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Choosing a model to predict hospital admission. An observational study of new variants of predictive models for case finding.

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ABSTRACT

Objectives: To test the performance of new variants of models to identify people at risk of an emergency hospital admission. We compared (1) the impact of using alternative data sources (hospital inpatient, A&E, outpatient, and GP electronic medical records) (2) the effects of local calibration on the performance of the models and (3) the choice of population denominators.

Design: Multivariate logistic regressions using person level data adding each data set sequentially to test value of additional variables and denominators.

Setting: Five Primary Care Trusts within England.

Participants: 1,836,099 people aged 18-95 registered with GPs on 31 July 2009.

Main outcome measures: Models to predict hospital admission and readmission were compared in terms of positive predictive value and sensitivity for various risk strata and with receiver operating curve C statistic.

Results: The addition of each data set showed moderate improvement in number of patients identified with little or no loss of positive predictive value. However, even with inclusion of GP electronic medical record information, the algorithms identified only a small number of patients with no emergency hospital admissions in the prior two years. The model pooled across all sites performed almost as well as models calibrated to local data from just one site. Using population denominators from GP registers led to better case finding.

Conclusions: These models provide a basis for wider application in the NHS. Each of the models examined produce reasonably robust performance and offers some predictive value. The addition of more complex data add some value, but we were unable to conclude that pooled models performed less well than those in individual sites. Choices about model should be linked to the intervention design. Characteristics of patients identified by the algorithms provide useful information in the design/costing of intervention strategies to improve care coordination/outcomes for these patients.

Article focus

- The use of statistical models to predict risk of hospital admissions are increasingly used to prioritise patients for preventive care. Models exist in several different forms and use a variety of input data sets.
- This paper compared the performance of a variety of models built using different datasets.

Key messages

- The addition of more detailed data sets led to moderate improvement in number of patients identified with little or no loss of positive predictive value.
- The use of GP registry data for the denominator proved to be of significant importance. By including all patients in an area, not just those with prior hospital use, improved rates of case finding were observed.
- Models calibrated to local data sets did not show a consistent improvement over models built on pooled data.

Strengths and limitations of this study

- The analysis is based on populations from only five areas in England, however this is the largest UK population (1.8M people) used in the development of a publicly available risk tool.
- The success of a predictive model depends on many factors beyond the statistical performance of the model.

INTRODUCTION

There remains continuing interest in identifying patients at risk of future hospital admissions. Policies providing penalties[1] or non-payment[2] for hospital readmissions that put providers at risk for a share of total health expenditures have been developed for in the U.S. and in England. These create even stronger incentives to identify high risk patients to target care coordination and management strategies that may potentially reduce future inpatient expenditures.

Most predictive modelling approaches have used administrative data from claims in the U.S. or hospital data from Hospital Episode Statistics (HES) or Secondary Uses Services (SUS) in England. These data provide the information on prior utilisation and diagnostic history to develop predictive models for patients at risk of future hospitalization.[3] Payor claims data in the U.S. provide rich information on care provided in hospitals, home care services and nursing home use, as well as detailed pharmacy prescription history.[4] In England, the most commonly used models (such as in the now outdated Patient at Risk of Readmission PARR algorithm)[5,6] are based on hospital admissions data (including day case use, and regular attendances) with some use of accident and emergency (A&E) and outpatient attendance data as well.[7]

While some predictive modeling efforts in the U.K. have included information from GP electronic medical records (EMRs),[8,9] using such data presents a number of challenges. These include obtaining permissions for access to EMRs for large populations, linking the records to hospital data, and use of Read codes[10] to develop GP variables. Data from EMRs include additional elements not available in the hospital data sets such as test results (e.g. blood pressure, HbA1c levels), diagnostic history for patients without recent inpatient admissions, prescription history, GP contact patterns (GP visits and telephone contacts), and other personal health markers (e.g. body mass index, smoking status). These additional data elements have the potential to add power to predictive modeling efforts, especially for patients with no or lower levels of recent inpatient use.

Despite the challenges, a number of initiatives around the UK are demonstrating population wide access to EMR data. A common application is in the use of models that assist local clinical commissioning groups (CCGs) in identifying high risk patients.

Though the choice of data sets for a predictive model makes a big difference to the investment required to run these models – at least initially – no studies have looked at the marginal value of different data sets. In this analysis we examine the added value of including data on A&E and outpatient visits (which are readily available) to predictive modeling efforts using hospital inpatient data alone. We also assess the marginal effect of adding GP EMR information to help identify patients at risk of future hospital admissions.

In addition to the depth of data used there is also a question about how generalisable models are across different sites. In many settings models are recalibrated on local data sets. Yet there is little systematic analysis of the value that this step adds and whether models built on data from one site outperform those built on a larger sample of pooled data. We therefore explore whether there is a need for development of individual site predictive models, or whether models developed from multiple sites can be applied effectively at a new individual site.

METHODS

We conducted analyses separately for five Primary Care Trust areas in England (Newham, Cornwall, Kent, Croydon, Redbridge; total adult population ranging from 209,661 to 693,089). Results are reported for the individual sites and as combined/pooled results (total population 1,836,099). Hospital data was extracted from the Secondary Users Services (SUS)[11] system which contained records of all hospital events (inpatient admissions, outpatient appointments and A&E visits) for the PCTs' registered populations between 1 August 2007 and 30 September 2010. The PCTs also extracted data from GP systems in two forms. Firstly as a register of the local adult population from 1 August 2007 and 31 July 2009, and secondly in the form of datasets recording details of GP consultations over the same time period.

Personally identifiable information was stripped out before any data were passed to the research team. Individuals' NHS numbers (the personal identifiers) were pseudonymised to allow for linkage between the hospital and the general practice data.

A series of variables were created from each data set that were believed to be potentially predictive of an unplanned (emergency) hospital admission in the last 12 months of the study period. These variables captured resource use, utilization patterns, diagnostic history, test results, and prescription history in the two years prior to the predictive period. They were created for all individuals aged 18+ registered with a GP in one of the five areas on 31 July 2009. To account for expected time required to obtain and process the hospital and GP EMR data, we included a two-month lag in our analyses, with data from 1 August 2007 to 31 July 2009 used to predict emergency admissions during the period 1 October 2009 to 30 September 2010.

Patient age and gender were obtained from the GP register. Patient area of residence was not available, and so GP practice attributed index of multiple deprivation (2007) was used as an area deprivation measure. The number of months the patient was registered with the PCT in the pre-period was calculated and included in the regression. Hospital inpatient data were used to capture utilization in the 0-90, 91-181, 180-365, and 366-730 days prior to the lag period. The number of emergency and elective admissions for these periods were included and dichotomous variables for any day case or regular attendance use were created.

A broad range of diagnostic variables were developed using primary and secondary diagnosis fields and a Charlson Comorbidity Index[12] was calculated for each patient and included in the model.

A&E data were used to determine A&E visit rates for various intervals in the pre-period, both total visits and unplanned follow-up visits. A&E diagnostic information was not reliably reported across the five sites and was not included, although X-ray use was included. Outpatient data provided variables on outpatient visit rates for various intervals, as well as missed appointment rates and the number of different specialty types consulted. Diagnostic information in outpatient data was missing in more than 95% of cases and was not included.

GP EMR data were used to create proxy visit rates (these may include both actual GP visits, in addition to other events documented in a person's records) for various intervals and to capture any increase in visit rates at the end of the pre-period that may reflect increased morbidity in a patient. EMR Read codes (CTV3 version) were used to obtain test results (blood pressure, blood serum levels, HbA1c levels, etc.), body mass index, smoking history, prescription history (number and type), and a range of diagnostic variables during the pre-period.

Variables from each data set (inpatient (including day case and regular attenders), A&E, outpatient, and GP EMRs) were added and modeled sequentially using standard logistic regression in SPSS v20. Emergency admission in the next 12 months was used as the dependent variable, producing a risk score ranging from 0-100. Separate models were developed for each PCT area, and analysis was limited to patients aged 18-95 who were on the GP register in the area. Over-fitting was tested using a split sample approach, with only minor differences observed in positive predictive values (PPV), sensitivity, and specificity.

Findings provided here include both individual site results and results combined across the five sites. We also created five additional predictive models (referred to below as the 'four-site regression models'), each one combining data from four sites and applying coefficients to the fifth remaining site. With this we could compare results with individual site predictive models to help assess the value of local model development.

The full list of more than 300 potential variables was ultimately reduced to 88 by exclusion of variables with low volumes and low significance levels across the sites. The 88 variables ultimately included in the model (and regression coefficients), may be found in Appendix B, and a full listing of the variables

considered for inclusion and detailed specification of each variable are available at http://www.nuffieldtrust.org.uk/.

Cost variables were examined, with secondary care activity costed according to the method used in development of the person based formula for allocating commissioning funds to general practices in England.[13] Ultimately, these were not included in the predictive models because of concerns about difficulties in constructing these variables by possible future users, however costs are included in descriptive findings to help in design of intervention strategies.

Predictive modeling performance is typically documented reporting PPV and sensitivity at the risk score threshold of 50. However, because interventions may be targeted at patients with higher or lower risk scores and interventions strategies may be calibrated differently depending on risk level and characteristics of patients at various risk score levels, we report PPV sensitivity at 20 risk score cutoff points (vigintiles) and provide detailed patient characteristics at risk score thresholds of 50 and 30 to facilitate intervention design.

RESULTS

Pooled Individual Site Results

There were 1,836,099 people aged 18 and over who were registered with a GP practice on 31 July 2009. Table 1 shows the combined results of individual site regressions including the number of patients correctly identified, PPV, and sensitivity for four models:

(i) IP based on hospital inpatient data only (including day cases and regular attendances)
(ii) IPAE using inpatient and A&E data
(iii) IPAEOP using inpatient A&E and outpatient data
(iv) IPAEOPGP using inpatient, A&E, outpatient data and GP EMR.

At the traditional risk score threshold level of 50 all four models perform respectably in terms of PPV (ranging from .523 to .538), but sensitivity remains quite low across all models (.049 to .060). Lowering the threshold to 30 increases sensitivity somewhat with a concomitant reduction in PPV (ranging from .417 to .422). The ROC area under the curve (C statistic) improved with the addition of each data set, increasing from .731 with the inpatient-only model to .780 with the full model.

Table 1 Model performance, four models: IP, IPAE, IPAEOP, IPAEOPGP. Five site individual runs combined.

Risk Score Threshold	IP Data			IP+AE Data			IP+AE+OP Data			IP+AE+OP+GP Data		
	True Positive	PPV	Sensitivity	True Positive	PPV	Sensitivity	True Positive	PPV	Sensitivity	True Positive	PPV	Sensitivity
1	94,692	0.052	1.000	94,692	0.052	1.000	94,692	0.052	1.000	94,692	0.052	1.000
5	54,450	0.126	0.575	56,117	0.128	0.593	56,438	0.131	0.596	61,498	0.133	0.649
10	33,053	0.219	0.349	34,102	0.221	0.360	35,033	0.223	0.370	39,986	0.220	0.422
15	22,898	0.285	0.242	23,166	0.293	0.245	24,261	0.290	0.256	28,697	0.283	0.303
20	16,181	0.346	0.171	16,915	0.347	0.179	17,719	0.344	0.187	21,601	0.333	0.228
25	12,670	0.385	0.134	13,182	0.386	0.139	13,754	0.383	0.145	16,672	0.378	0.176
30	10,061	0.421	0.106	10,555	0.422	0.111	11,010	0.419	0.116	13,196	0.417	0.139
35	8,130	0.449	0.086	8,600	0.450	0.091	8,986	0.448	0.095	10,516	0.450	0.111
40	6,700	0.477	0.071	7,139	0.478	0.075	7,421	0.476	0.078	8,494	0.479	0.090
45	5,535	0.501	0.058	5,976	0.504	0.063	6,167	0.499	0.065	6,921	0.510	0.073
50	4,627	0.529	0.049	5,027	0.531	0.053	5,172	0.523	0.055	5,669	0.538	0.060
55	3,862	0.551	0.041	4,222	0.551	0.045	4,359	0.543	0.046	4,581	0.562	0.048
60	3,239	0.574	0.034	3,555	0.569	0.038	3,658	0.567	0.039	3,735	0.587	0.039
65	2,711	0.593	0.029	3,012	0.590	0.032	3,041	0.587	0.032	3,034	0.618	0.032
70	2,245	0.617	0.024	2,481	0.612	0.026	2,519	0.610	0.027	2,453	0.645	0.026
75	1,816	0.634	0.019	2,049	0.639	0.022	2,064	0.631	0.022	1,921	0.666	0.020
80	1,418	0.666	0.015	1,662	0.656	0.018	1,646	0.654	0.017	1,478	0.696	0.016
85	1,064	0.679	0.011	1,293	0.674	0.014	1,276	0.679	0.013	1,114	0.711	0.012
90	769	0.710	0.008	932	0.688	0.010	935	0.702	0.010	754	0.738	0.008
95	478	0.748	0.005	592	0.725	0.006	586	0.728	0.006	437	0.771	0.005
Top 1%	8,214	0.447	0.087	8,353	0.455	0.088	8,410	0.458	0.089	8,722	0.475	0.092
Top 5%	24,873	0.271	0.263	25,355	0.276	0.268	25,712	0.280	0.272	26,991	0.294	0.285
	ROC C Statistic	0.731			0.745			0.752			0.780	

Of particular note is the finding that the addition of each data set added power, that is, correctly identified more patients with an admission in the next 12 months, with only a minor reduction in PPV. At a risk threshold of 50, the addition of A&E data resulted in increase of 400 (8.6%) correctly flagged patients, with no loss in PPV. The inclusion of outpatient data added a more modest 2.9%, but with a slight loss in PPV (.531 to .523). The addition of GP EMR data added an additional 9.6% of patients, while actually increasing the accuracy of the model (PPV increasing from .523 to .538). The added power of the A&E data set is less substantial at a risk score threshold of 30 (4.9%), but outpatient and GP EMR data sets had larger increases in correctly identified patients (4.3% and 19.9%).

