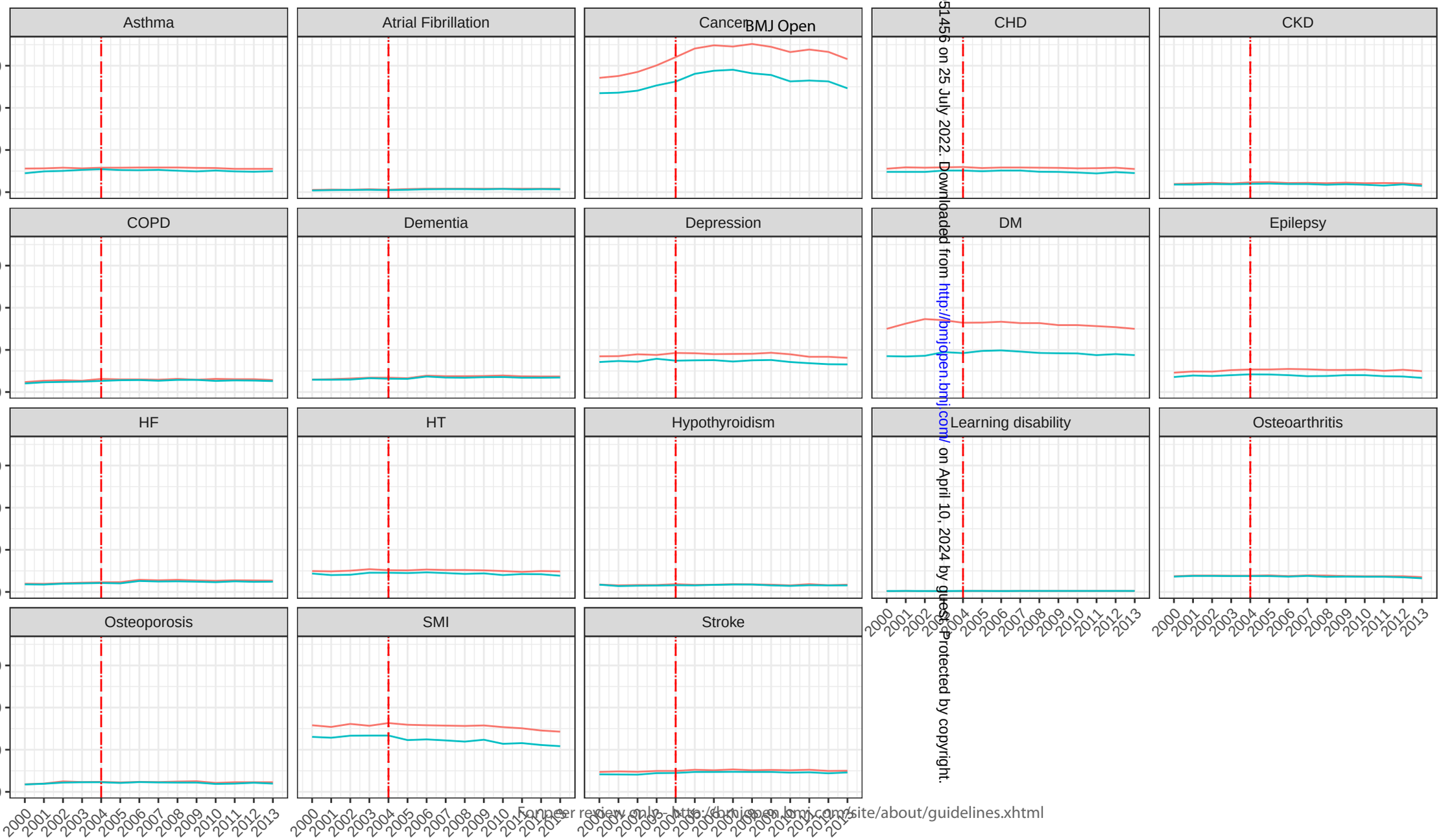
### Figure 5 Evenness (95% CI) of incident and all clinical code usage for 18 mental and physical conditions

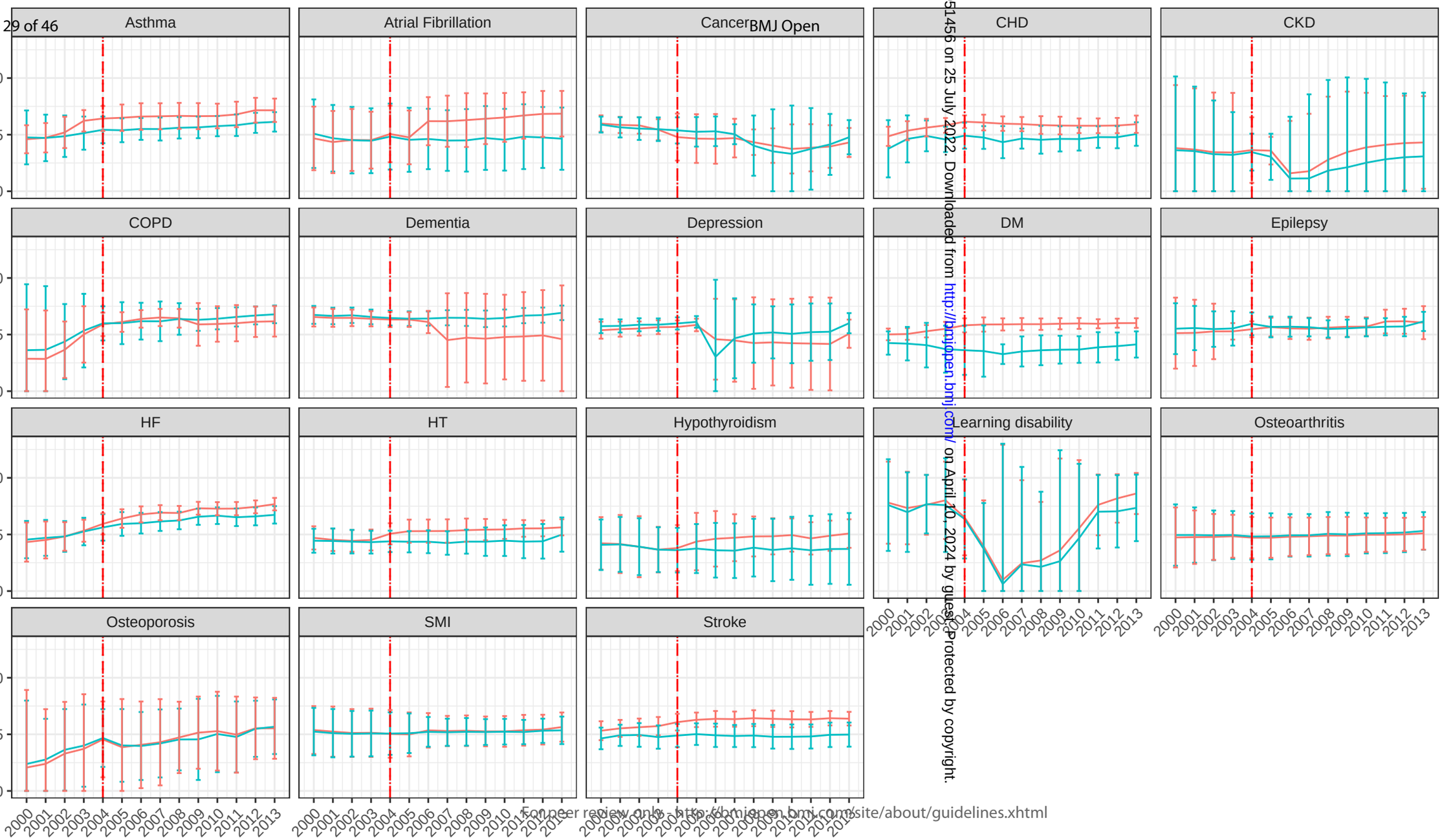
CHD, coronary heart disease; CKD, chronic kidney disease; COPD, chronic obstructive pulmonary disease; DM, diabetes mellitus; HF, heart failure; HT, hypertension; SMI, severe mental illness.
Incident code: a clinical code indicating new (incident) cases. All codes: any diagnostic clinical code for the condition incident and prevalent cases). The red line represents the launching year of the QOF in 2004. The 95% CIs were calculated as the mean +/- 1.96*SE (SE has been estimated using Jackknife approach).











