12/01/2022

GIRFT
GETTING IT RIGHT FIRST TIME

DiRAC

Assessing the Data Quality of HES

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Identifying "coding inconsistencies"

Mandatory codes should appear in **all episodes** following their first appearance.

We identify inconsistencies at the **episode level** by:

1) Find episodes where mandatory codes are used

2) Identify the first episode for each patient

3) All subsequent episodes should contain this mandatory code

SPELLS	PATIENT	EPISODES	MANDATORY CODE
Spell 1	HESID 1	Episode 1	No
Spell 1	HESID 1	Episode 2	Yes
Spell 1	HESID 1	Episode 3	Yes
Spell 2	HESID 1	Episode 1	No
Spell 2	HESID 1	Episode 2	No
Spell 2	HESID 1	Episode 3	No

Here, we would count 3 errors in 4 subsequent episodes.

We are focusing on:

- **Autism** → F84
- **Type II Diabetes** → E11
- **Parkinson's Dementia** → {F00, F01, F02, F03, F051; G301, G302, G308, G309}

How many inconsistencies can we identify, at the episode level?

For patients discharged between 2013-04-01 and 2021-03-31

	Proportion of subsequent episodes with missing mandatory codes
Autism	43.86%
Type II Diabetes	42.52%
Parkinson's Dementia	25.31%

Very small number of "false positives".

Is there a particular structure to these inconsistencies?

In time, across trusts, etc.

Are these errors related to poorer outcomes?

Stratification by age, sex, ethnicity, IMD scores

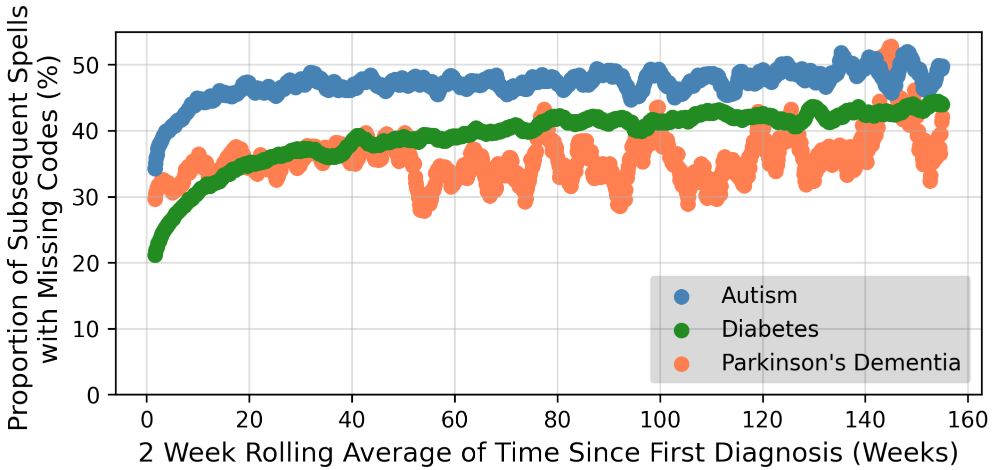
Multi-variate modelling

Proportion of inconsistencies across time

We are looking at a **3-year follow-up period** after a mandatory code first appears, for each patient.

We consider a **spell** to be inconsistently coded if **none of its episodes** mention the mandatory code.

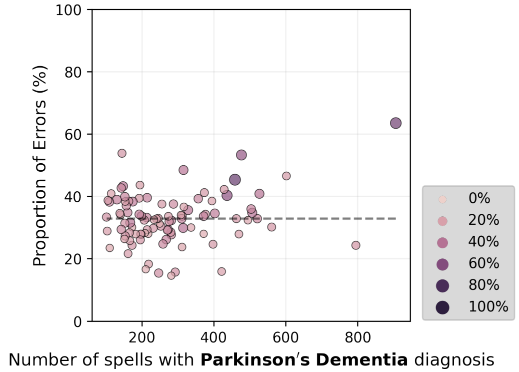
How do the error rates change as a function of time since the codes' first appearance?