There were also important differences between the models in terms of the characteristics of patients identified as high risk. For example, at a risk score cutoff of 50, patients identified using inpatient data alone had high prior emergency inpatient utilization rates with 2.62 admissions in the prior year compared to 2.43 when A&E data was added; 2.34 with addition of outpatient, and 2.20 with the addition of GP EMR data - see Table 2.

The inclusion of the additional data sets also led to a reduction in observed morbidity level of patients at the 50 threshold, with lower numbers of long term conditions, fewer patients with multiple long term conditions, lower Charlson Comorbidity Index scores, less history of alcohol abuse and mental illness, and lower emergency inpatient costs in the years prior to the predictive period. Similar, but less substantial differences were observed at the risk score threshold of 30. The addition of the A&E data set resulted in higher rates of A&E visits in the pre-period among patients identified at both risk score cutoff levels, and the addition of outpatient data resulted in higher outpatient visit and missed visit rates among identified patients

These findings suggest inclusion of the additional data sets added some predictive power and generally tended to find patients who were less severely ill. Thus they potentially offer an opportunity for intervention at earlier stages in the progression of a patient's condition. However, the number of patients identified with no prior emergency inpatient utilization in the prior two years was relatively small across all models. At a risk score threshold of 50, only 0.3% of patients correctly identified by the inpatient-only model had no prior emergency admissions in the previous two years, and increasing only modestly 3.2% in the full model (Table 3). At a risk threshold of 30, the rates were higher, but only reaching 12.4% for the full model.

Table 2 Patient characteristics by risk score threshold four models: IP, IPAE, IPAEOP, IPAEOPGP. Five site individual runs combined.

	Risk Score 50+				Risk Score 30+			
	IP Data	IPAE Data	IPAEOP Data	IPAEOPGP Data	IP Data	IPAE Data	IPAEOP Data	IPAEOPGP Data
Number of patients	8,743	9,473	9,892	10,545	23,912	25,021	26,304	31,653
Patients with adm next 12 mos	4,627	5,027	5,172	5,669	10,062	10,554	11,011	13,196
Mean Age	73.9	72.3	71.2	72.2	75.3	74.0	73.4	73.9
Age 18-39	6.2%	8.4%	8.7%	7.8%	5.1%	6.8%	7.0%	6.4%
Age 40-54	8.7%	9.6%	10.9%	10.6%	7.0%	7.8%	8.6%	8.5%
Age 55-64	6.9%	7.4%	7.8%	8.1%	6.4%	6.4%	7.0%	7.3%
Age 65-74	14.4%	13.9%	15.0%	13.5%	13.9%	13.8%	14.4%	13.7%
Age 75-84	30.5%	28.9%	28.2%	27.4%	32.1%	31.1%	30.3%	29.6%
Age 85+	33.3%	31.8%	29.3%	32.6%	35.5%	34.1%	32.7%	34.4%
Female	55.2%	55.2%	54.9%	54.7%	56.9%	57.1%	56.6%	56.5%
Practice IMD	24.6	24.9	24.8	24.3	24.2	24.3	24.3	23.8
Ischaemic Heart Disease	36.2%	34.2%	33.2%	32.1%	29.8%	28.4%	27.8%	25.2%
Angina	21.7%	20.5%	19.5%	19.3%	17.3%	16.4%	15.7%	14.5%
Hypertension	64.5%	61.2%	59.9%	59.0%	59.4%	56.7%	55.1%	50.9%
CHF	19.2%	17.8%	16.9%	15.9%	14.0%	13.2%	12.5%	10.7%
CVD	21.7%	20.1%	19.3%	18.1%	16.9%	15.8%	15.2%	13.3%
COPD	23.4%	21.4%	20.6%	19.1%	17.2%	16.3%	15.7%	13.4%
Asthma	21.3%	20.9%	20.1%	18.1%	17.4%	16.6%	16.1%	13.8%
Diabetes	34.1%	32.4%	31.6%	28.8%	30.1%	28.8%	27.6%	23.6%
Renal Failure	16.5%	14.6%	14.2%	13.3%	11.2%	10.4%	10.0%	8.5%
Any long term conditions	89.8%	87.0%	85.8%	85.0%	86.6%	83.6%	81.4%	75.2%
Any cancer	15.4%	13.8%	13.4%	12.4%	13.3%	12.7%	12.2%	10.5%
Alcohol misuse	10.0%	10.0%	9.6%	9.1%	7.0%	6.7%	6.4%	5.8%
Mental illness	32.0%	30.6%	28.9%	27.2%	23.5%	22.3%	21.3%	18.6%
Number long term conditions	2.67	2.51	2.43	2.31	2.20	2.10	2.02	1.79
Charlson Index	3.96	3.69	3.55	3.28	3.09	2.95	2.82	2.43
Emerg adms 1yr prior	2.62	2.43	2.34	2.20	1.64	1.57	1.50	1.29
Emerg adms 2 yr prior	1.78	1.67	1.61	1.50	1.15	1.10	1.05	0.91
No emerg adm prior 2 yrs	0.6%	1.9%	3.3%	4.3%	4.2%	6.5%	9.2%	16.2%
Elect adms 1yr prior	0.32	0.29	0.31	0.28	0.27	0.26	0.27	0.24
Elect adms 2 yr prior	0.24	0.23	0.26	0.24	0.20	0.20	0.22	0.19
Any day case 1yr prior	31.9%	30.8%	31.6%	28.7%	31.5%	30.7%	30.4%	26.9%
Any day case 2yr prior	28.9%	27.6%	28.0%	25.7%	27.8%	26.9%	26.7%	23.7%
Emerg adm cost 1yr prior	£4,500	£4,073	£3,920	£3,688	£2,893	£2,709	£2,604	£2,231
Emerg adm cost 2yr prior	£2,932	£2,675	£2,583	£2,422	£1,962	£1,822	£1,757	£1,521
AE visits 1yr prior	2.90	3.59	3.45	3.17	1.83	2.26	2.17	1.86
AE visits 2yr prior	1.90	2.40	2.31	2.10	1.23	1.52	1.46	1.25
OP visits 1yr prior	7.27	6.94	9.65	8.23	5.65	5.63	7.39	6.16
OP visits 2yr prior	4.30	4.10	5.92	5.08	3.39	3.38	4.54	3.81
OP visits missed 1yr prior	0.47	0.48	0.74	0.65	0.35	0.36	0.53	0.44
OP visits missed 2yr prior	0.49	0.48	0.71	0.61	0.33	0.34	0.48	0.40
GP visits 1yr prior	42.9	42.7	43.3	52.5	38.5	38.4	38.8	45.4
GP visits 2yr prior	35.5	35.2	35.7	42.5	32.4	32.1	32.5	37.7
Any high risk BNFs	73.9%	71.6%	72.2%	84.0%	69.3%	67.5%	68.1%	79.8%
Num high risk BNFs	1.94	1.85	1.88	2.20	1.64	1.59	1.61	1.84
High blood pressure	9.0%	9.0%	9.0%	9.0%	10.0%	10.0%	10.0%	9.0%
Smoker	18.0%	19.0%	19.0%	23.0%	16.0%	16.0%	16.0%	20.0%
BMI 30+	16.0%	17.0%	17.0%	17.0%	15.0%	16.0%	16.0%	18.0%
HbA1c > 10	5.0%	5.0%	5.0%	7.0%	5.0%	5.0%	4.0%	6.0%
Any Em adm next 12 mos	52.9%	53.1%	52.3%	53.8%	42.1%	42.2%	41.9%	41.7%
Num Em adm next 12 mos	1.34	1.33	1.29	1.31	0.89	0.89	0.87	0.84
0 Em adm next 12 mos	47.1%	46.9%	47.7%	46.2%	57.9%	57.8%	58.1%	58.3%
1 Em adm next 12 mos	23.0%	23.0%	23.2%	23.9%	21.7%	21.9%	21.7%	22.3%
2 Em adm next 12 mos	12.5%	12.5%	12.3%	13.2%	10.0%	10.0%	10.0%	9.9%
3 Em adm next 12 mos	7.3%	7.3%	7.0%	7.1%	4.8%	4.9%	4.8%	4.6%
4+ Em adm next 12 mos	10.2%	10.2%	9.8%	9.7%	5.5%	5.5%	5.3%	4.9%
Emerg adm cost next 12 mos	£2,358	£2,266	£2,199	£2,270	£1,608	£1,575	£1,546	£1,507

AE visits next 12 mos	1.88	2.11	2.04	2.04	1.24	1.37	1.36	1.29

Table 3 Proportion of patients correctly identified, who had no emergency admissions in the prior two years. Four models: IP, IPAE, IPAEOP, IPAEOPGP. Five site individual runs combined.

Prediction threshold	IP Data	IPAE Data	IPAEOP Data	IPAEOPGP Data
Risk Score 50+	0.3%	1.2%	2.3%	3.2%
Risk Score 30+	2.7%	4.4%	6.3%	12.4%
Top 1%	1.5%	2.9%	4.2%	6.5%
Top 5%	25.9%	26.4%	26.7%	30.8%

Individual Site and 'Four-Site Regression' Model Results

Overall the performance of the models was similar at the individual site level. Only modest differences were found in PPV levels and sensitivity across the sites. For runs using non-GP data only (IPAEOP), at the risk score threshold of 50, PPVs ranged from .512 to .552 and sensitivity ranged from .047 to .071. For the model including GP EMRs, PPVs ranged from .521 to .566 and sensitivity from .053 to .073. See Appendix A. There was some variation in the magnitude of regression coefficients between sites, but in general the coefficients were comparable for models based on the non-GP data model (IPAEOP). See Appendix B. For the model including variables from GP EMRs (IPAEOPGP), the level of variation in regression coefficients (size and direction) was somewhat greater for those variables derived from GP data. We observed substantial differences in frequency of reporting of Read codes across sites which no doubt contributed to this variation. The level of significance of individual variables also varied across sites (Appendix C), but most variables were consistently strongly significant across all sites, especially variables involving prior emergency inpatient admissions. Again, higher levels of variation in levels of significance were observed for the GP variables derived from Read codes.

We compared the results for these individual site models to a pooled model combining data from four of the sites and applied coefficients to the remaining individual site. We found generally only small differences in predictive accuracy (PPV) between these two approaches (Table 4), however the individual site models identified a greater number of true positives. For example, in Cornwall at a risk

score cutoff of 50, the individual site model using hospital data identified correctly 1,041 patients while the pooled model identified only 754. In Newham however, the four-site model was more powerful, correctly identifying 858 patients compared to 734 for the individual site approach. In both cases (and in general across all sites), the model identifying larger numbers of true positives had a somewhat lower PPV, suggesting improved case finding volume came at the expense of predictive accuracy.

Table 4 Individual site and four-site regression models. Case finding and predictive accuracy.

	IPOPAE				IPOPAEGP			
	Individual Site Regression		Four Site Regression		Individual Site Regression		Four Site Regression	
	True Positives	PPV	True Positives	PPV	True Positives	PPV	True Positives	PPV
Newham								
Risk Score 50+	734	0.552	858	0.517	768	0.566	835	0.523
Risk Score 30+	1,409	0.450	1,564	0.414	1,570	0.439	1,798	0.409
Cornwall								
Risk Score 50+	1,041	0.520	754	0.548	1,176	0.545	952	0.556
Risk Score 30+	2,439	0.406	1,970	0.426	3,032	0.410	2,746	0.411
Kent								
Risk Score 50+	1,565	0.513	1,387	0.519	1,736	0.521	1,873	0.493
Risk Score 30+	3,372	0.401	3,067	0.403	4,079	0.397	4,432	0.369
Croydon								
Risk Score 50+	1,089	0.528	1,192	0.523	1,182	0.550	1,230	0.537
Risk Score 30+	2,134	0.444	2,258	0.424	2,610	0.442	2,502	0.437
Redbridge								
Risk Score 50+	743	0.512	863	0.495	807	0.522	607	0.519
Risk Score 30+	1,656	0.420	1,693	0.415	1,905	0.423	1,390	0.436

Testing alternative population denominators

Models built using inpatient data only (IP) were also built for just the subset of patients who had some inpatient care in the prior two years (to reflect typical predictive modeling efforts that may have been conducted without access to GP registry information), as well as for the group who had had an emergency admission in the prior year (to replicate analyses conducted by PARR users).