Supplementary data to "Clinical code usage in UK general practice: a cohort study exploring 18 conditions over 14 years", Zghebi et al. 2021.

# Supplementary data

Supplementary data to "Clinical code usage in UK general practice: a cohort study exploring 18 conditions over 14 years", Zghebi et al. 2021.

## Table S1 Diabetes Read code list

| | Code | Coding system | Description |
|---|---|---|---|
| 1. | 66A3.00 | Read | Diabetic on diet only |
| 2. | 66A4.00 | Read | Diabetic on oral treatment |
| 3. | 66A5.00 | Read | Diabetic on insulin |
| 4. | 66AI.00 | Read | Diabetic - good control |
| 5. | 66AJ.00 | Read | Diabetic - poor control |
| 6. | 66AJ100 | Read | Brittle diabetes |
| 7. | 66AJ.11 | Read | Unstable diabetes |
| 8. | 66AJz00 | Read | Diabetic - poor control NOS |
| 9. | 66AK.00 | Read | Diabetic - cooperative patient |
| 10. | 66AL.00 | Read | Diabetic-uncooperative patient |
| 11. | 66AV.00 | Read | Diabetic on insulin and oral treatment |
| 12. | C10..00 | Read | Diabetes mellitus |
| 13. | C100.00 | Read | Diabetes mellitus with no mention of complication |
| 14. | C100000 | Read | Diabetes mellitus; juvenile type; no mention of complication |
| 15. | C100011 | Read | Insulin dependent diabetes mellitus |
| 16. | C100100 | Read | Diabetes mellitus; adult onset; no mention of complication |
| 17. | C100111 | Read | Maturity onset diabetes |
| 18. | C100112 | Read | Non-insulin dependent diabetes mellitus |
| 19. | C100z00 | Read | Diabetes mellitus NOS with no mention of complication |
| 20. | C101.00 | Read | Diabetes mellitus with ketoacidosis |
| 21. | C101000 | Read | Diabetes mellitus; juvenile type; with ketoacidosis |
| 22. | C101100 | Read | Diabetes mellitus; adult onset; with ketoacidosis |
| 23. | C101y00 | Read | Other specified diabetes mellitus with ketoacidosis |
| 24. | C101z00 | Read | Diabetes mellitus NOS with ketoacidosis |
| 25. | C102.00 | Read | Diabetes mellitus with hyperosmolar coma |
| 26. | C102000 | Read | Diabetes mellitus; juvenile type; with hyperosmolar coma |
| 27. | C102100 | Read | Diabetes mellitus; adult onset; with hyperosmolar coma |
| 28. | C102z00 | Read | Diabetes mellitus NOS with hyperosmolar coma |
| 29. | C103.00 | Read | Diabetes mellitus with ketoacidotic coma |
| 30. | C103000 | Read | Diabetes mellitus; juvenile type; with ketoacidotic coma |
| 31. | C103100 | Read | Diabetes mellitus; adult onset; with ketoacidotic coma |
| 32. | C103y00 | Read | Other specified diabetes mellitus with coma |
| 33. | C103z00 | Read | Diabetes mellitus NOS with ketoacidotic coma |
| 34. | C104.00 | Read | Diabetes mellitus with renal manifestation |
| 35. | C104000 | Read | Diabetes mellitus; juvenile type; with renal manifestation |
| 36. | C104100 | Read | Diabetes mellitus; adult onset; with renal manifestation |
| 37. | C104y00 | Read | Other specified diabetes mellitus with renal complications |
| 38. | C104z00 | Read | Diabetes mellitis with nephropathy NOS |
| 39. | C105.00 | Read | Diabetes mellitus with ophthalmic manifestation |
| 40. | C105000 | Read | Diabetes mellitus; juvenile type; + ophthalmic manifestation |
| 41. | C105100 | Read | Diabetes mellitus; adult onset; + ophthalmic manifestation |
| 42. | C105y00 | Read | Other specified diabetes mellitus with ophthalmic complicatn |
| 43. | C105z00 | Read | Diabetes mellitus NOS with ophthalmic manifestation |
| 44. | C106.00 | Read | Diabetes mellitus with neurological manifestation |
| 45. | C106000 | Read | Diabetes mellitus; juvenile; + neurological manifestation |
| 46. | C106100 | Read | Diabetes mellitus; adult onset; + neurological manifestation |
| 47. | C106.12 | Read | Diabetes mellitus with neuropathy |

Supplementary data to "Clinical code usage in UK general practice: a cohort study exploring 18 conditions over 14 years", Zghebi et al. 2021.

| | | | |
|---|---|---|---|
| 48. | C106.13 | Read | Diabetes mellitus with polyneuropathy |
| 49. | C106y00 | Read | Other specified diabetes mellitus with neurological comps |
| 50. | C106z00 | Read | Diabetes mellitus NOS with neurological manifestation |
| 51. | C107.00 | Read | Diabetes mellitus with peripheral circulatory disorder |
| 52. | C107000 | Read | Diabetes mellitus; juvenile +peripheral circulatory disorder |
| 53. | C107100 | Read | Diabetes mellitus; adult; + peripheral circulatory disorder |
| 54. | C107.11 | Read | Diabetes mellitus with gangrene |
| 55. | C107.12 | Read | Diabetes with gangrene |
| 56. | C107200 | Read | Diabetes mellitus; adult with gangrene |
| 57. | C107300 | Read | IDDM with peripheral circulatory disorder |
| 58. | C107400 | Read | NIDDM with peripheral circulatory disorder |
| 59. | C107z00 | Read | Diabetes mellitus NOS with peripheral circulatory disorder |
| 60. | C108.00 | Read | Insulin dependent diabetes mellitus |
| 61. | C108000 | Read | Insulin-dependent diabetes mellitus with renal complications |
| 62. | C108011 | Read | Type I diabetes mellitus with renal complications |
| 63. | C108012 | Read | Type 1 diabetes mellitus with renal complications |
| 64. | C108100 | Read | Insulin-dependent diabetes mellitus with ophthalmic comps |
| 65. | C108.11 | Read | IDDM-Insulin dependent diabetes mellitus |
| 66. | C108.12 | Read | Type 1 diabetes mellitus |
| 67. | C108.13 | Read | Type I diabetes mellitus |
| 68. | C108200 | Read | Insulin-dependent diabetes mellitus with neurological comps |
| 69. | C108211 | Read | Type I diabetes mellitus with neurological complications |
| 70. | C108212 | Read | Type 1 diabetes mellitus with neurological complications |
| 71. | C108300 | Read | Insulin dependent diabetes mellitus with multiple complicatn |
| 72. | C108400 | Read | Unstable insulin dependent diabetes mellitus |
| 73. | C108411 | Read | Unstable type I diabetes mellitus |
| 74. | C108500 | Read | Insulin dependent diabetes mellitus with ulcer |
| 75. | C108511 | Read | Type I diabetes mellitus with ulcer |
| 76. | C108600 | Read | Insulin dependent diabetes mellitus with gangrene |
| 77. | C108700 | Read | Insulin dependent diabetes mellitus with retinopathy |
| 78. | C108711 | Read | Type I diabetes mellitus with retinopathy |
| 79. | C108712 | Read | Type 1 diabetes mellitus with retinopathy |
| 80. | C108800 | Read | Insulin dependent diabetes mellitus - poor control |
| 81. | C108811 | Read | Type I diabetes mellitus - poor control |
| 82. | C108812 | Read | Type 1 diabetes mellitus - poor control |
| 83. | C108900 | Read | Insulin dependent diabetes maturity onset |
| 84. | C108911 | Read | Type I diabetes mellitus maturity onset |
| 85. | C108A00 | Read | Insulin-dependent diabetes without complication |
| 86. | C108B00 | Read | Insulin dependent diabetes mellitus with mononeuropathy |
| 87. | C108B11 | Read | Type I diabetes mellitus with mononeuropathy |
| 88. | C108C00 | Read | Insulin dependent diabetes mellitus with polyneuropathy |
| 89. | C108D00 | Read | Insulin dependent diabetes mellitus with nephropathy |
| 90. | C108D11 | Read | Type I diabetes mellitus with nephropathy |
| 91. | C108E00 | Read | Insulin dependent diabetes mellitus with hypoglycaemic coma |
| 92. | C108E11 | Read | Type I diabetes mellitus with hypoglycaemic coma |
| 93. | C108E12 | Read | Type 1 diabetes mellitus with hypoglycaemic coma |
| 94. | C108F00 | Read | Insulin dependent diabetes mellitus with diabetic cataract |
| 95. | C108F11 | Read | Type I diabetes mellitus with diabetic cataract |
| 96. | C108G00 | Read | Insulin dependent diab mell with peripheral angiopathy |
| 97. | C108H00 | Read | Insulin dependent diabetes mellitus with arthropathy |