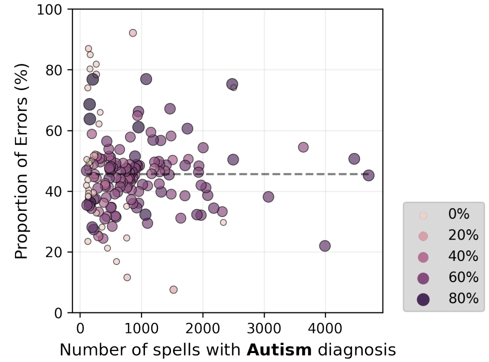


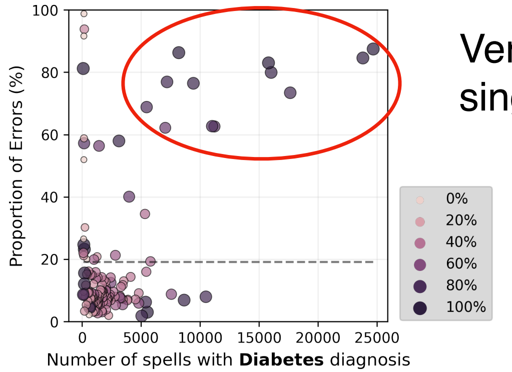
Fewer coding errors are identified close to the first spell where the code was used

The proportion of errors at the spell level increases and levels off eventually

Proportion of inconsistencies across trusts

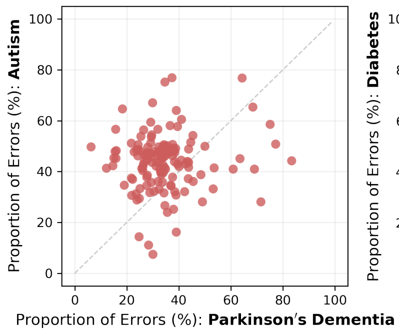


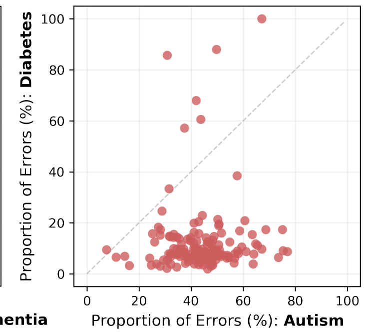


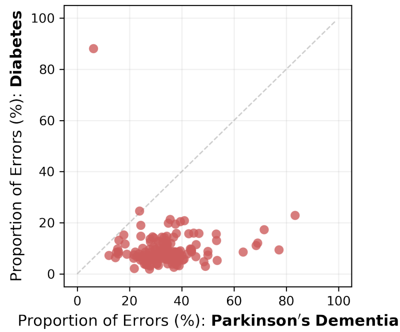


Very large proportion of single-day spells

Many patients with a very large number of spells, only a few of which mention the mandatory codes







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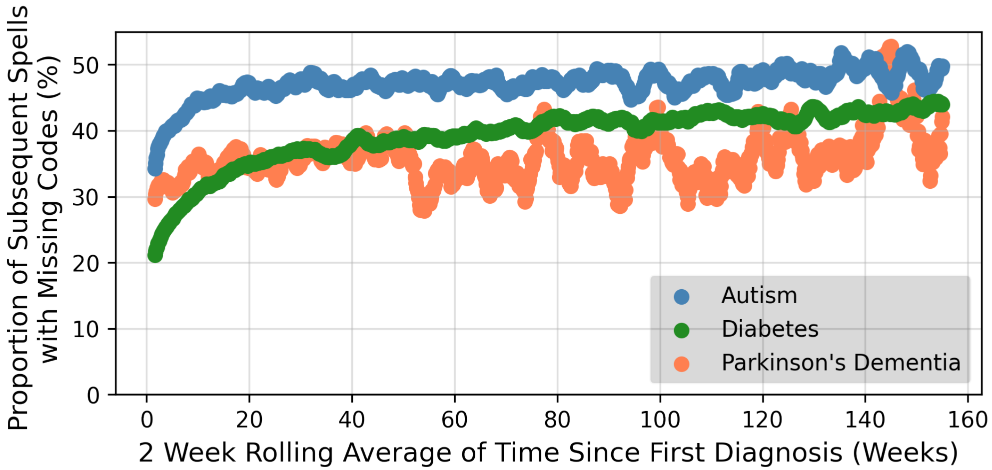