Combining the results from the five sites at a risk score threshold of 50, models using GP list denominator correctly identified 4,627 patients compared with 3,572 patients in runs restricted to patients with prior inpatient care and 3,060 to runs limited to patients with an emergency admission in the prior year. This substantial increase in case finding was obtained with only moderate loss in PPV (.529 GP list, .559 prior inpatient and .589 emergency admissions in last year). Similar results were also found for all hospital data models (IPOPAE, though with any hospital use in prior two years, rather than just any inpatient use).

Using the full GP registry population did not result in finding substantial numbers of patients with no emergency admissions in the prior two years, but the increased numbers of patients identified included more patients with less prior use and lower levels of morbidity. For a profile of patients identified using these alternative denominators see http://www.nuffieldtrust.org.uk/.

DISCUSSION

This analysis has looked at the performance of new variants of predictive models for case finding. These models are intended to update and improve upon the established combined predictive model-like [14] and PARR models [5] widely used in the NHS.

Each of the models examined produced reasonably robust performance. At a risk threshold of 50, patients identified by the models had PPVs ranging from .523 to .538. While the percent of all patients with future admissions identified was relatively low (sensitivity .049 to .060), lowering the risk threshold allows the identification of more patients with relatively small loss in PPV (e.g. at a risk threshold of 30, the full model identified 14% of future admissions with a PPV of .417). Users of predictive modeling algorithms have obvious trade-offs between maximizing the number of patients identified and predictive accuracy. Lower risk score thresholds will find more patients, but these patients are increasingly less likely to have future admissions.

The implications for intervention design are important. Patients at lower risk thresholds have less prior inpatient use and lower morbidity, so an intervention here might be calibrated to be less intensive. But because the models are less accurate at lower risk scores, the amount that can be spent on an intervention is also reduced if you wish to achieve financial break-even (ie where the cost of intervention is off-set by cost savings from reduction in future admissions). As documented in Table 2, at a risk score threshold of 50, the rate of future admission for patients identified by the full model

(IPAEOPGP data) was 1.31 admissions per year with an associated cost of £2,270. If there were a 10% reduction in future admissions, £227 could be spent on an intervention to improve care coordination and still achieve break-even. However, at a lower risk threshold of 30, the lower rates of future admissions and costs means that lower intervention expenditures are required to achieve break-even (£151 with a 10% reduction in future admissions). A detailed business case analysis with mean emergency inpatient costs in the next 12 months within each risk vigintile level is available via http://www.nuffieldtrust.org.uk/.

These data also provide other information that may be useful in the development of intervention strategies. As shown in Table 2, patients identified by the models have extremely high rates of chronic disease (85-90% with long term conditions at risk threshold of 50), often with multiple long term conditions and high Charlson Comorbidity Index levels, indicating serious medical needs. However, these patients already have high use of outpatient care and very high GP visit rates. This suggests simple access to ambulatory care is not the issue, but prevention needs to look at care coordination and management of complex problems and at the ability of patients and their families to manage chronic illness. High risk patients identified by the models also have relatively high rates of mental illness (27-32% at risk threshold of 50) and moderate levels of alcohol abuse, factors that are likely to complicate any intervention strategy.

It is also important to note the limitations of these data in helping frame the design of any intervention strategy. Other studies have documented that high risk patients often have important characteristics related to care needs and patient capacity not captured by administrative data and EMRs. For example, interviews with high risk patients and their families have documented high levels of social isolation for many, as well as precarious housing status.[15] These non-medical factors are likely to have significant impact on health status and utilization patterns. Moreover, not much is known about how/whether care coordination and management has actually failed for these patients. Are these high risk patients just very sick patients whose hospitalizations are largely not preventable/avoidable, or has the care delivery system failed in some important dimensions that can be corrected with improved care coordination and management? These data cannot answer this very critical question, and it is clear that the field would benefit from further study that examined the circumstances of patients identified as high risk by predictive modeling algorithms to sort out more clearly the factors contributing to high rates of emergency admission.

This study does document the value of incorporating data sets beyond inpatient records. The addition of A&E and outpatient records resulted in identification of more high risk patients with little or no loss of predictive accuracy. These data sets are readily available and have standardized reporting formats that facilitate analysis. While the absence of useful diagnostic information in these data sets is a limiting factor, the improvement in case finding and usefulness in descriptive profiling of high risk patients to help in intervention design (e.g. high rates of A&E use rates, high rates of missed outpatient appointments) suggests their inclusion is clearly merited.

Use of GP EMRs presents significant challenges. While the lack of access to these data is unlikely to remain a problem, the variation in completeness and quality of data is problematic. The use of the unwieldy Read codes system makes analysis difficult, and we observed significant differences across sites in reporting patterns. However, the potential improvement in case finding, especially among patients with lower rates of utilization in the pre-period, suggests these barriers are worth confronting. Our development of new variables beyond those included in prior predictive modeling efforts [8] contributed substantially to enhanced case finding, and further work on variable development is likely to lead to further improvements. Again, these data are also useful in providing descriptive information on high risk patients to help in intervention design (e.g. documenting potential targets of opportunity such as uncontrolled hypertension or diabetes).

This study does not provide definitive findings on the value of developing individual site models compared to simply applying coefficients from multi-site or national model coefficients to local data. Our four-site regression models generally had comparable PPVs to individual site models, but for the majority of sites (but not all) the four-site regression approach correctly identified somewhat fewer number patients with future admissions. Our analysis is somewhat limited by the small number of sites involved which might cause somewhat greater variability in regression coefficients (regression coefficients for each of the five four-site models are available at http://www.nuffieldtrust.org.uk/). Development of a national model using SUS data only is planned to further assess the need/value of locally developed models.

Finally, it is worthy of note that use of the GP registry data for the denominator also proved to be of significant importance. Many prior predictive modeling efforts have been limited to patients with utilization history in whatever data sets were included. By including all patients in an area, not just those with prior use, the impact on predictive modeling of prior use was apparently enhanced. As a

result, patients with more moderate levels of prior use and morbidity were found to be of higher risk than patients with no prior use at all, and were often assigned higher risk scores than when the analysis included just patients who had prior use. Accordingly, the use of the GP registry as the denominator can improve rates of case finding and may permit identification of patients at earlier stages.

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Contributors

The preparation of data sets and input variables and costs were undertaken by TG and by IB; JB did the central modelling. MB advised on the analysis and results and managed the work of the research team at the Nuffield Trust. All authors contributed to the writing of the paper. JB is the guarantor.

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Competing interests

All authors have completed the Unified Competing Interest form at www.icmje.org/coi_disclosure.pdf and declare that no authors have any relationships with any companies that might have an interest in the submitted work in the previous 3 years; none of their spouses, partners or children have any financial relationships that may be relevant to the submitted work; and no authors have any non-financial interests that may be relevant to the submitted work.

Ethical approval

This study only involved the analysis of pseudonymous secondary data. Since there were no identifiable human subjects, ethics approval was not required for this research and informed consent was not sought.

Provenance and peer review

Not commissioned; externally peer reviewed.

Data sharing statement

Details of the derived models variables and definitions are available from the authors at the Nuffield trust at research@nuffieldtrust.org.uk.

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Appendix A. PPV and sensitivity IPAEOP and IPAEOPGP models. Individual site runs.

	IP+AE+OP Data									
Risk Score	Newham		Cornwall		Kent		Croydon		Redbridge	
Threshold	PPV	Sensitivity	PPV	Sensitivity	PPV	Sensitivity	PPV	Sensitivity	PPV	Sensitivity
1	0.049	1.000	0.061	1.000	0.052	1.000	0.046	1.000	0.047	1.000
10	0.236	0.361	0.216	0.391	0.213	0.339	0.241	0.378	0.238	0.425
20	0.368	0.201	0.328	0.188	0.326	0.158	0.377	0.210	0.357	0.236
30	0.450	0.136	0.406	0.109	0.401	0.094	0.444	0.142	0.420	0.149
40	0.506	0.098	0.477	0.072	0.457	0.062	0.486	0.100	0.475	0.098
50	0.552	0.071	0.520	0.047	0.513	0.043	0.528	0.073	0.512	0.067
60	0.585	0.052	0.560	0.030	0.569	0.031	0.580	0.055	0.532	0.044
70	0.632	0.037	0.622	0.021	0.618	0.022	0.610	0.040	0.555	0.028
80	0.678	0.024	0.655	0.013	0.673	0.014	0.659	0.028	0.571	0.016
90	0.717	0.013	0.692	0.007	0.724	0.008	0.710	0.016	0.617	0.008
Top 1%	0.501	0.102	0.470	0.077	0.417	0.080	0.482	0.106	0.474	0.101
Top 5%	0.287	0.291	0.292	0.240	0.259	0.249	0.290	0.318	0.296	0.316

	IP+AE+OP+GP Data									
Risk Score	Newham		Cornwall		Kent		Croydon		Redbridge	
Threshold	PPV	Sensitivity	PPV	Sensitivity	PPV	Sensitivity	PPV	Sensitivity	PPV	Sensitivity
1	0.049	1.000	0.061	1.000	0.052	1.000	0.046	1.000	0.047	1.000
10	0.228	0.410	0.213	0.439	0.210	0.392	0.237	0.452	0.237	0.457
20	0.360	0.235	0.323	0.232	0.314	0.194	0.358	0.267	0.348	0.272
30	0.439	0.152	0.410	0.136	0.397	0.113	0.442	0.174	0.423	0.172
40	0.499	0.103	0.481	0.084	0.459	0.072	0.494	0.114	0.482	0.113
50	0.566	0.074	0.545	0.053	0.521	0.048	0.550	0.079	0.522	0.073
60	0.606	0.052	0.602	0.033	0.580	0.032	0.589	0.052	0.563	0.047
70	0.657	0.036	0.659	0.021	0.644	0.021	0.643	0.035	0.616	0.030
80	0.723	0.021	0.714	0.013	0.694	0.013	0.694	0.021	0.651	0.018
90	0.766	0.012	0.745	0.006	0.752	0.007	0.735	0.011	0.655	0.007
Top 1%	0.504	0.102	0.490	0.081	0.438	0.084	0.502	0.110	0.487	0.104
Top 5%	0.296	0.300	0.309	0.254	0.272	0.262	0.307	0.337	0.312	0.333

Appendix B Regression coefficients. IPAEOP and IPAEOPGP models. Individual site runs.