Supplementary data to "Clinical code usage in UK general practice: a cohort study exploring 18 conditions over 14 years", Zghebi et al. 2021.

| | | | |
|---|---|---|---|
| 98. | C108H11 | Read | Type I diabetes mellitus with arthropathy |
| 99. | C108J00 | Read | Insulin dependent diab mell with neuropathic arthropathy |
| 100. | C108J12 | Read | Type 1 diabetes mellitus with neuropathic arthropathy |
| 101. | C108y00 | Read | Other specified diabetes mellitus with multiple comps |
| 102. | C108z00 | Read | Unspecified diabetes mellitus with multiple complications |
| 103. | C109.00 | Read | Non-insulin-dependent diabetes mellitus |
| 104. | C109000 | Read | Non-insulin-dependent diabetes mellitus with renal comps |
| 105. | C109011 | Read | Type II diabetes mellitus with renal complications |
| 106. | C109012 | Read | Type 2 diabetes mellitus with renal complications |
| 107. | C109100 | Read | Non-insulin-dependent diabetes mellitus with ophthalm comps |
| 108. | C109.11 | Read | NIDDM - Non-insulin dependent diabetes mellitus |
| 109. | C109111 | Read | Type II diabetes mellitus with ophthalmic complications |
| 110. | C109112 | Read | Type 2 diabetes mellitus with ophthalmic complications |
| 111. | C109.12 | Read | Type 2 diabetes mellitus |
| 112. | C109.13 | Read | Type II diabetes mellitus |
| 113. | C109200 | Read | Non-insulin-dependent diabetes mellitus with neuro comps |
| 114. | C109211 | Read | Type II diabetes mellitus with neurological complications |
| 115. | C109212 | Read | Type 2 diabetes mellitus with neurological complications |
| 116. | C109300 | Read | Non-insulin-dependent diabetes mellitus with multiple comps |
| 117. | C109400 | Read | Non-insulin dependent diabetes mellitus with ulcer |
| 118. | C109411 | Read | Type II diabetes mellitus with ulcer |
| 119. | C109412 | Read | Type 2 diabetes mellitus with ulcer |
| 120. | C109500 | Read | Non-insulin dependent diabetes mellitus with gangrene |
| 121. | C109511 | Read | Type II diabetes mellitus with gangrene |
| 122. | C109600 | Read | Non-insulin-dependent diabetes mellitus with retinopathy |
| 123. | C109611 | Read | Type II diabetes mellitus with retinopathy |
| 124. | C109612 | Read | Type 2 diabetes mellitus with retinopathy |
| 125. | C109700 | Read | Non-insulin dependant diabetes mellitus - poor control |
| 126. | C109711 | Read | Type II diabetes mellitus - poor control |
| 127. | C109712 | Read | Type 2 diabetes mellitus - poor control |
| 128. | C109900 | Read | Non-insulin-dependent diabetes mellitus without complication |
| 129. | C109A00 | Read | Non-insulin dependent diabetes mellitus with mononeuropathy |
| 130. | C109A11 | Read | Type II diabetes mellitus with mononeuropathy |
| 131. | C109B00 | Read | Non-insulin dependent diabetes mellitus with polyneuropathy |
| 132. | C109B11 | Read | Type II diabetes mellitus with polyneuropathy |
| 133. | C109C00 | Read | Non-insulin dependent diabetes mellitus with nephropathy |
| 134. | C109C11 | Read | Type II diabetes mellitus with nephropathy |
| 135. | C109C12 | Read | Type 2 diabetes mellitus with nephropathy |
| 136. | C109D00 | Read | Non-insulin dependent diabetes mellitus with hypoglyca coma |
| 137. | C109D11 | Read | Type II diabetes mellitus with hypoglycaemic coma |
| 138. | C109D12 | Read | Type 2 diabetes mellitus with hypoglycaemic coma |
| 139. | C109E00 | Read | Non-insulin depend diabetes mellitus with diabetic cataract |
| 140. | C109E11 | Read | Type II diabetes mellitus with diabetic cataract |
| 141. | C109E12 | Read | Type 2 diabetes mellitus with diabetic cataract |
| 142. | C109F00 | Read | Non-insulin-dependent d m with peripheral angiopath |
| 143. | C109F11 | Read | Type II diabetes mellitus with peripheral angiopathy |
| 144. | C109F12 | Read | Type 2 diabetes mellitus with peripheral angiopathy |
| 145. | C109G00 | Read | Non-insulin dependent diabetes mellitus with arthropathy |
| 146. | C109G11 | Read | Type II diabetes mellitus with arthropathy |
| 147. | C109G12 | Read | Type 2 diabetes mellitus with arthropathy |

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| | | | |
|---|---|---|---|
| 148. | C109H00 | Read | Non-insulin dependent d m with neuropathic arthropathy |
| 149. | C109H11 | Read | Type II diabetes mellitus with neuropathic arthropathy |
| 150. | C109H12 | Read | Type 2 diabetes mellitus with neuropathic arthropathy |
| 151. | C109J00 | Read | Insulin treated Type 2 diabetes mellitus |
| 152. | C109J11 | Read | Insulin treated non-insulin dependent diabetes mellitus |
| 153. | C109J12 | Read | Insulin treated Type II diabetes mellitus |
| 154. | C109K00 | Read | Hyperosmolar non-ketotic state in type 2 diabetes mellitus |
| 155. | C10C.00 | Read | Diabetes mellitus autosomal dominant |
| 156. | C10C.11 | Read | Maturity onset diabetes in youth |
| 157. | C10D.00 | Read | Diabetes mellitus autosomal dominant type 2 |
| 158. | C10D.11 | Read | Maturity onset diabetes in youth type 2 |
| 159. | C10E.00 | Read | Type 1 diabetes mellitus |
| 160. | C10E000 | Read | Type 1 diabetes mellitus with renal complications |
| 161. | C10E100 | Read | Type 1 diabetes mellitus with ophthalmic complications |
| 162. | C10E.11 | Read | Type I diabetes mellitus |
| 163. | C10E.12 | Read | Insulin dependent diabetes mellitus |
| 164. | C10E200 | Read | Type 1 diabetes mellitus with neurological complications |
| 165. | C10E300 | Read | Type 1 diabetes mellitus with multiple complications |
| 166. | C10E312 | Read | Insulin dependent diabetes mellitus with multiple complicat |
| 167. | C10E400 | Read | Unstable type 1 diabetes mellitus |
| 168. | C10E411 | Read | Unstable type I diabetes mellitus |
| 169. | C10E412 | Read | Unstable insulin dependent diabetes mellitus |
| 170. | C10E500 | Read | Type 1 diabetes mellitus with ulcer |
| 171. | C10E600 | Read | Type 1 diabetes mellitus with gangrene |
| 172. | C10E700 | Read | Type 1 diabetes mellitus with retinopathy |
| 173. | C10E800 | Read | Type 1 diabetes mellitus - poor control |
| 174. | C10E812 | Read | Insulin dependent diabetes mellitus - poor control |
| 175. | C10E900 | Read | Type 1 diabetes mellitus maturity onset |
| 176. | C10EA00 | Read | Type 1 diabetes mellitus without complication |
| 177. | C10EA11 | Read | Type I diabetes mellitus without complication |
| 178. | C10EB00 | Read | Type 1 diabetes mellitus with mononeuropathy |
| 179. | C10EC00 | Read | Type 1 diabetes mellitus with polyneuropathy |
| 180. | C10ED00 | Read | Type 1 diabetes mellitus with nephropathy |
| 181. | C10EE00 | Read | Type 1 diabetes mellitus with hypoglycaemic coma |
| 182. | C10EF00 | Read | Type 1 diabetes mellitus with diabetic cataract |
| 183. | C10EG00 | Read | Type 1 diabetes mellitus with peripheral angiopathy |
| 184. | C10EH00 | Read | Type 1 diabetes mellitus with arthropathy |
| 185. | C10EJ00 | Read | Type 1 diabetes mellitus with neuropathic arthropathy |
| 186. | C10EK00 | Read | Type 1 diabetes mellitus with persistent proteinuria |
| 187. | C10EL00 | Read | Type 1 diabetes mellitus with persistent microalbuminuria |
| 188. | C10EM00 | Read | Type 1 diabetes mellitus with ketoacidosis |
| 189. | C10EM11 | Read | Type I diabetes mellitus with ketoacidosis |
| 190. | C10EN00 | Read | Type 1 diabetes mellitus with ketoacidotic coma |
| 191. | C10EN11 | Read | Type I diabetes mellitus with ketoacidotic coma |
| 192. | C10EP00 | Read | Type 1 diabetes mellitus with exudative maculopathy |
| 193. | C10EQ00 | Read | Type 1 diabetes mellitus with gastroparesis |
| 194. | C10F.00 | Read | Type 2 diabetes mellitus |
| 195. | C10F000 | Read | Type 2 diabetes mellitus with renal complications |
| 196. | C10F011 | Read | Type II diabetes mellitus with renal complications |
| 197. | C10F100 | Read | Type 2 diabetes mellitus with ophthalmic complications |