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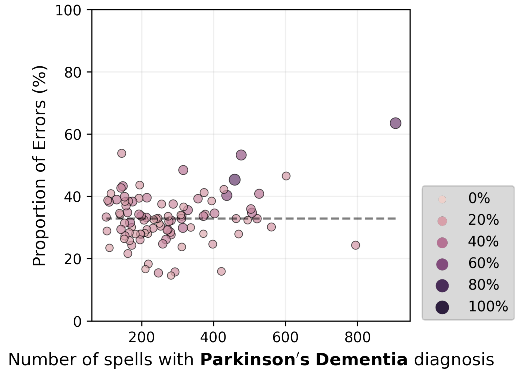

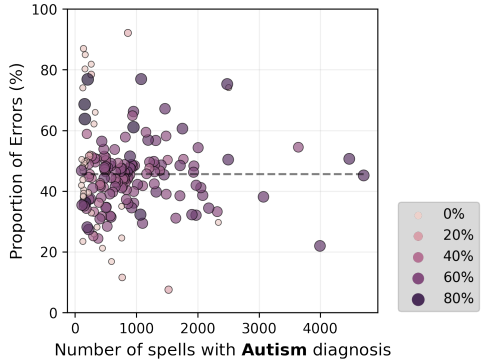

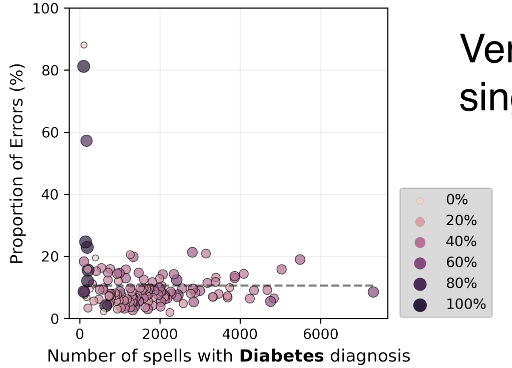

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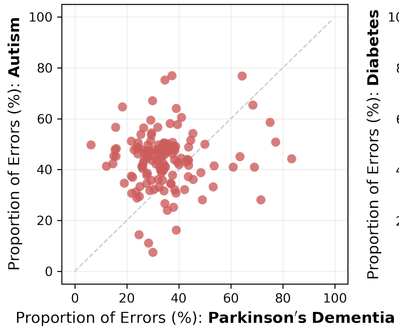
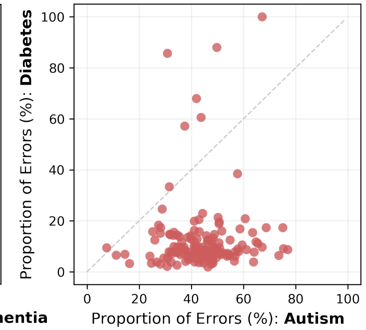
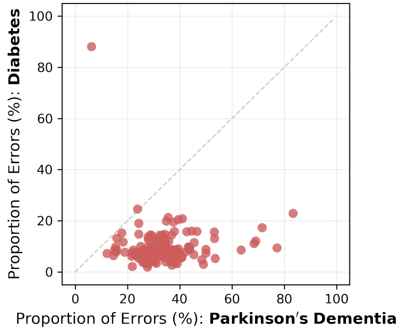






Characteristics of coding inconsistencies

How are these errors distributed across patients' characteristics?