	IP+AE+OP Data					IP+AE+OP+GP Data				
	NH	CW	KT	CR	RB	NH	CW	KT	CR	RB
Age	0.015	0.003	0.009	0.010	0.019	0.001	-0.004	0.002	0.001	0.009
Age 65-74	0.280	0.409	0.295	0.380	0.261	0.236	0.276	0.203	0.244	0.245
Age 75-84	0.738	0.905	0.731	0.847	0.734	0.721	0.672	0.605	0.708	0.749
Age 85+	1.076	1.483	1.226	1.178	1.109	1.150	1.206	1.086	1.187	1.213
Female	0.239	0.002	0.044	0.178	0.058	0.114	-0.095	-0.075	-0.014	-0.030
Practice IMD	0.013	0.003	0.016	0.018	0.012	0.008	0.004	0.017	0.010	0.015
Months registered 1 yr prior	0.014	-0.011	-0.005	-0.018	-0.013	0.011	-0.011	-0.003	-0.010	-0.006
Months registered 2 yrs prior	-0.022	-0.019	-0.016	-0.007	-0.023	-0.021	-0.024	-0.019	-0.011	-0.021
EM Adms prior 0-90 days	0.382	0.471	0.321	0.310	0.282	0.367	0.420	0.283	0.269	0.259
EL Adms prior 0-90 days	0.045	0.216	0.155	0.153	0.148	0.033	0.159	0.074	0.097	0.069
Any attender prior 0-90 days	0.115	0.027	0.001	0.041	0.073	0.135	0.026	0.010	0.042	0.064
Any day case prior 0-90 days	0.094	0.234	0.110	0.111	0.251	0.037	0.173	0.039	-0.019	0.130
EM Adms prior 91-180 days	0.215	0.310	0.351	0.282	0.185	0.217	0.262	0.297	0.243	0.160
EL Adms prior 91-180 days	0.321	0.150	0.062	0.204	0.081	0.283	0.128	0.027	0.118	0.024
EM Adms prior 181-365 days	0.113	0.345	0.350	0.248	0.146	0.124	0.289	0.292	0.227	0.129
EL Adms prior 181-365 days	0.097	0.120	0.104	0.118	0.170	0.072	0.079	0.060	0.035	0.108
Em Adms 2 yrs prior	0.102	0.269	0.307	0.181	0.143	0.116	0.216	0.250	0.178	0.149
Any day case 2 yrs prior	0.096	0.157	0.186	0.151	0.179	0.058	0.092	0.112	0.005	0.103
DX MI	-0.108	0.097	-0.105	-0.004	0.376	-0.197	-0.003	-0.163	-0.111	0.228
DX CHF	-0.348	-0.070	-0.246	-0.069	-0.337	-0.370	-0.178	-0.269	-0.110	-0.216
DX CVD	0.296	0.227	0.033	0.037	-0.040	0.269	0.166	-0.001	-0.099	-0.061
CD CTD	0.030	-0.024	0.101	-0.380	-0.029	0.071	-0.192	-0.010	-0.427	-0.039
DX PVD	-0.245	0.124	0.099	-0.100	0.021	-0.253	0.048	0.026	-0.096	0.003
DX Asthma	0.082	0.143	0.184	0.099	0.192	-0.114	-0.107	-0.023	-0.081	0.028
DX COPD	0.204	0.251	0.277	0.193	0.123	-0.169	-0.139	-0.036	-0.330	-0.269
DX Diabetes	0.240	0.303	0.285	0.253	0.276	-0.046	-0.052	-0.016	-0.124	0.011
DX Diabetes with complications	0.059	-0.221	0.062	-0.014	0.334	0.062	-0.176	0.095	0.004	0.262
DX Renal Disease	0.408	0.022	0.085	0.128	0.199	0.356	0.005	0.073	0.063	0.120
DX Cancer	-0.165	-0.019	-0.062	-0.308	0.041	0.041	0.098	-0.010	-0.207	0.034
DX Mental	0.498	0.316	0.363	0.484	0.077	0.340	0.131	0.111	0.266	-0.061
DX Alcohol	0.569	0.684	0.578	0.673	0.974	0.281	0.530	0.357	0.409	0.754
DX Dementia	-0.548	-0.589	-0.551	-0.402	-0.596	-0.530	-0.486	-0.440	-0.669	-0.641
DX Cognitive Impairment	-0.117	0.016	0.025	0.110	0.187	-0.075	0.046	0.031	0.088	0.152
DX ACS Condition	0.364	0.270	0.239	0.267	0.306	0.269	0.161	0.134	0.114	0.224
Charlson Index	0.055	0.063	0.060	0.101	0.025	0.048	0.062	0.037	0.086	0.029
AE visits prior 0-90 days	0.236	0.267	0.355	0.309	0.359	0.179	0.230	0.265	0.199	0.260
AE unplanned follow-up visits prior 0-90 days	-0.094	-0.583	-0.533	-0.874	-0.383	-0.107	-0.566	-0.452	-0.703	-0.315
AE X-ray prior 0-90 days	0.348	0.437	0.058	0.104	0.367	0.303	0.382	0.027	0.040	0.317
AE visits prior 91-180 days	0.265	0.262	0.220	0.225	0.277	0.197	0.225	0.165	0.142	0.210
AE unplanned follow-up visits prior 91-180 days	-0.023	-0.560	-0.229	-0.296	-0.298	-0.026	-0.543	-0.177	-0.225	-0.286
AE X-ray prior 91-180 days	0.227	0.117	0.120	0.346	-0.064	0.210	0.015	0.101	0.237	0.010
AE visits prior 181-365 days	0.264	0.205	0.135	0.171	0.181	0.216	0.174	0.090	0.115	0.138
AE unplanned follow-up visits prior 181-365 days	-0.251	-0.490	-0.184	-0.261	-0.203	-0.214	-0.449	-0.131	-0.175	-0.221
AE X-ray prior 181-365 days	0.262	-0.040	0.281	0.324	0.110	0.225	0.085	0.251	0.244	0.072
AE visits 2 yrs prior	0.211	0.159	0.154	0.140	0.160	0.170	0.138	0.114	0.077	0.121
AE unplanned follow-up visits 2 yrs prior	-0.307	-0.352	-0.239	-0.433	-0.339	-0.228	-0.317	-0.178	-0.262	-0.288
AE X-ray 2yrs prior	0.083	0.231	0.100	0.128	0.179	0.063	0.390	0.082	0.069	0.152
Outpatient specialty visits prior 0-90 days	0.046	0.055	0.091	0.061	0.059	0.025	0.033	0.047	0.030	0.027
Outpatient specialty visits missed prior 0-90 days	0.155	0.182	0.250		0.146	0.108	0.118	0.171		0.097
Outpatient specialty visits prior 91-180 days	0.030	0.013	0.023	0.034	0.029	0.007	0.003	-0.004	0.015	0.011
Outpatient specialty visits missed	0.113	0.239	0.168		0.193	0.087	0.184	0.113		0.159

prior 91-180 days										
Outpatient specialty visits prior 181-365 days	0.016	0.010	-0.005	0.019	0.031	-0.003	0.001	-0.024	0.003	0.018
Outpatient specialty visits missed prior 181-365 days	0.128	0.164	0.075		0.140	0.086	0.095	0.036		0.122
Outpatient specialty visits 2 yrs prior	0.019	0.030	0.014	0.028	0.019	0.008	0.014	-0.009	0.011	0.021
Outpatient specialty visits missed 2 yrs prior	0.142	0.162	0.140	0.190	0.082	0.097	0.090	0.085	0.129	0.057
GP DX COPD						0.218	0.174	0.112	0.287	0.295
GP - 1 long term condition						0.131	0.025	0.017	0.106	0.192
GP - 2 or more long term conditions						0.166	0.109	0.038	0.070	0.182
GP - Glomerular filtration rate group 3 last 0-365 days						-0.075	0.092	-0.017		0.050
GP - 10+ unique drugs prescribed						0.342	0.570	0.166	2.741	1.949
GP - 5-9 unique drugs prescribed						0.424	0.444	0.164	2.804	1.953
GP - 0-4 unique drugs prescribed						0.328	0.254	0.114	2.559	1.809
GP - Psychoactive substance misuse disorder						0.388	0.323	0.583	0.431	0.810
GP - 7+ distinct disorders						-0.049	0.057	0.017	-0.163	-0.062
GP - GP visits prior 0-3 months						-0.001	0.008	0.022	0.021	0.042
GP - GP visits prior 4-6 months						0.015	0.004	0.012	0.009	0.019
GP - GP visits prior 7-12 months						0.005	0.003	0.007	0.000	0.008
GP - GP visits 2yrs prior						0.000	0.002	0.004	0.006	0.002
GP - Increasing rate of GP visits during last 12 months						0.184	0.087	0.126	0.207	0.094
GP - Number of high risk BNFs						0.063	0.006	-0.036	-0.026	-0.075
GP - Any high risk						0.219	0.202	0.241	0.324	0.249
GP - Count of BNF chapters						0.066	0.053	0.059	0.066	-0.024
GP - DX Dementia						0.421	0.266	0.296	0.471	0.437
GP - Exception reported from quality indicators						0.157	0.108	0.111	0.118	0.132
GP - Health visitor or district nurse visit						0.278	0.244	0.199	0.168	0.184
GP - Record of IHD/angina						0.069	-0.048	0.110	-0.062	0.081
GP - Nebuliser used						0.113	0.315	0.207	0.191	0.448
GP - Salbutamol prescribed						0.021	0.017	0.074	0.000	-0.011
GP - Warfarin prescribed						-0.041	0.031	-0.026	-0.100	-0.244
GP - High blood pressure						-0.040	-0.001	-0.013	-0.048	-0.087
GP - Smoker						0.298	0.231	0.248	0.240	0.220
GP - BMI 30+						0.050	0.002	0.085	0.046	0.199
GP - HbA1c > 10						0.236	0.270	0.210	0.362	0.354
GD - QOF ARTF						0.176	0.064	0.095	-0.047	0.143
GP - QOF CKD						0.206	-0.003	-0.037	0.091	0.210
GP - QOF Depression						0.069	0.248	0.183	0.133	0.186
GP - Number of QOF DX categories 3+						0.003	-0.023	-0.072	-0.135	-0.009
GP - Number of phone contacts last 0-3 months						-0.004	0.046	0.004	-0.005	-0.004
Constant	-4.665	-3.262	-3.987	-4.363	-4.368	-4.381	-3.275	-4.069	-6.497	-5.939

Appendix C Regression significance levels. IPAEOP and IPAEOPGP models. Individual site runs.

	IP+AE+OP Data					IP+AE+OP+GP Data				
	NH	CW	KT	CR	RB	NH	CW	KT	CR	RB
Age	0.000	0.000	0.000	0.000	0.000	0.344	0.000	0.001	0.158	0.000
Age 65-74	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Age 75-84	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Age 85+	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Female	0.007	0.897	0.000	0.001	0.125	0.000	0.000	0.000	0.466	0.165
Practice IMD	0.008	0.036	0.000	0.000	0.000	0.015	0.010	0.000	0.000	0.000
Months registered 1 yr prior	0.002	0.006	0.085	0.247	0.047	0.009	0.011	0.387	0.026	0.255
Months registered 2 yrs prior	0.001	0.014	0.006	0.232	0.276	0.009	0.003	0.001	0.211	0.025
EM Adms prior 0-90 days	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
EL Adms prior 0-90 days	0.664	0.000	0.000	0.029	0.081	0.714	0.000	0.070	0.102	0.373
Any attender prior 0-90 days	0.002	0.000	0.955	0.006	0.004	0.001	0.000	0.489	0.005	0.008
Any day case prior 0-90 days	0.769	0.000	0.001	0.682	0.001	0.561	0.000	0.233	0.699	0.015
EM Adms prior 91-180 days	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002
EL Adms prior 91-180 days	0.000	0.000	0.068	0.022	0.528	0.000	0.001	0.437	0.016	0.680
EM Adms prior 181-365 days	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000
EL Adms prior 181-365 days	0.548	0.000	0.000	0.757	0.019	0.167	0.009	0.030	0.372	0.014
Em Adms 2 yrs prior	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Any day case 2 yrs prior	0.877	0.000	0.000	0.536	0.035	0.177	0.000	0.000	0.864	0.005
DX MI	0.366	0.134	0.049	0.611	0.000	0.076	0.966	0.002	0.216	0.017
DX CHF	0.024	0.253	0.000	0.448	0.008	0.001	0.005	0.000	0.194	0.026
DX CVD	0.015	0.000	0.446	0.610	0.571	0.013	0.002	0.977	0.179	0.504
CD CTD	0.263	0.756	0.150	0.010	0.759	0.645	0.013	0.891	0.000	0.766
DX PVD	0.230	0.061	0.097	0.567	0.665	0.079	0.462	0.661	0.270	0.982
DX Asthma	0.351	0.002	0.000	0.241	0.015	0.135	0.024	0.580	0.184	0.698
DX COPD	0.005	0.000	0.000	0.009	0.098	0.098	0.021	0.483	0.002	0.041
DX Diabetes	0.000	0.000	0.000	0.000	0.000	0.444	0.227	0.649	0.016	0.845
DX Diabetes with complications	0.478	0.025	0.540	0.363	0.013	0.674	0.073	0.347	0.973	0.083
DX Renal Disease	0.000	0.731	0.142	0.068	0.025	0.001	0.942	0.208	0.405	0.210
DX Cancer	0.753	0.751	0.271	0.001	0.421	0.727	0.104	0.862	0.009	0.721
DX Mental	0.000	0.000	0.000	0.000	0.370	0.000	0.005	0.008	0.000	0.447
DX Alcohol	0.000	0.000	0.000	0.000	0.000	0.029	0.000	0.000	0.000	0.000
DX Dementia	0.005	0.000	0.000	0.000	0.000	0.004	0.000	0.000	0.000	0.000
DX Cognitive Impairment	0.430	0.804	0.620	0.191	0.026	0.456	0.474	0.534	0.199	0.080
DX ACS Condition	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000
Charlson Index	0.012	0.000	0.000	0.000	0.212	0.042	0.000	0.006	0.000	0.160
AE visits prior 0-90 days	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AE unplanned follow-up visits prior 0-90 days	0.895	0.001	0.000	0.000	0.133	0.654	0.001	0.000	0.000	0.121
AE X-ray prior 0-90 days	0.002	0.000	0.301	0.374	0.052	0.004	0.002	0.636	0.662	0.035
AE visits prior 91-180 days	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AE unplanned follow-up visits prior 91-180 days	0.836	0.000	0.000	0.149	0.130	0.899	0.000	0.005	0.214	0.055
AE X-ray prior 91-180 days	0.070	0.582	0.045	0.002	0.672	0.062	0.946	0.090	0.009	0.985
AE visits prior 181-365 days	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AE unplanned follow-up visits prior 181-365 days	0.182	0.000	0.001	0.122	0.124	0.098	0.001	0.013	0.127	0.041
AE X-ray prior 181-365 days	0.000	0.936	0.000	0.000	0.461	0.001	0.866	0.000	0.000	0.485
AE visits 2 yrs prior	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AE unplanned follow-up visits 2 yrs prior	0.021	0.008	0.000	0.003	0.009	0.020	0.016	0.000	0.008	0.005
AE X-ray 2yrs prior	0.183	0.555	0.019	0.022	0.005	0.210	0.320	0.048	0.161	0.006
Outpatient specialty visits prior 0-90 days	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Outpatient specialty visits missed prior 0-90 days	0.000	0.000	0.000		0.002	0.000	0.000	0.000		0.008
Outpatient specialty visits prior 91-180 days	0.196	0.043	0.003	0.002	0.016	0.516	0.630	0.648	0.054	0.184
Outpatient specialty visits missed prior 91-180 days	0.027	0.000	0.000		0.000	0.039	0.000	0.002		0.000
Outpatient specialty visits prior 181-365 days	0.763	0.009	0.400	0.094	0.000	0.595	0.844	0.000	0.491	0.002
Outpatient specialty visits missed prior 181-365 days	0.000	0.000	0.009		0.000	0.001	0.002	0.206		0.000
Outpatient specialty visits 2 yrs prior	0.000	0.000	0.000	0.000	0.000	0.068	0.000	0.046	0.001	0.000
Outpatient specialty visits missed 2 yrs prior	0.000	0.000	0.000	0.000	0.001	0.000	0.006	0.000	0.000	0.000
GP DX COPD						0.002	0.000	0.001	0.000	0.003