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| | | | |
|---|---|---|---|
| 198. | C10F.11 | Read | Type II diabetes mellitus |
| 199. | C10F200 | Read | Type 2 diabetes mellitus with neurological complications |
| 200. | C10F300 | Read | Type 2 diabetes mellitus with multiple complications |
| 201. | C10F311 | Read | Type II diabetes mellitus with multiple complications |
| 202. | C10F400 | Read | Type 2 diabetes mellitus with ulcer |
| 203. | C10F500 | Read | Type 2 diabetes mellitus with gangrene |
| 204. | C10F511 | Read | Type II diabetes mellitus with gangrene |
| 205. | C10F600 | Read | Type 2 diabetes mellitus with retinopathy |
| 206. | C10F611 | Read | Type II diabetes mellitus with retinopathy |
| 207. | C10F700 | Read | Type 2 diabetes mellitus - poor control |
| 208. | C10F711 | Read | Type II diabetes mellitus - poor control |
| 209. | C10F900 | Read | Type 2 diabetes mellitus without complication |
| 210. | C10F911 | Read | Type II diabetes mellitus without complication |
| 211. | C10FA00 | Read | Type 2 diabetes mellitus with mononeuropathy |
| 212. | C10FB00 | Read | Type 2 diabetes mellitus with polyneuropathy |
| 213. | C10FB11 | Read | Type II diabetes mellitus with polyneuropathy |
| 214. | C10FC00 | Read | Type 2 diabetes mellitus with nephropathy |
| 215. | C10FC11 | Read | Type II diabetes mellitus with nephropathy |
| 216. | C10FD00 | Read | Type 2 diabetes mellitus with hypoglycaemic coma |
| 217. | C10FE00 | Read | Type 2 diabetes mellitus with diabetic cataract |
| 218. | C10FF00 | Read | Type 2 diabetes mellitus with peripheral angiopathy |
| 219. | C10FG00 | Read | Type 2 diabetes mellitus with arthropathy |
| 220. | C10FH00 | Read | Type 2 diabetes mellitus with neuropathic arthropathy |
| 221. | C10FJ00 | Read | Insulin treated Type 2 diabetes mellitus |
| 222. | C10FJ11 | Read | Insulin treated Type II diabetes mellitus |
| 223. | C10FK00 | Read | Hyperosmolar non-ketotic state in type 2 diabetes mellitus |
| 224. | C10FL00 | Read | Type 2 diabetes mellitus with persistent proteinuria |
| 225. | C10FL11 | Read | Type II diabetes mellitus with persistent proteinuria |
| 226. | C10FM00 | Read | Type 2 diabetes mellitus with persistent microalbuminuria |
| 227. | C10FN00 | Read | Type 2 diabetes mellitus with ketoacidosis |
| 228. | C10FP00 | Read | Type 2 diabetes mellitus with ketoacidotic coma |
| 229. | C10FQ00 | Read | Type 2 diabetes mellitus with exudative maculopathy |
| 230. | C10FR00 | Read | Type 2 diabetes mellitus with gastroparesis |
| 231. | C10G.00 | Read | Secondary pancreatic diabetes mellitus |
| 232. | C10G000 | Read | Secondary pancreatic diabetes mellitus without complication |
| 233. | C10y.00 | Read | Diabetes mellitus with other specified manifestation |
| 234. | C10y100 | Read | Diabetes mellitus; adult; + other specified manifestation |
| 235. | C10yy00 | Read | Other specified diabetes mellitus with other spec comps |
| 236. | C10yz00 | Read | Diabetes mellitus NOS with other specified manifestation |
| 237. | C10z.00 | Read | Diabetes mellitus with unspecified complication |
| 238. | C10z000 | Read | Diabetes mellitus; juvenile type; + unspecified complication |
| 239. | C10z100 | Read | Diabetes mellitus; adult onset; + unspecified complication |
| 240. | C10zy00 | Read | Other specified diabetes mellitus with unspecified comps |
| 241. | C10zz00 | Read | Diabetes mellitus NOS with unspecified complication |
| 242. | Cyu2.00 | Read | [X]Diabetes mellitus |
| 243. | Cyu2000 | Read | [X]Other specified diabetes mellitus |
| 244. | Cyu2300 | Read | [X]Unspecified diabetes mellitus with renal complications |
| 245. | L180500 | Read | Pre-existing diabetes mellitus; insulin-dependent |
| 246. | L180600 | Read | Pre-existing diabetes mellitus; non-insulin-dependent |
| 247. | L180X00 | Read | Pre-existing diabetes mellitus; unspecified |

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## Table S2 R code

**1, 3, 5, year Jackknife correlations (Figures 2, S3, S4)**

```
library(dplyr)
library(tidyr)
library(ggplot2)
library(stringr)

setwd("Q:/code_usage")
rm(list=ls())
conditions <- c("asthma", "atrial_fibrillation", "cancer", "chd", "ckd",
            "copd", "dementia", "depression", "dm", "epilepsy", "hf", "ht","hypothyroidism" ,
            "learning_disability", "osteoarthritis", "osteoporosis", "smi", "stroke")


jack_incidence <- new.env()
jack_total <- new.env()

for(condition in conditions){
   if(file.exists(myfile <- paste0("data/", condition, "_year_cors.rda"))){
      message("Loading ", myfile)
      load(myfile, envir = jack_incidence)
   }
   if(file.exists(myfile <- paste0("data/", condition, "_total_cors.rda"))){
      message("Loading ", myfile)
      load(myfile, envir = jack_total)
   }

}

incid_data <- bind_rows(lapply(ls(jack_incidence), function(condition){
   bind_rows(jack_incidence[[condition]]) %>%
      mutate(condition = str_replace(condition, "_year_cors", ""),
           type = "incident codes")
}))

total_data <- bind_rows(lapply(ls(jack_total), function(condition){
   bind_rows(jack_total[[condition]]) %>%
      mutate(condition = str_replace(condition, "_total_cors", ""),
           type = "all codes")
}))

jack_data <- bind_rows(incid_data, total_data) %>%
   mutate(year1 = as.numeric(year1))


## Year-on-year correlations:
p <- ggplot(jack_data %>% filter(num < 14),
         aes(x = year1, y = cor, colour = type))
p + geom_point() +
   geom_line() +
```