	Autism	Diabetes	Parkinson's disease dementia
Number of subsequent episodes	491,190	1,377,121	132,113
Number of data inconsistencies at episode level	208,971 (42.5 %)	360,396 (26.2 %)	31,909 (24.1 %)
Data inconsistencies by age band			
0-17	62,691 (35.2 %)	147 (94.8 %)	12 (100.0 %)
18-39	89,414 (45.3 %)	4,930 (33.2 %)	85 (83.3 %)
40-59	35,959 (49.3 %)	108,999 (33.2 %)	701 (49.2 %)
60-79	17,982 (47.7 %)	199,234 (26.4 %)	15,654 (26.3 %)
80 years and over	2,891 (57.2 %)	47,048 (16.8 %)	15,456 (21.7 %)
Not recorded	34 (43.6 %)	38 (5.5 %)	7 (17.9 %)
Data inconsistencies by sex			
Female	80,241 (45.9 %)	106,240 (25.5 %)	11,068 (25.3 %)
Male	128,730 (40.7 %)	254,156 (26.5 %)	20,847 (23.6 %)
Not recorded/other	0	0	0
Data inconsistencies by deprivation quintile			
1 (most deprived)	61,608 (43.8 %)	119,156 (29.3 %)	6,225 (24.4 %)
2	48,829 (43.2 %)	86,482 (26.7 %)	6,111 (23.3 %)
3	38,381 (41.0 %)	64,885 (24.0 %)	7,831 (27.1 %)
4	32,192 (41.9 %)	47,344 (22.9 %)	6,061 (23.0 %)
5 (least deprived)	25,157 (41.0 %)	40,026 (24.7 %)	5,513 (22.5 %)
Not recorded *	5,839 (0.01 %)	7,983 (0.01 %)	693 (0.01 %)
Data inconsistencies by ethnicity			
White	141,881 (43.7 %)	211,257 (19.7 %)	23,722 (24.4 %)
Asian	5,557 (35.8 %)	29,612 (36.9 %)	1,349 (29.0 %)
Black	4,887 (39.9 %)	46,093 (57.6 %)	500 (20.3 %)
Mixed	2,836 (37.0 %)	2,056 (31.8 %)	104 (34.4 %)
Other ethnic groups	11,810 (39.9 %)	45,655 (46.7 %)	351 (26.8 %)
Not recorded/stated	42,000 (41.2 %)	25,723 (61.9 %)	5,998 (23.2 %)

* Where data are not recorded for deprivation, this is due to the Lower Super Output Area (LSOA) of residence not being recorded. In most cases this is due to the patient not having a permanent residence in England (typically they would be residents of other parts of the UK).

'Evident' coding inconsistencies

The exploratory analysis flagged 'evident' coding inconsistencies, related to:

- **Age of the patients**, e.g.
  Patients with Diabetes younger than 18 years old
  Patients with PDD younger than 40 years old

- **Unknown diagnoses**, through the use of the R69.X ICD10 code
  · Autism: 11,888 (1.7 % of all episodes)
  · Diabetes: 23,914 (2.4 % of all episodes)
  · PDD: 1,950 (1.2 % of all episodes)

- **Diabetes patients with dialysis treatments**: recurrent spells with no consistent coding for diabetes
  · X40-X43 OPCS codes (dialysis treatment): 382,098
  · Use of single N185 ICD10 code (chronic renal failure): 3,667

The corresponding spells were excluded from our multi-variate modelling.

Multi-variate modelling

- Exploratory analysis of coding inconsistencies without *a priori* causal model
- Large datasets
- Potentially large number of variables