GP - 1 long term condition						0.000	0.229	0.310	0.000	0.000
GP - 2 or more long term conditions						0.001	0.000	0.100	0.098	0.000
GP - Glomerular filtration rate group 3 last 0-365 days						0.097	0.002	0.463		0.162
GP - 10+ unique drugs prescribed						0.000	0.000	0.000	0.000	0.000
GP - 5-9 unique drugs prescribed						0.000	0.000	0.000	0.000	0.000
GP - 0-4 unique drugs prescribed						0.000	0.000	0.000	0.000	0.000
GP - Psychoactive substance misuse disorder						0.000	0.000	0.000	0.000	0.000
GP - 7+ distinct disorders						0.311	0.290	0.523	0.002	0.263
GP visits prior 0-3 months						0.873	0.002	0.000	0.000	0.000
GP visits prior 4-6 months						0.000	0.182	0.000	0.008	0.000
GP visits prior 7-12 months						0.075	0.136	0.000	0.987	0.006
GP visits 2yrs prior						0.934	0.013	0.000	0.000	0.263
GP - Increasing rate of GP visits during last 12 months						0.000	0.001	0.000	0.000	0.010
GP - Number of high risk BNFs						0.009	0.691	0.004	0.216	0.002
GP - Any high risk						0.000	0.000	0.000	0.000	0.000
GP - Count of BNF chapters						0.000	0.000	0.000	0.000	0.000
GP - DX Dementia						0.000	0.000	0.000	0.000	0.000
GP - Exception reported from quality indicators						0.020	0.003	0.001	0.020	0.062
GP - Health visitor or district nurse visit						0.000	0.000	0.000	0.000	0.000
GP - Record of IHD/angina						0.355	0.361	0.006	0.202	0.288
GP - Nebuliser used						0.359	0.000	0.001	0.019	0.001
GP - Salbutamol prescribed						0.550	0.523	0.001	0.989	0.795
GP - Warfarin prescribed						0.643	0.423	0.440	0.106	0.001
GP - High blood pressure						0.269	0.984	0.549	0.725	0.325
GP - Smoker						0.000	0.000	0.000	0.000	0.000
GP - BMI 30+						0.074	0.956	0.000	0.074	0.000
GP - HbA1c > 10						0.000	0.000	0.000	0.000	0.000
GD - QOF ARTF						0.130	0.240	0.024	0.586	0.136
GP - QOF CKD						0.003	0.924	0.203	0.063	0.000
GP - QOF Depression						0.240	0.000	0.000	0.024	0.016
GP - Number of QOF DX categories 3+						0.974	0.717	0.123	0.342	0.948
GP - Number of phone contacts last 0-3 months						0.927	0.000	0.600	0.788	0.899
Constant	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

STROBE Statement—checklist of items that should be included in reports of observational studies

Please fill out the page numbers on this form and upload the file as a supplemental file when you submit your revision

Manuscript Number_____

	Item No	Recommendation	Indicate page number ↓ (Or n/a if not applicable)
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	2
Introduction			4-5
Background/rationale	2	Explain the scientific background and rationale for the investigation being reported	4-5
Objectives	3	State specific objectives, including any prespecified hypotheses	5
Methods			6-8
Study design	4	Present key elements of study design early in the paper	6-7
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection	6
Participants	6	(*a*) *Cohort study*—Give the eligibility criteria, and the sources and methods of selection of participants. Describe methods of follow-up *Case-control study*—Give the eligibility criteria, and the sources and methods of case ascertainment and control selection. Give the rationale for the choice of cases and controls *Cross-sectional study*—Give the eligibility criteria, and the sources and methods of selection of participants	6
		(*b*) *Cohort study*—For matched studies, give matching criteria and number of exposed and unexposed *Case-control study*—For matched studies, give matching criteria and the number of controls per case	n/a
Variables	7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable	6-7
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	6-8
Bias	9	Describe any efforts to address potential sources of bias	7
Study size	10	Explain how the study size was arrived at	6
Quantitative variables	11	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen and why	7-8
Statistical methods	12	(*a*) Describe all statistical methods, including those used to control for confounding	7-8
		(*b*) Describe any methods used to examine subgroups and interactions	7-8
		(*c*) Explain how missing data were addressed	n/a
		(*d*) *Cohort study*—If applicable, explain how loss to follow-up was addressed *Case-control study*—If applicable, explain how matching of cases and controls was addressed *Cross-sectional study*—If applicable, describe analytical methods taking account of sampling strategy	n/a
		(*e*) Describe any sensitivity analyses	7
Results			8-14
Participants	13*	(a) Report numbers of individuals at each stage of study—eg numbers potentially eligible, examined for eligibility, confirmed eligible, included in the study, completing follow-up, and analysed	8
		(b) Give reasons for non-participation at each stage	n/a
		(c) Consider use of a flow diagram	n/a
Descriptive data	14*	(a) Give characteristics of study participants (eg demographic, clinical, social) and information on exposures and potential confounders	9
		(b) Indicate number of participants with missing data for each variable of interest	n/a
		(c) *Cohort study*—Summarise follow-up time (eg, average and total amount)	9
Outcome data	15*	*Cohort study*—Report numbers of outcome events or summary measures over time	n/a
		Case-control study—Report numbers in each exposure category, or summary measures of exposure	n/a
		Cross-sectional study—Report numbers of outcome events or summary measures	n/a
Main results	16	(*a*) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision (eg, 95%	

		confidence interval). Make clear which confounders were adjusted for and why they were included	8-10
		(*b*) Report category boundaries when continuous variables were categorized	9,11
		(*c*) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period	n/a
Other analyses	17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses	12-13
Discussion			14-17
Key results	18	Summarise key results with reference to study objectives	14-17
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	15
Interpretation	20	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence	15-16
Generalisability	21	Discuss the generalisability (external validity) of the study results	16
Other information			18
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	18

*Give information separately for cases and controls in case-control studies and, if applicable, for exposed and unexposed groups in cohort and cross-sectional studies.

Note: An Explanation and Elaboration article discusses each checklist item and gives methodological background and published examples of transparent reporting. The STROBE checklist is best used in conjunction with this article (freely available on the Web sites of PLoS Medicine at http://www.plosmedicine.org/, Annals of Internal Medicine at http://www.annals.org/, and Epidemiology at http://www.epidem.com/). Information on the STROBE Initiative is available at www.strobe-statement.org.

Choosing a model to predict hospital admission. An observational study of new variants of predictive models for case finding.

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Choosing a model to predict hospital admission. An observational study of new variants of predictive models for case finding.

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Key words:

Predictive Risk, Urgent care, Hospital admission

Word count: 4,090

ABSTRACT

Objectives: To test the performance of new variants of models to identify people at risk of an emergency hospital admission. We compared (1) the impact of using alternative data sources (hospital inpatient, A&E, outpatient, and GP electronic medical records) (2) the effects of local calibration on the performance of the models and (3) the choice of population denominators.

Design: Multivariate logistic regressions using person level data adding each data set sequentially to test value of additional variables and denominators.

Setting: Five Primary Care Trusts within England.

Participants: 1,836,099 people aged 18-95 registered with GPs on 31 July 2009.

Main outcome measures: Models to predict hospital admission and readmission were compared in terms of positive predictive value and sensitivity for various risk strata and with receiver operating curve C statistic.

Results: The addition of each data set showed moderate improvement in number of patients identified with little or no loss of positive predictive value. However, even with inclusion of GP electronic medical record information, the algorithms identified only a small number of patients with no emergency hospital admissions in the prior two years. The model pooled across all sites performed almost as well as models calibrated to local data from just one site. Using population denominators from GP registers led to better case finding.

Conclusions: These models provide a basis for wider application in the NHS. Each of the models examined produce reasonably robust performance and offers some predictive value. The addition of more complex data add some value, but we were unable to conclude that pooled models performed less well than those in individual sites. Choices about model should be linked to the intervention design. Characteristics of patients identified by the algorithms provide useful information in the design/costing of intervention strategies to improve care coordination/outcomes for these patients.

Article focus

- The use of statistical models to predict risk of hospital admissions are increasingly used to prioritise patients for preventive care. Models exist in several different forms and use a variety of input data sets.
- This paper compared the performance of a variety of models built using different datasets.

Key messages

- The addition of more detailed data sets led to moderate improvement in number of patients identified with little or no loss of positive predictive value.
- The use of GP registry data for the denominator proved to be of significant importance. By including all patients in an area, not just those with prior hospital use, improved rates of case finding were observed.
- Models calibrated to local data sets did not show a consistent improvement over models built on pooled data.

Strengths and limitations of this study

- The analysis is based on populations from only five areas in England, however this is the largest UK population (1.8M people) used in the development of a publicly available risk tool.
- The success of a predictive model depends on many factors beyond the statistical performance of the model.

INTRODUCTION

There remains continuing interest in identifying patients at risk of future hospital admissions. Policies providing penalties[1] or non-payment[2] for hospital readmissions that put providers at risk for a share of total health expenditures have been developed for in the U.S. and in England. These create even stronger incentives to identify high risk patients to target care coordination and management strategies that may potentially reduce future inpatient expenditures.

Most predictive modelling approaches have used administrative data from claims in the U.S. or hospital data from Hospital Episode Statistics (HES) or Secondary Uses Services (SUS) in England. These data provide the information on prior utilisation and diagnostic history to develop predictive models for patients at risk of future hospitalization.[3] Payor claims data in the U.S. provide rich information on care provided in hospitals, home care services and nursing home use, as well as detailed pharmacy prescription history.[4] In England, the most commonly used models (such as in the now outdated Patient at Risk of Readmission PARR algorithm)[5,6] are based on hospital admissions data (including day case use, and regular attendances) with some use of accident and emergency (A&E) and outpatient attendance data as well.[7]

While some predictive modeling efforts in the U.K. have included information from GP electronic medical records (EMRs),[8,9] using such data presents a number of challenges. These include obtaining permissions for access to EMRs for large populations, linking the records to hospital data, and use of Read codes[10] to develop GP variables. Data from EMRs include additional elements not available in the hospital data sets such as test results (e.g. blood pressure, HbA1c levels), diagnostic history for patients without recent inpatient admissions, prescription history, GP contact patterns (GP visits and telephone contacts), and other personal health markers (e.g. body mass index, smoking status). These additional data elements have the potential to add power to predictive modeling efforts, especially for patients with no or lower levels of recent inpatient use.

Despite the challenges, a number of initiatives around the UK are demonstrating population wide access to EMR data. A common application is in the use of models that assist local clinical commissioning groups (CCGs) in identifying high risk patients.