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```
   geom_errorbar(aes(ymin = lower, ymax = upper), width = 0.25) +
   facet_wrap( ~ condition) +
   theme_bw() +
   scale_x_continuous("Year", breaks = c(2000, 2002, 2004, 2006, 2008, 2010, 2012)) +
   scale_y_continuous("1st cannonical correlation", limits = c(0,1)) +
   theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
   #labs(title = "")
ggsave("analysis/1-jack_corr_1yearwindow.pdf")


## Bi-yearly correlations:
p <- ggplot(jack_data %>% filter(num >= 14, num < 24),
        aes(x = year1, y = cor, colour = type))
p + geom_point() +
   geom_line() +
   geom_errorbar(aes(ymin = lower, ymax = upper), width = 0.25) +
   facet_wrap( ~ condition) +
   theme_bw() +
   scale_x_continuous("Year", breaks = c(2000, 2002, 2004, 2006, 2008, 2010, 2012)) +
   scale_y_continuous("1st cannonical correlation",
                limits = c(0,1)) +
   theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
   #labs(title = "")
ggsave("analysis/2-jack_corr_3yearwindow.pdf")

## 5-yearly correlations:
p <- ggplot(jack_data %>% filter(num >= 14, num < 24),
        aes(x = year1, y = cor, colour = type))
p + geom_point() +
   geom_line() +
   geom_errorbar(aes(ymin = lower, ymax = upper), width = 0.25) +
   facet_wrap( ~ condition) +
   theme_bw() +
   scale_x_continuous("Year", breaks = c(2000, 2002, 2004, 2006, 2008, 2010, 2012)) +
   scale_y_continuous("1st cannonical correlation", limits = c(0,1)) +
   #labs(title = "")
ggsave("analysis/3-jack_corr_5yearwindow.pdf")
```

**Canonical_correlations_5-year windows (for Figure S2)**

```
library(rEHR)
library(dplyr)
library(tidyr)
library(ggplot2)

rm(list=ls())
conditions <- c("asthma", "atrial_fibrillation", "cancer", "chd", "ckd",
            "copd", "dementia", "depression", "dm", "epilepsy", "hf", "ht","hypothyroidism" ,
            "learning_disability", "osteoarthritis", "osteoporosis", "smi", "stroke")
correlations <- new.env()
```

Supplementary data to "Clinical code usage in UK general practice: a cohort study exploring 18 conditions over 14 years", Zghebi et al. 2021.

```
for(condition in conditions){
   load(paste0("data/", condition, "_year_cors.rda"), envir = correlations)
   my_corr <- get(paste0(condition, "_year_cors"),  envir = correlations)
   my_corr <-  lapply(my_corr, function(x) {
        x$condition <- condition
        x
   })
   assign(paste0(condition, "_year_cors"), my_corr, envir = correlations)
}
rm(my_corr)

all_corrs <- bind_rows(lapply(correlations, function(corr){
   data_frame(year = 2005:2013,
           cor = unlist(lapply(corr, function(x) x$cor)),
           condition = corr[[1]]$condition)
}))


p <- ggplot(all_corrs, aes(x = year, y = cor))
p + geom_line() +
   facet_wrap( ~ condition) +
#    geom_vline(x = 2004, linetype  = "longdash", colour = "red", width = 4) +
   theme_bw() +
   labs(title  = "Correlations of clinical code usage (Five year windows)") +
   scale_y_continuous("Spearman's canonical correlation coefficient") +
   scale_x_continuous(breaks = c(2004, 2006, 2008, 2010, 2012)) +
   theme(axis.text.x = element_text(angle = 45, hjust = 1))

ggsave("analysis/canonical_correlations_5yearwindows.pdf")
```

**Three diversity measures (Figures 3, 4, 5)**

```
library(rEHR)
library(dplyr)
library(tidyr)
library(parallel)
library(ggplot2)
library(bootstrap)

setwd("Q:/code_usage")
#' calculates the Shannon index of diversity/entropy
shannon <- function(x)
{
   x <- drop(as.matrix(x))
   if (length(dim(x)) > 1) {
      total <- apply(x, 1, sum)
      x <- sweep(x, 1, total, "/")
   }
   else {
      x <- x/sum(x)
   }
```

Supplementary data to "Clinical code usage in UK general practice: a cohort study exploring 18 conditions over 14 years", Zghebi et al. 2021.

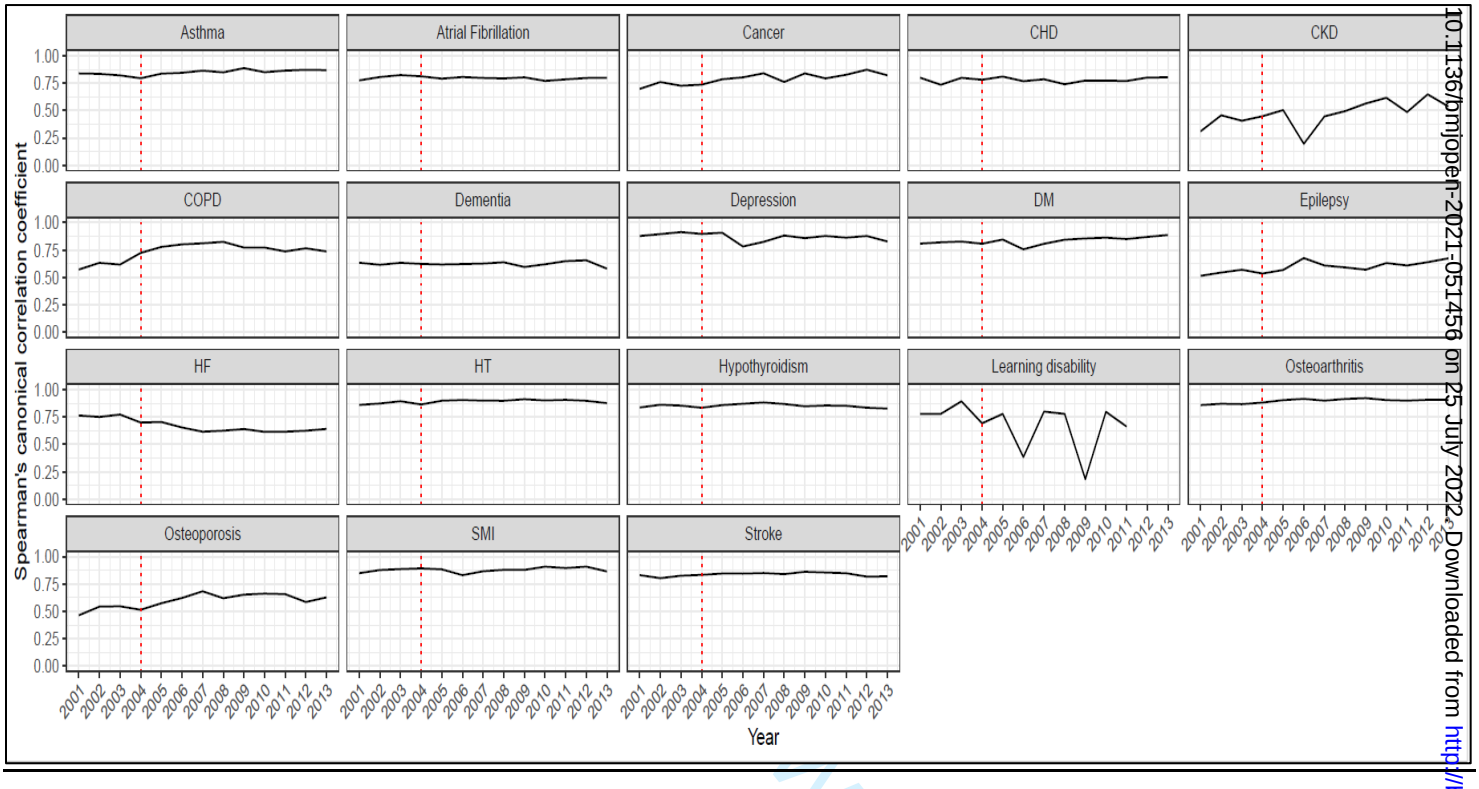
```
  x <- -x * log(x)