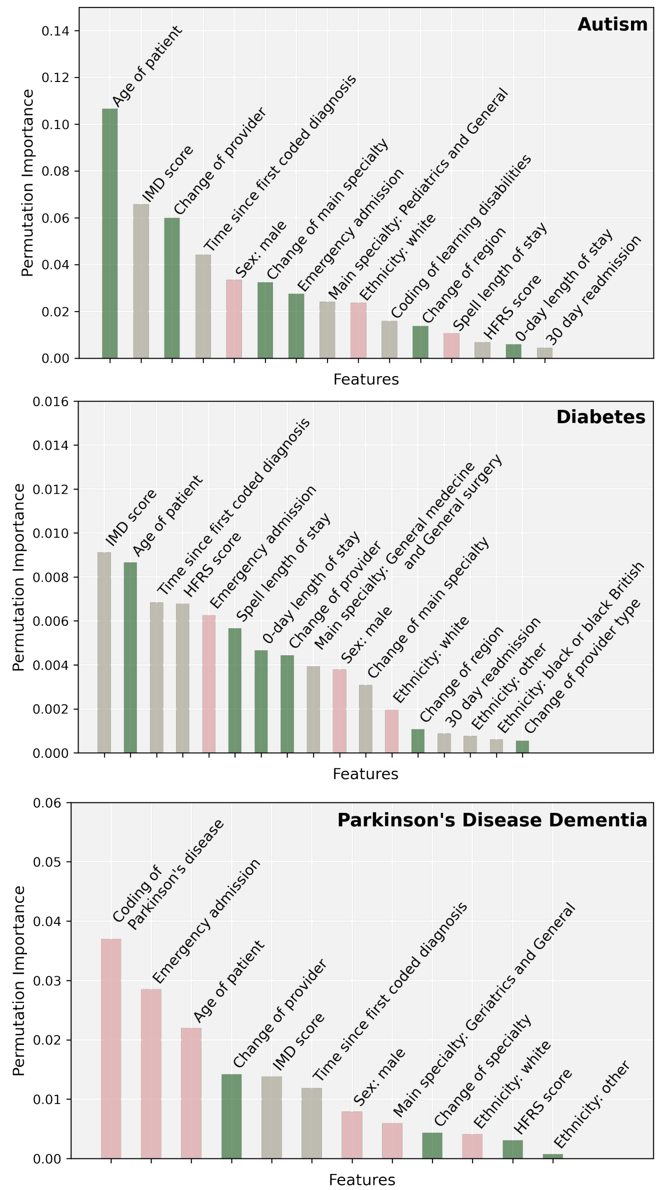
→ Lends itself well to a machine learning model

Goal: building a model that predicts whether a spell is likely to be missing a mandatory code

Covariates: - Time since first appearance of the code
- Change in providers
- Change in region
- Change in speciality
- Age, sex, ethnicity, frailty, deprivation index
- Readmission, mortality, length of stay

Important predictors are found to include:

- Time since first appearance of the code
- Age
- Spell length of stay
- Provider change
- IMD score



Exploration of Errors in Autism Dataset

Mortality is an important outcome to consider in the context of autism coding errors.

Goal: analysing the conditions under which there will be an error in a deceased patient's autism coding

- 2662 (0.4%) patients died.
- 843 (31.7%) of all deceased patients had an error in their **final spell**
- 716 (26.9%) of **all deceased patients** had the palliative care code (Z515).
- 259 (30.7%) of **deceased patients with an error in their final spell** had the palliative care code.

Breakdown of Patients

Patient Ages	Number of Patients with Errors (%)	Number of Patients without Errors (%)
0-18	61 (7.2%)	125 (6.9%)
19-29	65 (7.7%)	181 (10.0%)
30-39	45 (5.3%)	136 (7.5%)
40-49	71 (8.4%)	185 (10.2%)
50-59	160 (19.0%)	347 (19.1%)
60-69	168 (18.7%)	392 (21.6%)
70-79	150 (17.8%)	295 (16.2%)
≥ 80	133 (15.8%)	158 (8.7%)

Deprivation Decile	Number of Patients with Errors (%)	Number of Patients without Errors (%)
1 (most deprived)	130 (15.4%)	231 (12.7%)
2	103 (12.2%)	191 (10.5%)
3	110 (13.0%)	199 (10.9%)
4	74 (8.8%)	234 (12.9%)
5	90 (10.7%)	204 (11.2%)
6	78 (9.3%)	174 (9.6%)
7	66 (7.9%)	186 (10.2%)
8	69 (8.2%)	151 (8.3%)
9	68 (8.1%)	120 (6.6%)
10 (least deprived)	51 (6.0%)	105 (5.8%)

Ethnicity	Number of Patients with Errors (%)	Number of Patients without Errors (%)
White	546 (64.8%)	1194 (65.6%)
Black or Black British	11 (1.3%)	18 (1.0%)
Asian or Asian British	19 (2.3%)	43 (2.4%)
Mixed	5 (0.6%)	10 (0.5%)
Other	49 (5.8%)	108 (5.9%)
No ethnicity listed	213 (25.2%)	446 (24.5%)