Though the choice of data sets for a predictive model makes a big difference to the investment required to run these models – at least initially – no studies have looked at the marginal value of different data sets. In this analysis we examine the added value of including data on A&E and outpatient visits (which are readily available) to predictive modeling efforts using hospital inpatient data alone. We also assess the marginal effect of adding GP EMR information to help identify patients at risk of future hospital admissions. Most existing models in use were developed using logistic regression techniques and we used this standard approach throughout this paper. We recognize that different modelling methods may yield different results but in this analysis we were concerned with the impact of changes in the underlying data sets. Such models will always be limited by the scope and quality of data available, the ways data are grouped and classified and the ways that users can assess up to date information. Despite these problems these models have become commonly used tools.In addition to the depth of data used there is also a question about how generalisable models are across different sites. In many settings models are recalibrated on local data sets. Yet there is little systematic analysis of the value that this step adds and whether models built on data from one site outperform those built on a larger sample of pooled data. We therefore explore whether there is a need for development of individual site predictive models, or whether models developed from multiple sites can be applied effectively at a new individual site.

METHODS

We conducted analyses separately for five Primary Care Trust areas in England (Newham, Cornwall, Kent, Croydon, Redbridge; total adult population ranging from 209,661 to 693,089). Results are reported for the individual sites and as combined/pooled results (total population 1,836,099). Hospital data was extracted from the Secondary Users Services (SUS)[11] system which contained records of all hospital events (inpatient admissions, outpatient appointments and A&E visits) for the PCTs' registered populations between 1 August 2007 and 30 September 2010. The PCTs also extracted data from GP systems in two forms. Firstly as a register of the local adult population from 1 August 2007 and 31 July 2009, and secondly in the form of datasets recording details of GP consultations over the same time period.

Personally identifiable information was stripped out before any data were passed to the research team. Individuals' NHS numbers (the personal identifiers) were concatenated with a passcode chosen by each of the five PCT areas (and unknown to the research team) and these were pseudonymised at source using secure hash algorithm SHA-256 [12]. This allowed for linkage between the hospital and the general practice data from each area, whilst preserving individuals' anonymity.

A series of variables were created from each data set that were believed to be potentially predictive of an unplanned (emergency) hospital admission in the last 12 months of the study period. These variables captured resource use, utilization patterns, diagnostic history, test results, and prescription history in the two years prior to the predictive period. They were created for all individuals aged 18+ registered with a GP in one of the five areas on 31 July 2009. To account for expected time required to obtain and process the hospital and GP EMR data, we included a two-month lag in our analyses, with data from 1 August 2007 to 31 July 2009 used to predict emergency admissions during the period 1 October 2009 to 30 September 2010.

Patient age and gender were obtained from the GP register. Patient area of residence was not available, and so GP practice attributed index of multiple deprivation (2007) was used as an area deprivation measure. The number of months the patient was registered with the PCT in the pre-period was calculated and included in the regression. Hospital inpatient data were used to capture utilization in the 0-90, 91-181, 180-365, and 366-730 days prior to the lag period. The number of emergency and elective admissions for these periods were included and dichotomous variables for any day case or regular attendance use were created.

A broad range of diagnostic variables were developed using primary and secondary diagnosis fields and a Charlson Comorbidity Index[13] was calculated for each patient and included in the model.

A&E data were used to determine A&E visit rates for various intervals in the pre-period, both total visits and unplanned follow-up visits. A&E diagnostic information was not reliably reported across the five sites and was not included, although X-ray use was included. Outpatient data provided variables on outpatient visit rates for various intervals, as well as missed appointment rates and the number of different specialty types consulted. Diagnostic information in outpatient data was missing in more than 95% of cases and was not included.

GP EMR data were used to create proxy visit rates (these may include both actual GP visits, in addition to other events documented in a person's records) for various intervals and to capture any increase in visit rates at the end of the pre-period that may reflect increased morbidity in a patient. EMR Read codes (CTV3 version) were used to obtain test results (blood pressure, blood serum levels, HbA1c levels, etc.), body mass index, smoking history, prescription history (number and type), and a range of diagnostic variables during the pre-period.

Variables from each data set (inpatient (including day case and regular attenders), A&E, outpatient, and GP EMRs) were added and modeled sequentially using standard logistic regression in SPSS v20. Emergency admission in the next 12 months was used as the dependent variable, producing a risk score ranging from 0-100. Separate models were developed for each PCT area, and analysis was limited to patients aged 18-95 who were on the GP register in the area. Over-fitting was tested using a split sample approach, with only minor differences observed in positive predictive values (PPV), sensitivity, and specificity.

Findings provided here include both individual site results and results combined across the five sites. We also created five additional predictive models (referred to below as the 'four-site regression models'), each one combining data from four sites and applying coefficients to the fifth remaining site. With this we could compare results with individual site predictive models to help assess the value of local model development.

The full list of more than 300 potential variables was ultimately reduced to 88 by exclusion of variables with low volumes and low significance levels across the sites. The 88 variables ultimately included in the model (and regression coefficients), may be found in Appendix B and D, and a full listing of the variables

considered for inclusion and detailed specification of each variable are available at http://www.nuffieldtrust.org.uk/.

Cost variables were examined, with secondary care activity costed according to the method used in development of the person based formula for allocating commissioning funds to general practices in England.[14] Ultimately, these were not included in the predictive models because of concerns about difficulties in constructing these variables by possible future users, however costs are included in descriptive findings to help in design of intervention strategies.

Predictive modeling performance is typically documented reporting PPV and sensitivity at the risk score threshold of 50. However, because interventions may be targeted at patients with higher or lower risk scores and interventions strategies may be calibrated differently depending on risk level and characteristics of patients at various risk score levels, we report PPV sensitivity at 20 risk score cutoff points (vigintiles) and provide detailed patient characteristics at risk score thresholds of 50 and 30 to facilitate intervention design.

RESULTS

Pooled Individual Site Results

There were 1,836,099 people aged 18 and over who were registered with a GP practice on 31 July 2009. Table 1 shows the combined results of individual site regressions including the number of patients correctly identified, PPV, and sensitivity for four models:

(i) IP based on hospital inpatient data only (including day cases and regular attendances)
(ii) IPAE using inpatient and A&E data
(iii) IPAEOP using inpatient A&E and outpatient data
(iv) IPAEOPGP using inpatient, A&E, outpatient data and GP EMR.

At the traditional risk score threshold level of 50 all four models perform respectably in terms of PPV (ranging from .523 to .538), but sensitivity remains quite low across all models (.049 to .060). Lowering the threshold to 30 increases sensitivity somewhat with a concomitant reduction in PPV (ranging from .417 to .422). The ROC area under the curve (C statistic) improved with the addition of each data set, increasing from .731 with the inpatient-only model to .780 with the full model.

Table 1 Model performance, four models: IP, IPAE, IPAEOP, IPAEOPGP. Five site individual runs combined.

Risk Score Threshold	IP Data			IP+AE Data			IP+AE+OP Data			IP+AE+OP+GP Data		
	True Positive	PPV	Sensitivity	True Positive	PPV	Sensitivity	True Positive	PPV	Sensitivity	True Positive	PPV	Sensitivity
1	94,692	0.052	1.000	94,692	0.052	1.000	94,692	0.052	1.000	94,692	0.052	1.000
5	54,450	0.126	0.575	56,117	0.128	0.593	56,438	0.131	0.596	61,498	0.133	0.649
10	33,053	0.219	0.349	34,102	0.221	0.360	35,033	0.223	0.370	39,986	0.220	0.422
15	22,898	0.285	0.242	23,166	0.293	0.245	24,261	0.290	0.256	28,697	0.283	0.303
20	16,181	0.346	0.171	16,915	0.347	0.179	17,719	0.344	0.187	21,601	0.333	0.228
25	12,670	0.385	0.134	13,182	0.386	0.139	13,754	0.383	0.145	16,672	0.378	0.176
30	10,061	0.421	0.106	10,555	0.422	0.111	11,010	0.419	0.116	13,196	0.417	0.139
35	8,130	0.449	0.086	8,600	0.450	0.091	8,986	0.448	0.095	10,516	0.450	0.111
40	6,700	0.477	0.071	7,139	0.478	0.075	7,421	0.476	0.078	8,494	0.479	0.090
45	5,535	0.501	0.058	5,976	0.504	0.063	6,167	0.499	0.065	6,921	0.510	0.073
50	4,627	0.529	0.049	5,027	0.531	0.053	5,172	0.523	0.055	5,669	0.538	0.060
55	3,862	0.551	0.041	4,222	0.551	0.045	4,359	0.543	0.046	4,581	0.562	0.048
60	3,239	0.574	0.034	3,555	0.569	0.038	3,658	0.567	0.039	3,735	0.587	0.039
65	2,711	0.593	0.029	3,012	0.590	0.032	3,041	0.587	0.032	3,034	0.618	0.032
70	2,245	0.617	0.024	2,481	0.612	0.026	2,519	0.610	0.027	2,453	0.645	0.026
75	1,816	0.634	0.019	2,049	0.639	0.022	2,064	0.631	0.022	1,921	0.666	0.020
80	1,418	0.666	0.015	1,662	0.656	0.018	1,646	0.654	0.017	1,478	0.696	0.016
85	1,064	0.679	0.011	1,293	0.674	0.014	1,276	0.679	0.013	1,114	0.711	0.012
90	769	0.710	0.008	932	0.688	0.010	935	0.702	0.010	754	0.738	0.008
95	478	0.748	0.005	592	0.725	0.006	586	0.728	0.006	437	0.771	0.005
Top 1%	8,214	0.447	0.087	8,353	0.455	0.088	8,410	0.458	0.089	8,722	0.475	0.092
Top 5%	24,873	0.271	0.263	25,355	0.276	0.268	25,712	0.280	0.272	26,991	0.294	0.285
	ROC C Statistic	0.731			0.745			0.752			0.780	

Of particular note is the finding that the addition of each data set added power, that is, correctly identified more patients with an admission in the next 12 months, with only a minor reduction in PPV. At a risk threshold of 50, the addition of A&E data resulted in increase of 400 (8.6%) correctly flagged patients, with no loss in PPV. The inclusion of outpatient data added a more modest 2.9%, but with a slight loss in PPV (.531 to .523). The addition of GP EMR data added an additional 9.6% of patients, while actually increasing the accuracy of the model (PPV increasing from .523 to .538). The added power of the A&E data set is less substantial at a risk score threshold of 30 (4.9%), but outpatient and GP EMR data sets had larger increases in correctly identified patients (4.3% and 19.9%).

There were also important differences between the models in terms of the characteristics of patients identified as high risk. For example, at a risk score cutoff of 50, patients identified using inpatient data alone had high prior emergency inpatient utilization rates with 2.62 admissions in the prior year compared to 2.43 when A&E data was added; 2.34 with addition of outpatient, and 2.20 with the addition of GP EMR data - see Table 2.

The inclusion of the additional data sets also led to a reduction in observed morbidity level of patients at the 50 threshold, with lower numbers of long term conditions, fewer patients with multiple long term conditions, lower Charlson Comorbidity Index scores, less history of alcohol abuse and mental illness, and lower emergency inpatient costs in the years prior to the predictive period. Similar, but less substantial differences were observed at the risk score threshold of 30. The addition of the A&E data set resulted in higher rates of A&E visits in the pre-period among patients identified at both risk score cutoff levels, and the addition of outpatient data resulted in higher outpatient visit and missed visit rates among identified patients.

These findings suggest inclusion of the additional data sets added some predictive power and generally tended to find additional patients who were less severely ill (more severely ill patients tended to remain high risk). Thus they potentially offer an opportunity for intervention at earlier stages in the progression of a patient's condition. However, the number of patients identified with no prior emergency inpatient utilization in the prior two years was relatively small across all models. At a risk score threshold of 50, only 0.3% of patients correctly identified by the inpatient-only model had no prior emergency admissions in the previous two years, and increasing only modestly 3.2% in the full model (Table 3). At a risk threshold of 30, the rates were higher, but only reaching 12.4% for the full model.

Table 2 Patient characteristics by risk score threshold four models: IP, IPAE, IPAEOP, IPAEOPGP. Five site individual runs combined.