  if (length(dim(x)) > 1)
    H <- apply(x, sum, na.rm = TRUE)
  else H <- sum(x, na.rm = TRUE)
  H
}

evenness_fn <- function(x){
  H <- shannon(x)
  R <- length(x)
  H / log(R)
}


jack_stats <- function(x, thetahat){
  n <- length(x)
  bias <- (n - 1) * (mean(x) - thetahat)
  se <- sqrt(((n - 1)/n) * sum((x - mean(x))^2))
  list(param = thetahat, bias = bias, se = se)
}

conditions <- c("asthma", "atrial_fibrillation", "blood_pressure", "cancer", "chd", "ckd",
          "copd", "dementia", "depression", "dm", "epilepsy", "hf", "ht","hypothyroidism" ,
          "learning_disability", "osteoarthritis", "osteoporosis", "smi", "stroke")
frequencies <- new.env()

for(condition in conditions){
  load(paste0("data/", condition, "_frequencies.rda"), envir = frequencies)
  incid <- get(paste0(condition, "_incidence_freqs"),  envir = frequencies)
  incid$type <- "incident codes"
  assign(paste0(condition, "_incidence_freqs"), incid, envir = frequencies)

  total <- get(paste0(condition, "_total_freqs"),  envir = frequencies)
  total$type <- "all codes"
  assign(paste0(condition, "_total_freqs"), total, envir = frequencies)

}

all_freqs <- bind_rows(lapply(frequencies, function(x) x))

years <- 2000:2013
jacks <- bind_rows(lapply(frequencies, function(condition){
  bind_rows(mclapply(years, function(this_year){
    dat <- condition %>%
      filter(year == this_year)
    H <- shannon(dat$freq)
    H_jack <- jackknife(dat$freq, theta = shannon)
    richness <- nrow(dat)
    evenness <- evenness_fn(dat$freq)
    evenness_jack <- jackknife(dat$freq, theta = evenness_fn)
    data_frame(year = rep(this_year, 3),
          condition = rep(dat$condition[1], 3),
```

Supplementary data to "Clinical code usage in UK general practice: a cohort study exploring 18 conditions over 14 years", Zghebi et al. 2021.

```
            type = rep(dat$type[1], 3),
            index = c("H", "richness", "evenness"),
            value = c(H, richness, evenness),
            upper = c(H + 1.96 * H_jack$jack.se,
                  NA,
                  evenness + 1.96 * evenness_jack$jack.se),
            lower = c(H - 1.96 * H_jack$jack.se,
                  NA,
                  evenness - 1.96 * evenness_jack$jack.se),
            bias = c(H_jack$jack.bias, NA, evenness_jack$jack.bias))

  }, mc.cores = 1))
}))

p <- ggplot(jacks %>% filter(index == "H", condition != "blood_pressure"),
       aes(x = year, y = value, colour = type))
p + geom_line() +
  facet_wrap( ~ condition) +
  geom_errorbar(aes(ymin = lower, ymax = upper), width = 0.25) +
  #geom_vline(x = 2004, linetype  = "longdash", colour = "red", width = 4) +
  theme_bw() +
  labs(title  = "Entropy of clinical code usage") +
  scale_y_continuous("H, Entropy (diversity) of code useage")
ggsave("analysis/4-entropy.pdf")
ggsave("analysis/4-entropy.png")

p <- ggplot(jacks %>% filter(index == "richness", condition != "blood_pressure"),
       aes(x = year, y = value, colour = type))
p + geom_line() +
  facet_wrap( ~ condition) +
  geom_errorbar(aes(ymin = lower, ymax = upper), width = 0.25) +
  #geom_vline(x = 2004, linetype  = "longdash", colour = "red", width = 4) +
  theme_bw() +
  labs(title  = "Richness of clinical code usage") +
  scale_y_continuous("Total number of codes used")
ggsave("analysis/5-richness.pdf")
ggsave("analysis/5-richness.png")


p <- ggplot(jacks %>% filter(index == "evenness", condition != "blood_pressure"),
       aes(x = year, y = value, colour = type))
p + geom_line() +
  facet_wrap( ~ condition) +
  geom_errorbar(aes(ymin = lower, ymax = upper), width = 0.25) +
  #geom_vline(x = 2004, linetype  = "longdash", colour = "red", width = 4) +
  theme_bw() +
  labs(title  = "Evenness of clinical code usage") +
  scale_y_continuous("J, Evenness of code useage")
ggsave("analysis/6-evenness.pdf")
ggsave("analysis/6-evenness.png")

save(jacks, file = "data/jackknife_entropy.rda")
```

Supplementary data to "Clinical code usage in UK general practice: a cohort study exploring 18 conditions over 14 years", Zghebi et al. 2021.

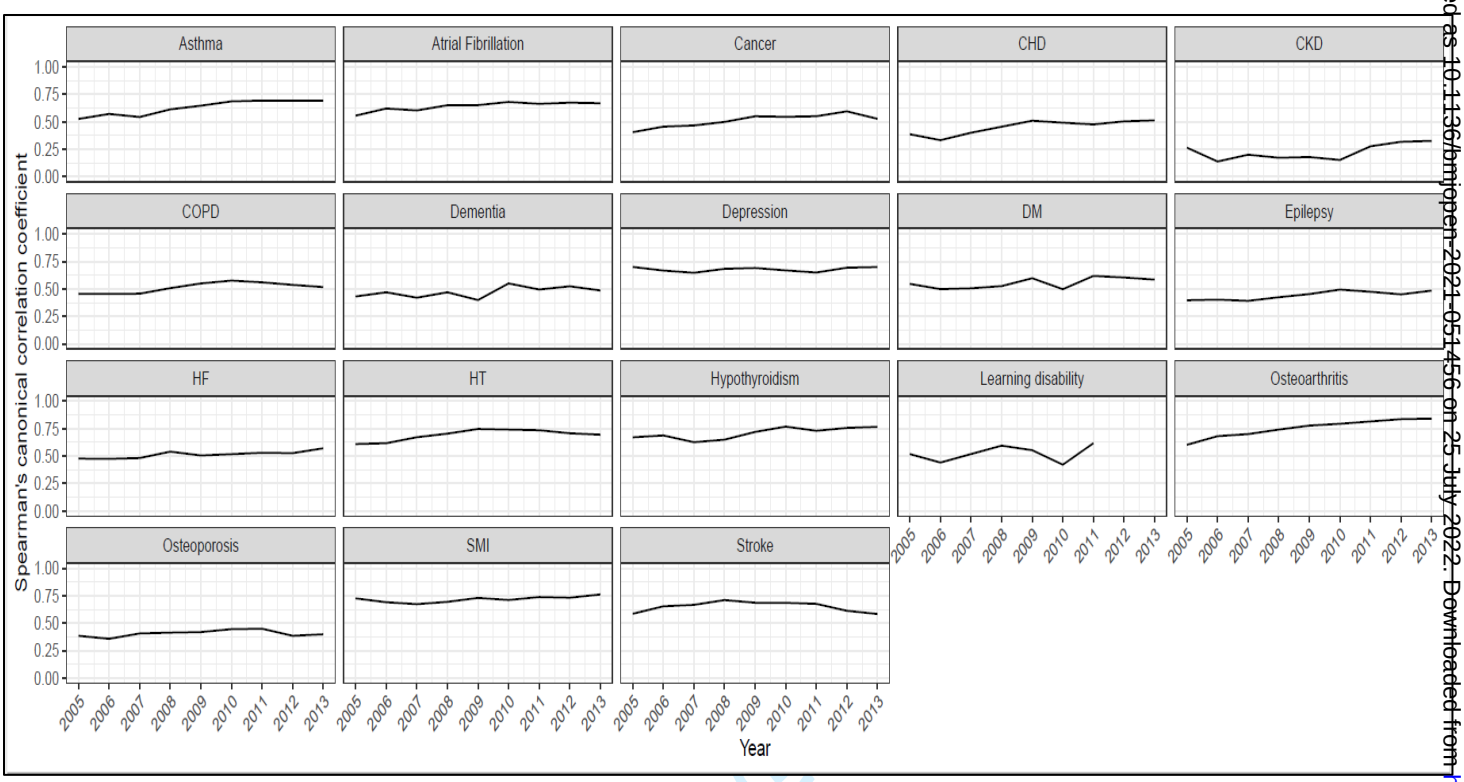
## Figure S1 Canonical correlation using 1-year window of clinical code usage for 18 mental and physical conditions




CHD, coronary heart disease; CKD, chronic kidney disease; COPD, chronic obstructive pulmonary disease; DM, diabetes mellitus; HF, heart failure; HT, hypertension; SMI, severe mental illness. The red line represents the launching year of the QOF in 2004.

Supplementary data to "Clinical code usage in UK general practice: a cohort study exploring 18 conditions over 14 years", Zghebi et al. 2021.

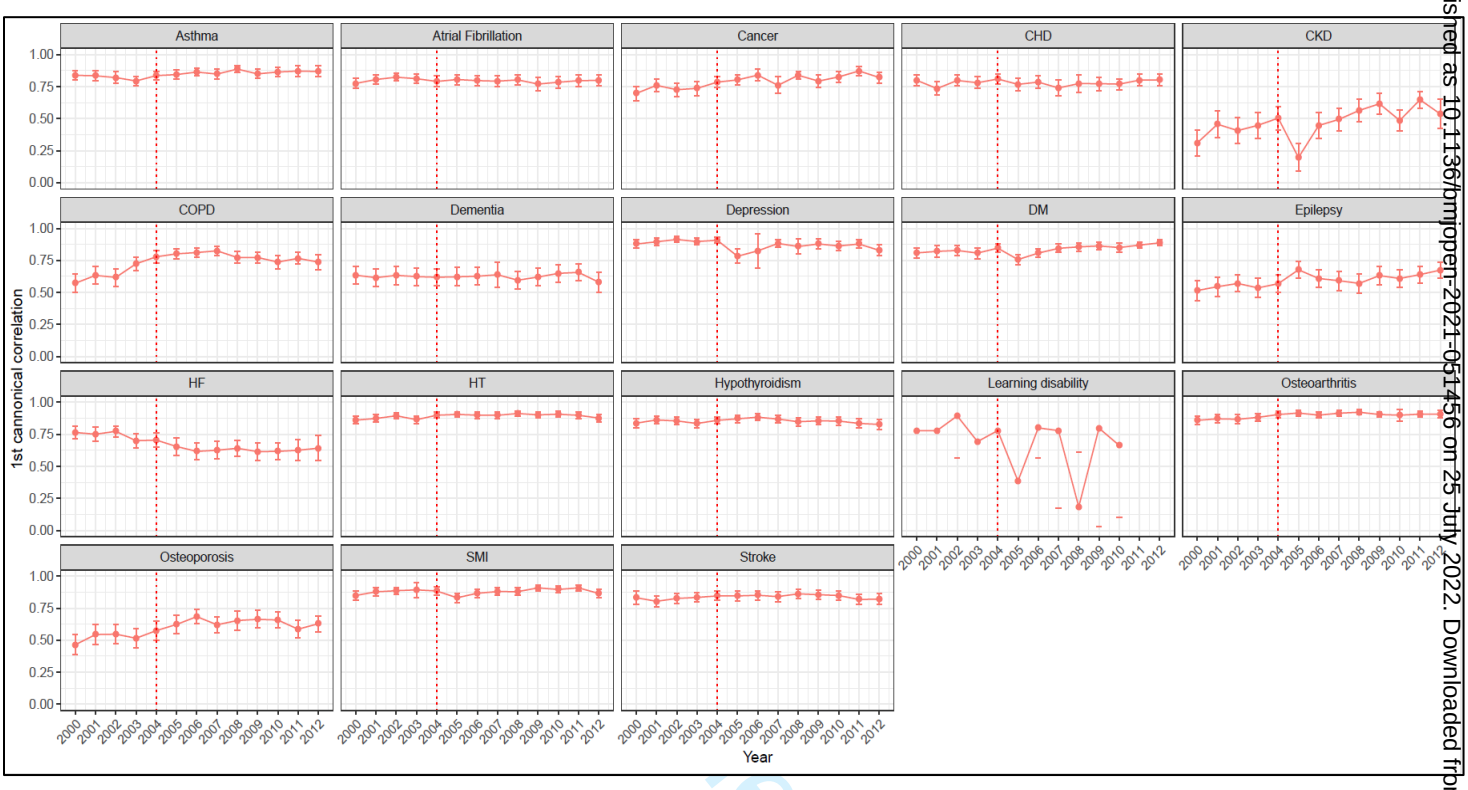
## Figure S2 Canonical correlation using 5-year window of clinical code usage for 18 mental and physical conditions




CHD, coronary heart disease; CKD, chronic kidney disease; COPD, chronic obstructive pulmonary disease; DM, diabetes mellitus; HF, heart failure; HT, hypertension; SMI, severe mental illness. The red line represents the launching year of the QOF in 2004.

Supplementary data to "Clinical code usage in UK general practice: a cohort study exploring 18 conditions over 14 years", Zghebi et al. 2021.

**Figure S3 Bias-corrected canonical correlations (95%CI) using 1-year window for incident clinical code usage for 18 mental and physical conditions**

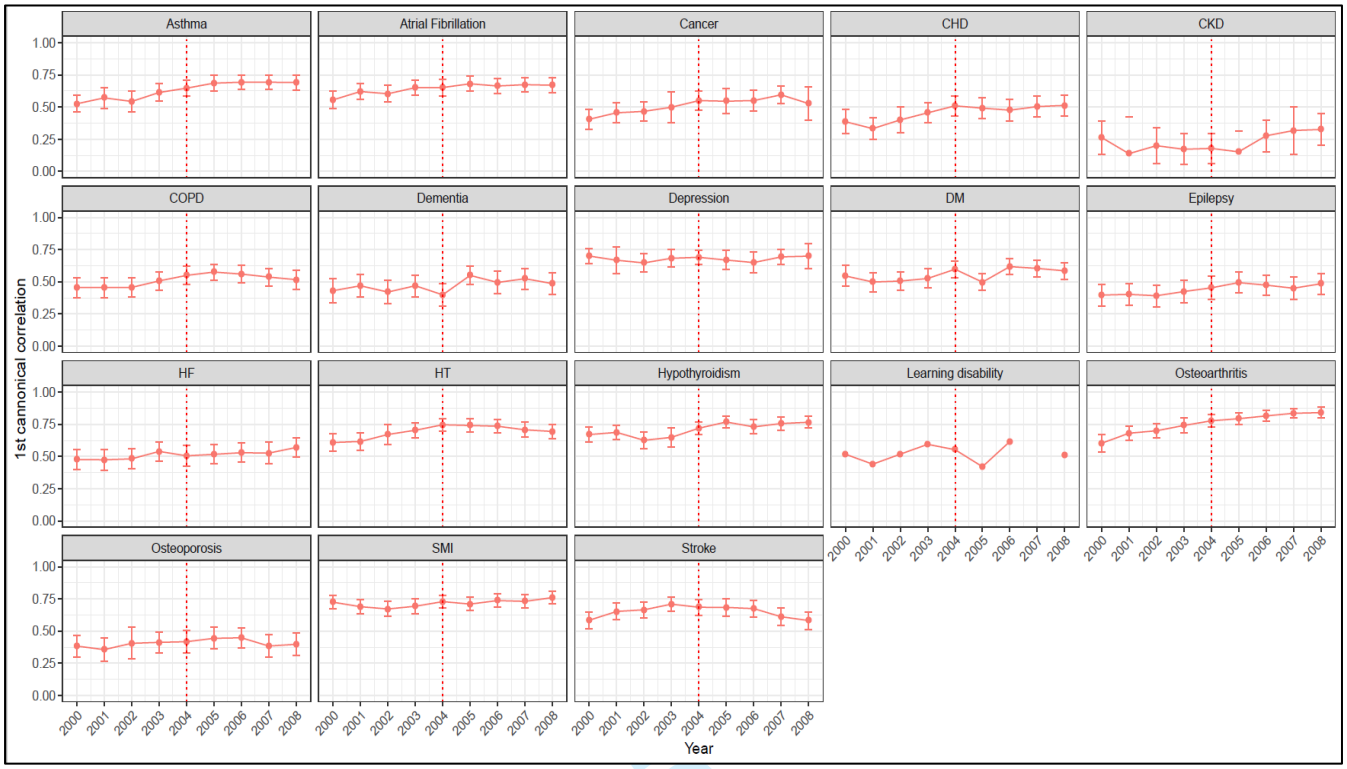



CHD, coronary heart disease; CKD, chronic kidney disease; COPD, chronic obstructive pulmonary disease; DM, diabetes mellitus; HF, heart failure; HT, hypertension; SMI, severe mental illness.

Incident code: a clinical code indicating new (incident) cases. The red line represents the launching year of the QOF in 2004.

Supplementary data to "Clinical code usage in UK general practice: a cohort study exploring 18 conditions over 14 years", Zghebi et al. 2021.

**Figure S4 Bias-corrected canonical correlations using 5-year window for incident clinical code usage for 18 mental and physical conditions**




CHD, coronary heart disease; CKD, chronic kidney disease; COPD, chronic obstructive pulmonary disease; DM, diabetes mellitus; HF, heart failure; HT, hypertension; SMI, severe mental illness.

Incident code: a clinical code indicating new (incident) cases. The red line represents the launching year of the QOF in 2004.

**The RECORD statement – checklist of items, extended from the STROBE statement, that should be reported in observational studies using routinely collected health data.**

| | Item No. | STROBE items | Location in manuscript where items are reported | RECORD items | Location in manuscript where items are reported |
|---|---|---|---|---|---|
| **Title and abstract** | | | | | |
| | 1 | (a) Indicate the study's design with a commonly used term in the title or the abstract (b) Provide in the abstract an informative and balanced summary of what was done and what was found | **Title and Abstract** | RECORD 1.1: The type of data used should be specified in the title or abstract. When possible, the name of the databases used should be included.<br><br>RECORD 1.2: If applicable, the geographic region and timeframe within which the study took place should be reported in the title or abstract.<br><br>RECORD 1.3: If linkage between databases was conducted for the study, this should be clearly stated in the title or abstract. | **Abstract**<br><br>**Title and Abstract**<br><br>**Not applicable** |
| **Introduction** | | | | | |
| Background rationale | 2 | Explain the scientific background and rationale for the investigation being reported | **Introduction** | | |
| Objectives | 3 | State specific objectives, including any prespecified hypotheses | **Abstract, Introduction** | | |
| **Methods** | | | | | |
| Study Design | 4 | Present key elements of study design early in the paper | **Methods** | | |
| Setting | 5 | Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection | **Abstract, Methods** | | |
| Participants | 6 | *(a)* ***Cohort study*** - Give the eligibility criteria, and the sources and methods of selection of participants. Describe methods of follow-up | **Methods** | RECORD 6.1: The methods of study population selection (such as codes or algorithms used to identify subjects) should be listed in detail. If this is not possible, an explanation should be provided.<br><br>RECORD 6.2: Any validation studies of the codes or algorithms used to select the population should be referenced. If validation was conducted for this study and not | **Methods**<br><br>**Not applicable** |







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| | | | | | |
|---|---|---|---|---|---|
| | | *(b)* ***Cohort study*** - For matched studies, give matching criteria and number of exposed and unexposed<br>*Case-control study* - For matched studies, give matching criteria and the number of controls per case | **Not applicable** | published elsewhere, detailed methods and results should be provided.<br><br>RECORD 6.3: If the study involved linkage of databases, consider use of a flow diagram or other graphical display to demonstrate the data linkage process, including the number of individuals with linked data at each stage. | **Not applicable** |