	Risk Score 50+				Risk Score 30+			
	IP Data	IPAE Data	IPAEOP Data	IPAEOPGP Data	IP Data	IPAE Data	IPAEOP Data	IPAEOPGP Data
Number of patients	8,743	9,473	9,892	10,545	23,912	25,021	26,304	31,653
Patients with adm next 12 mos	4,627	5,027	5,172	5,669	10,062	10,554	11,011	13,196
Mean Age	73.9	72.3	71.2	72.2	75.3	74.0	73.4	73.9
Age 18-39	6.2%	8.4%	8.7%	7.8%	5.1%	6.8%	7.0%	6.4%
Age 40-54	8.7%	9.6%	10.9%	10.6%	7.0%	7.8%	8.6%	8.5%
Age 55-64	6.9%	7.4%	7.8%	8.1%	6.4%	6.4%	7.0%	7.3%
Age 65-74	14.4%	13.9%	15.0%	13.5%	13.9%	13.8%	14.4%	13.7%
Age 75-84	30.5%	28.9%	28.2%	27.4%	32.1%	31.1%	30.3%	29.6%
Age 85+	33.3%	31.8%	29.3%	32.6%	35.5%	34.1%	32.7%	34.4%
Female	55.2%	55.2%	54.9%	54.7%	56.9%	57.1%	56.6%	56.5%
Practice IMD	24.6	24.9	24.8	24.3	24.2	24.3	24.3	23.8
Ischaemic Heart Disease	36.2%	34.2%	33.2%	32.1%	29.8%	28.4%	27.8%	25.2%
Angina	21.7%	20.5%	19.5%	19.3%	17.3%	16.4%	15.7%	14.5%
Hypertension	64.5%	61.2%	59.9%	59.0%	59.4%	56.7%	55.1%	50.9%
CHF	19.2%	17.8%	16.9%	15.9%	14.0%	13.2%	12.5%	10.7%
CVD	21.7%	20.1%	19.3%	18.1%	16.9%	15.8%	15.2%	13.3%
COPD	23.4%	21.4%	20.6%	19.1%	17.2%	16.3%	15.7%	13.4%
Asthma	21.3%	20.9%	20.1%	18.1%	17.4%	16.6%	16.1%	13.8%
Diabetes	34.1%	32.4%	31.6%	28.8%	30.1%	28.8%	27.6%	23.6%
Renal Failure	16.5%	14.6%	14.2%	13.3%	11.2%	10.4%	10.0%	8.5%
Any long term conditions	89.8%	87.0%	85.8%	85.0%	86.6%	83.6%	81.4%	75.2%
Any cancer	15.4%	13.8%	13.4%	12.4%	13.3%	12.7%	12.2%	10.5%
Alcohol misuse	10.0%	10.0%	9.6%	9.1%	7.0%	6.7%	6.4%	5.8%
Mental illness	32.0%	30.6%	28.9%	27.2%	23.5%	22.3%	21.3%	18.6%
Number long term conditions	2.67	2.51	2.43	2.31	2.20	2.10	2.02	1.79
Charlson Index	3.96	3.69	3.55	3.28	3.09	2.95	2.82	2.43
Emerg adms 1yr prior	2.62	2.43	2.34	2.20	1.64	1.57	1.50	1.29
Emerg adms 2 yr prior	1.78	1.67	1.61	1.50	1.15	1.10	1.05	0.91
No emerg adm prior 2 yrs	0.6%	1.9%	3.3%	4.3%	4.2%	6.5%	9.2%	16.2%
Elect adms 1yr prior	0.32	0.29	0.31	0.28	0.27	0.26	0.27	0.24
Elect adms 2 yr prior	0.24	0.23	0.26	0.24	0.20	0.20	0.22	0.19
Any day case 1yr prior	31.9%	30.8%	31.6%	28.7%	31.5%	30.7%	30.4%	26.9%
Any day case 2yr prior	28.9%	27.6%	28.0%	25.7%	27.8%	26.9%	26.7%	23.7%
Emerg adm cost 1yr prior	£4,500	£4,073	£3,920	£3,688	£2,893	£2,709	£2,604	£2,231
Emerg adm cost 2yr prior	£2,932	£2,675	£2,583	£2,422	£1,962	£1,822	£1,757	£1,521
AE visits 1yr prior	2.90	3.59	3.45	3.17	1.83	2.26	2.17	1.86
AE visits 2yr prior	1.90	2.40	2.31	2.10	1.23	1.52	1.46	1.25
OP visits 1yr prior	7.27	6.94	9.65	8.23	5.65	5.63	7.39	6.16
OP visits 2yr prior	4.30	4.10	5.92	5.08	3.39	3.38	4.54	3.81
OP visits missed 1yr prior	0.47	0.48	0.74	0.65	0.35	0.36	0.53	0.44
OP visits missed 2yr prior	0.49	0.48	0.71	0.61	0.33	0.34	0.48	0.40
GP visits 1yr prior	42.9	42.7	43.3	52.5	38.5	38.4	38.8	45.4
GP visits 2yr prior	35.5	35.2	35.7	42.5	32.4	32.1	32.5	37.7
Any high risk BNFs	73.9%	71.6%	72.2%	84.0%	69.3%	67.5%	68.1%	79.8%
Num high risk BNFs	1.94	1.85	1.88	2.20	1.64	1.59	1.61	1.84
High blood pressure	9.0%	9.0%	9.0%	9.0%	10.0%	10.0%	10.0%	9.0%
Smoker	18.0%	19.0%	19.0%	23.0%	16.0%	16.0%	16.0%	20.0%
BMI 30+	16.0%	17.0%	17.0%	17.0%	15.0%	16.0%	16.0%	18.0%
HbA1c > 10	5.0%	5.0%	5.0%	7.0%	5.0%	5.0%	4.0%	6.0%
Any Em adm next 12 mos	52.9%	53.1%	52.3%	53.8%	42.1%	42.2%	41.9%	41.7%
Num Em adm next 12 mos	1.34	1.33	1.29	1.31	0.89	0.89	0.87	0.84
0 Em adm next 12 mos	47.1%	46.9%	47.7%	46.2%	57.9%	57.8%	58.1%	58.3%
1 Em adm next 12 mos	23.0%	23.0%	23.2%	23.9%	21.7%	21.9%	21.7%	22.3%
2 Em adm next 12 mos	12.5%	12.5%	12.3%	13.2%	10.0%	10.0%	10.0%	9.9%
3 Em adm next 12 mos	7.3%	7.3%	7.0%	7.1%	4.8%	4.9%	4.8%	4.6%
4+ Em adm next 12 mos	10.2%	10.2%	9.8%	9.7%	5.5%	5.5%	5.3%	4.9%
Emerg adm cost next 12 mos	£2,358	£2,266	£2,199	£2,270	£1,608	£1,575	£1,546	£1,507

AE visits next 12 mos	1.88	2.11	2.04	2.04	1.24	1.37	1.36	1.29

Table 3 Proportion of patients correctly identified, who had no emergency admissions in the prior two years. Four models: IP, IPAE, IPAEOP, IPAEOPGP. Five site individual runs combined.

Prediction threshold	IP Data	IPAE Data	IPAEOP Data	IPAEOPGP Data
Risk Score 50+	0.3%	1.2%	2.3%	3.2%
Risk Score 30+	2.7%	4.4%	6.3%	12.4%
Top 1%	1.5%	2.9%	4.2%	6.5%
Top 5%	25.9%	26.4%	26.7%	30.8%

Individual Site and 'Four-Site Regression' Model Results

Overall the performance of the models was similar at the individual site level. Only modest differences were found in PPV levels and sensitivity across the sites. For runs using non-GP data only (IPAEOP), at the risk score threshold of 50, PPVs ranged from .512 to .552 and sensitivity ranged from .047 to .071. For the model including GP EMRs, PPVs ranged from .521 to .566 and sensitivity from .053 to .073. See Appendix A. There was some variation in the magnitude of regression coefficients between sites, but in general the coefficients were comparable for models based on the non-GP data model (IPAEOP). See Appendix B. For the model including variables from GP EMRs (IPAEOPGP), the level of variation in regression coefficients (size and direction) was somewhat greater for those variables derived from GP data. We observed substantial differences in frequency of reporting of Read codes across sites which no doubt contributed to this variation. The level of significance of individual variables also varied across sites (Appendix C), but most variables were consistently strongly significant across all sites, especially variables involving prior emergency inpatient admissions. Again, higher levels of variation in levels of significance were observed for the GP variables derived from Read codes.

We compared the results for these individual site models to a pooled model combining data from four of the sites and applied coefficients to the remaining individual site. We found generally only small differences in predictive accuracy (PPV) between these two approaches (Table 4), however the individual site models identified a greater number of true positives. For example, in Cornwall at a risk

score cutoff of 50, the individual site model using hospital data identified correctly 1,041 patients while the pooled model identified only 754. In Newham however, the four-site model was more powerful, correctly identifying 858 patients compared to 734 for the individual site approach. In both cases (and in general across all sites), the model identifying larger numbers of true positives had a somewhat lower PPV, suggesting improved case finding volume came at the expense of predictive accuracy.

Table 4 Individual site and four-site regression models. Case finding and predictive accuracy.

	IPOPAE				IPOPAEGP			
	Individual Site Regression		Four Site Regression		Individual Site Regression		Four Site Regression	
	True Positives	PPV	True Positives	PPV	True Positives	PPV	True Positives	PPV
Newham								
Risk Score 50+	734	0.552	858	0.517	768	0.566	835	0.523
Risk Score 30+	1,409	0.450	1,564	0.414	1,570	0.439	1,798	0.409
Cornwall								
Risk Score 50+	1,041	0.520	754	0.548	1,176	0.545	952	0.556
Risk Score 30+	2,439	0.406	1,970	0.426	3,032	0.410	2,746	0.411
Kent								
Risk Score 50+	1,565	0.513	1,387	0.519	1,736	0.521	1,873	0.493
Risk Score 30+	3,372	0.401	3,067	0.403	4,079	0.397	4,432	0.369
Croydon								
Risk Score 50+	1,089	0.528	1,192	0.523	1,182	0.550	1,230	0.537
Risk Score 30+	2,134	0.444	2,258	0.424	2,610	0.442	2,502	0.437
Redbridge								
Risk Score 50+	743	0.512	863	0.495	807	0.522	607	0.519
Risk Score 30+	1,656	0.420	1,693	0.415	1,905	0.423	1,390	0.436

Testing alternative population denominators

Models built using inpatient data only (IP) were also built for just the subset of patients who had some inpatient care in the prior two years (to reflect typical predictive modeling efforts that may have been conducted without access to GP registry information), as well as for the group who had had an emergency admission in the prior year (to replicate analyses conducted by PARR users).

Combining the results from the five sites at a risk score threshold of 50, models using the full GP register correctly identified 4,627 patients compared with 3,572 patients in runs restricted to patients with prior inpatient care and 3,060 to runs limited to patients with an emergency admission in the prior year. This substantial increase in case finding was obtained with only moderate loss in PPV (.529 GP list, .559 prior inpatient and .589 emergency admissions in last year). Similar results were also found for all hospital data models (IPOPAE, though with any hospital use in prior two years, rather than just any inpatient use).

Using the full GP registry population did not result in finding substantial numbers of patients with no emergency admissions in the prior two years, but the increased numbers of patients identified included more patients with less prior use and lower levels of morbidity. For a profile of patients identified using these alternative denominators see http://www.nuffieldtrust.org.uk/.

DISCUSSION

This analysis has looked at the performance of new variants of predictive models for case finding. These models are intended to update and improve upon the established combined predictive model-like [15] and PARR models [5] widely used in the NHS.

Each of the models examined produced reasonably robust performance, by some measures better or at least comparable to similar prior models [9]. At a risk threshold of 50, patients identified by the models had PPVs ranging from .523 to .538. While the percent of all patients with future admissions identified was relatively low (sensitivity .049 to .060), lowering the risk threshold allows the identification of more patients with relatively small loss in PPV (e.g. at a risk threshold of 30, the full model identified 14% of future admissions with a PPV of .417). Users of predictive modeling algorithms have obvious trade-offs between maximizing the number of patients identified and predictive accuracy. Lower risk score thresholds will find more patients, but these patients are increasingly less likely to have future admissions.

The implications for intervention design are important. Patients at lower risk thresholds have less prior inpatient use and lower morbidity, so an intervention here might be calibrated to be less intensive. But because the models are less accurate at lower risk scores, the amount that can be spent on an intervention is also reduced if you wish to achieve financial break-even (ie where the cost of intervention is off-set by cost savings from reduction in future admissions). As documented in Table 2,

at a risk score threshold of 50, the rate of future admission for patients identified by the full model (IPAEOPGP data) was 1.31 admissions per year with an associated cost of £2,270. If there were a 10% reduction in future admissions, £227 could be spent on an intervention to improve care coordination and still achieve break-even. However, at a lower risk threshold of 30, the lower rates of future admissions and costs means that lower intervention expenditures are required to achieve break-even (£151 with a 10% reduction in future admissions). A detailed business case analysis with mean emergency inpatient costs in the next 12 months within each risk vigintile level is available via http://www.nuffieldtrust.org.uk/.

These data also provide other information that may be useful in the development of intervention strategies. As shown in Table 2, patients identified by the models have extremely high rates of chronic disease (85-90% with long term conditions at risk threshold of 50), often with multiple long term conditions and high Charlson Comorbidity Index levels, indicating serious medical needs. However, these patients already have high use of outpatient care and very high GP visit rates. This suggests simple access to ambulatory care is not the issue, but prevention needs to look at care coordination and management of complex problems and at the ability of patients and their families to manage chronic illness. High risk patients identified by the models also have relatively high rates of mental illness (27-32% at risk threshold of 50) and moderate levels of alcohol abuse, factors that are likely to complicate any intervention strategy.