| Variables | 7 | Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable. | **Methods** | RECORD 7.1: A complete list of codes and algorithms used to classify exposures, outcomes, confounders, and effect modifiers should be provided. If these cannot be reported, an explanation should be provided. | **Methods**<br>(codes available from online repository: clinicalcodes.org) |
| Data sources/ measurement | 8 | For each variable of interest, give sources of data and details of methods of assessment (measurement). Describe comparability of assessment methods if there is more than one group | **Methods** | | |
| Bias | 9 | Describe any efforts to address potential sources of bias | **Methods**<br>Also, the used population (CPRD) is representative of the UK population | | |
| Study size | 10 | Explain how the study size was arrived at | **Methods** | | |
| Quantitative variables | 11 | Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen, and why | **Methods** | | |
| Statistical methods | 12 | (a) Describe all statistical methods, including those used to control for confounding<br>(b) Describe any methods used to examine subgroups and interactions<br>(c) Explain how missing data were addressed<br>(d) ***Cohort study*** - If applicable, explain how loss to follow-up was addressed<br>(e) Describe any sensitivity analyses | **Methods** | | |
| Data access and cleaning methods | | **Not applicable in STROBE** | | RECORD 12.1: Authors should describe the extent to which the investigators had access to | **Methods** |

| | | | | | |
|---|---|---|---|---|---|
| | | | | the database population used to create the study population.<br><br>RECORD 12.2: Authors should provide information on the data cleaning methods used in the study. | **Not applicable** |
| Linkage | | **Not applicable in STROBE** | | RECORD 12.3: State whether the study included person-level, institutional-level, or other data linkage across two or more databases. The methods of linkage and methods of linkage quality evaluation should be provided. | **Not applicable** |
| **Results** | | | | | |
| Participants | 13 | (a) Report the numbers of individuals at each stage of the study (*e.g.*, numbers potentially eligible, examined for eligibility, confirmed eligible, included in the study, completing follow-up, and analysed)<br>(b) Give reasons for non-participation at each stage.<br>(c) Consider use of a flow diagram | **Not applicable** | RECORD 13.1: Describe in detail the selection of the persons included in the study (*i.e.,* study population selection) including filtering based on data quality, data availability and linkage. The selection of included persons can be described in the text and/or by means of the study flow diagram. | **Methods / Results** |
| Descriptive data | 14 | (a) Give characteristics of study participants (*e.g.*, demographic, clinical, social) and information on exposures and potential confounders<br>(b) Indicate the number of participants with missing data for each variable of interest<br>(c) ***Cohort study*** - summarise follow-up time (*e.g.*, average and total amount) | **Not applicable** | | |
| Outcome data | 15 | ***Cohort study*** - Report numbers of outcome events or summary measures over time | **Results** | | |
| Main results | 16 | (a) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision (e.g., 95% confidence interval). Make clear which confounders were adjusted for and why they were included<br>(b) Report category boundaries when continuous variables were categorized | **Results, Figures 1-5, Figures S1 – S4.** | | |

| | | | | | |
|---|---|---|---|---|---|
| | | (c) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period | | | |
| Other analyses | 17 | Report other analyses done—e.g., analyses of subgroups and interactions, and sensitivity analyses | **Not applicable** | | |
| **Discussion** | | | | | |
| Key results | 18 | Summarise key results with reference to study objectives | **Discussion** | | |
| Limitations | 19 | Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias | **Discussion** | RECORD 19.1: Discuss the implications of using data that were not created or collected to answer the specific research question(s). Include discussion of misclassification bias, unmeasured confounding, missing data, and changing eligibility over time, as they pertain to the study being reported. | **Discussion / Conclusion** |
| Interpretation | 20 | Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence | **Discussion** | | |
| Generalisability | 21 | Discuss the generalisability (external validity) of the study results | **Not applicable** | | |
| **Other Information** | | | | | |
| Funding | 22 | Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based | **Funding** | | |
| Accessibility of protocol, raw data, and programming code | | .. | | RECORD 22.1: Authors should provide information on how to access any supplemental information such as the study protocol, raw data, or programming code. | **Methods** (raw data can only by accessed via the CPRD) |

*Reference: Benchimol EI, Smeeth L, Guttmann A, Harron K, Moher D, Petersen I, Sørensen HT, von Elm E, Langan SM, the RECORD Working Committee. The REporting of studies Conducted using Observational Routinely-collected health Data (RECORD) Statement. *PLoS Medicine* 2015; in press.