It is also important to note the limitations of these data in helping frame the design of any intervention strategy. Other studies have documented that high risk patients often have important characteristics related to care needs and patient capacity not captured by administrative data and EMRs. For example, interviews with high risk patients and their families have documented high levels of social isolation for many, as well as precarious housing status.[16] These non-medical factors are likely to have significant impact on health status and utilization patterns. Moreover, not much is known about how/whether care coordination and management has actually failed for these patients. Are these high risk patients just very sick patients whose hospitalizations are largely not preventable/avoidable [17], or has the care delivery system failed in some important dimensions that can be corrected with improved care coordination and management? These data cannot answer this very critical question, and it is clear that the field would benefit from further study that examined the circumstances of patients identified as

high risk by predictive modeling algorithms to sort out more clearly the factors contributing to high rates of emergency admission.

This study does document the value of incorporating data sets beyond inpatient records. The addition of A&E and outpatient records resulted in identification of more high risk patients with little or no loss of predictive accuracy. These data sets are readily available and have standardized reporting formats that facilitate analysis. While the absence of useful diagnostic information in these data sets is a limiting factor, the improvement in case finding and usefulness in descriptive profiling of high risk patients to help in intervention design (e.g. high rates of A&E use rates, high rates of missed outpatient appointments) suggests their inclusion is clearly merited.

Use of GP EMRs presents significant challenges. While the lack of access to these data is unlikely to remain a problem, the variation in completeness and quality of data is problematic. The use of the unwieldy Read codes system makes analysis difficult, and we observed significant differences across sites in reporting patterns. Some of these differences may be caused by under reporting of diagnostic variables, others by differences in coding approaches. However, the potential improvement in case finding, especially among patients with lower rates of utilization in the pre-period, suggests these barriers are worth confronting. Our development of new variables beyond those included in prior predictive modeling efforts [8] contributed substantially to enhanced case finding, and further work on variable development is likely to lead to further improvements. Again, these data are also useful in providing descriptive information on high risk patients to help in intervention design (e.g. documenting potential targets of opportunity such as uncontrolled hypertension or diabetes).

This study does not provide definitive findings on the value of developing individual site models compared to simply applying coefficients from multi-site or national model coefficients to local data. Our four-site regression models generally had comparable PPVs to individual site models, but for the majority of sites the four-site regression approach correctly identified somewhat fewer number patients with future admissions. Though it is tempting to speculate on whether differences in the health needs of the population or coding differences affect model performance, we did not observe any clear patterns between the areas. Our analysis is somewhat limited by the small number of sites involved which might cause somewhat greater variability in regression coefficients (regression coefficients for each of the five four-site models are available at http://www.nuffieldtrust.org.uk/). Development of a

national model using SUS data only is planned to further assess the need/value of locally developed models.

Finally, it is worthy of note that use of the GP registry data for the denominator also proved to be of significant importance. Many prior predictive modeling efforts have been limited to patients with utilization history in whatever data sets were included. By including all patients in an area, not just those with prior use, the impact on predictive modeling of prior use was apparently enhanced. As a result, patients with more moderate levels of prior use and morbidity were found to be of higher risk than patients with no prior use at all, and were often assigned higher risk scores than when the analysis included just patients who had prior use. Accordingly, the use of the GP registry as the denominator can improve rates of case finding and may permit identification of patients at earlier stages.

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Contributors

The preparation of data sets and input variables and costs were undertaken by TG and by IB; JB did the central modelling. MB advised on the analysis and results and managed the work of the research team at the Nuffield Trust. All authors contributed to the writing of the paper. JB is the guarantor.

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Competing interests

All authors have completed the Unified Competing Interest form at www.icmje.org/coi_disclosure.pdf and declare that no authors have any relationships with any companies that might have an interest in the submitted work in the previous 3 years; none of their spouses, partners or children have any financial relationships that may be relevant to the submitted work; and no authors have any non-financial interests that may be relevant to the submitted work.

Ethical approval

This study only involved the analysis of pseudonymous secondary data. Since there were no identifiable human subjects, ethics approval was not required for this research and informed consent was not sought.

Provenance and peer review

Not commissioned; externally peer reviewed.

Data sharing statement

Details of the derived models variables and definitions are available from the authors at the Nuffield trust at research@nuffieldtrust.org.uk.

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Appendix A. PPV and sensitivity IPAEOP and IPAEOPGP models. Individual site runs.

	IP+AE+OP Data									
Risk Score	Newham		Cornwall		Kent		Croydon		Redbridge	
Threshold	PPV	Sensitivity	PPV	Sensitivity	PPV	Sensitivity	PPV	Sensitivity	PPV	Sensitivity
1	0.049	1.000	0.061	1.000	0.052	1.000	0.046	1.000	0.047	1.000
10	0.236	0.361	0.216	0.391	0.213	0.339	0.241	0.378	0.238	0.425
20	0.368	0.201	0.328	0.188	0.326	0.158	0.377	0.210	0.357	0.236
30	0.450	0.136	0.406	0.109	0.401	0.094	0.444	0.142	0.420	0.149
40	0.506	0.098	0.477	0.072	0.457	0.062	0.486	0.100	0.475	0.098
50	0.552	0.071	0.520	0.047	0.513	0.043	0.528	0.073	0.512	0.067
60	0.585	0.052	0.560	0.030	0.569	0.031	0.580	0.055	0.532	0.044
70	0.632	0.037	0.622	0.021	0.618	0.022	0.610	0.040	0.555	0.028
80	0.678	0.024	0.655	0.013	0.673	0.014	0.659	0.028	0.571	0.016
90	0.717	0.013	0.692	0.007	0.724	0.008	0.710	0.016	0.617	0.008
Top 1%	0.501	0.102	0.470	0.077	0.417	0.080	0.482	0.106	0.474	0.101
Top 5%	0.287	0.291	0.292	0.240	0.259	0.249	0.290	0.318	0.296	0.316

	IP+AE+OP+GP Data									
Risk Score	Newham		Cornwall		Kent		Croydon		Redbridge	
Threshold	PPV	Sensitivity	PPV	Sensitivity	PPV	Sensitivity	PPV	Sensitivity	PPV	Sensitivity
1	0.049	1.000	0.061	1.000	0.052	1.000	0.046	1.000	0.047	1.000
10	0.228	0.410	0.213	0.439	0.210	0.392	0.237	0.452	0.237	0.457
20	0.360	0.235	0.323	0.232	0.314	0.194	0.358	0.267	0.348	0.272
30	0.439	0.152	0.410	0.136	0.397	0.113	0.442	0.174	0.423	0.172
40	0.499	0.103	0.481	0.084	0.459	0.072	0.494	0.114	0.482	0.113
50	0.566	0.074	0.545	0.053	0.521	0.048	0.550	0.079	0.522	0.073
60	0.606	0.052	0.602	0.033	0.580	0.032	0.589	0.052	0.563	0.047
70	0.657	0.036	0.659	0.021	0.644	0.021	0.643	0.035	0.616	0.030
80	0.723	0.021	0.714	0.013	0.694	0.013	0.694	0.021	0.651	0.018
90	0.766	0.012	0.745	0.006	0.752	0.007	0.735	0.011	0.655	0.007
Top 1%	0.504	0.102	0.490	0.081	0.438	0.084	0.502	0.110	0.487	0.104
Top 5%	0.296	0.300	0.309	0.254	0.272	0.262	0.307	0.337	0.312	0.333

Appendix B Regression coefficients. IPAEOP and IPAEOPGP models. Individual site runs.

	IP+AE+OP Data					IP+AE+OP+GP Data				
	NH	CW	KT	CR	RB	NH	CW	KT	CR	RB
Age	0.015	0.003	0.009	0.010	0.019	0.001	-0.004	0.002	0.001	0.009
Age 65-74	0.280	0.409	0.295	0.380	0.261	0.236	0.276	0.203	0.244	0.245
Age 75-84	0.738	0.905	0.731	0.847	0.734	0.721	0.672	0.605	0.708	0.749
Age 85+	1.076	1.483	1.226	1.178	1.109	1.150	1.206	1.086	1.187	1.213
Female	0.239	0.002	0.044	0.178	0.058	0.114	-0.095	-0.075	-0.014	-0.030
Practice IMD	0.013	0.003	0.016	0.018	0.012	0.008	0.004	0.017	0.010	0.015
Months registered 1 yr prior	0.014	-0.011	-0.005	-0.018	-0.013	0.011	-0.011	-0.003	-0.010	-0.006
Months registered 2 yrs prior	-0.022	-0.019	-0.016	-0.007	-0.023	-0.021	-0.024	-0.019	-0.011	-0.021
EM Adms prior 0-90 days	0.382	0.471	0.321	0.310	0.282	0.367	0.420	0.283	0.269	0.259
EL Adms prior 0-90 days	0.045	0.216	0.155	0.153	0.148	0.033	0.159	0.074	0.097	0.069
Any attender prior 0-90 days	0.115	0.027	0.001	0.041	0.073	0.135	0.026	0.010	0.042	0.064
Any day case prior 0-90 days	0.094	0.234	0.110	0.111	0.251	0.037	0.173	0.039	-0.019	0.130
EM Adms prior 91-180 days	0.215	0.310	0.351	0.282	0.185	0.217	0.262	0.297	0.243	0.160
EL Adms prior 91-180 days	0.321	0.150	0.062	0.204	0.081	0.283	0.128	0.027	0.118	0.024
EM Adms prior 181-365 days	0.113	0.345	0.350	0.248	0.146	0.124	0.289	0.292	0.227	0.129
EL Adms prior 181-365 days	0.097	0.120	0.104	0.118	0.170	0.072	0.079	0.060	0.035	0.108
Em Adms 2 yrs prior	0.102	0.269	0.307	0.181	0.143	0.116	0.216	0.250	0.178	0.149
Any day case 2 yrs prior	0.096	0.157	0.186	0.151	0.179	0.058	0.092	0.112	0.005	0.103
DX MI	-0.108	0.097	-0.105	-0.004	0.376	-0.197	-0.003	-0.163	-0.111	0.228
DX CHF	-0.348	-0.070	-0.246	-0.069	-0.337	-0.370	-0.178	-0.269	-0.110	-0.216
DX CVD	0.296	0.227	0.033	0.037	-0.040	0.269	0.166	-0.001	-0.099	-0.061
CD CTD	0.030	-0.024	0.101	-0.380	-0.029	0.071	-0.192	-0.010	-0.427	-0.039
DX PVD	-0.245	0.124	0.099	-0.100	0.021	-0.253	0.048	0.026	-0.096	0.003
DX Asthma	0.082	0.143	0.184	0.099	0.192	-0.114	-0.107	-0.023	-0.081	0.028
DX COPD	0.204	0.251	0.277	0.193	0.123	-0.169	-0.139	-0.036	-0.330	-0.269
DX Diabetes	0.240	0.303	0.285	0.253	0.276	-0.046	-0.052	-0.016	-0.124	0.011
DX Diabetes with complications	0.059	-0.221	0.062	-0.014	0.334	0.062	-0.176	0.095	0.004	0.262
DX Renal Disease	0.408	0.022	0.085	0.128	0.199	0.356	0.005	0.073	0.063	0.120
DX Cancer	-0.165	-0.019	-0.062	-0.308	0.041	0.041	0.098	-0.010	-0.207	0.034
DX Mental	0.498	0.316	0.363	0.484	0.077	0.340	0.131	0.111	0.266	-0.061
DX Alcohol	0.569	0.684	0.578	0.673	0.974	0.281	0.530	0.357	0.409	0.754
DX Dementia	-0.548	-0.589	-0.551	-0.402	-0.596	-0.530	-0.486	-0.440	-0.669	-0.641
DX Cognitive Impairment	-0.117	0.016	0.025	0.110	0.187	-0.075	0.046	0.031	0.088	0.152
DX ACS Condition	0.364	0.270	0.239	0.267	0.306	0.269	0.161	0.134	0.114	0.224
Charlson Index	0.055	0.063	0.060	0.101	0.025	0.048	0.062	0.037	0.086	0.029
AE visits prior 0-90 days	0.236	0.267	0.355	0.309	0.359	0.179	0.230	0.265	0.199	0.260
AE unplanned follow-up visits prior 0-90 days	-0.094	-0.583	-0.533	-0.874	-0.383	-0.107	-0.566	-0.452	-0.703	-0.315
AE X-ray prior 0-90 days	0.348	0.437	0.058	0.104	0.367	0.303	0.382	0.027	0.040	0.317
AE visits prior 91-180 days	0.265	0.262	0.220	0.225	0.277	0.197	0.225	0.165	0.142	0.210
AE unplanned follow-up visits prior 91-180 days	-0.023	-0.560	-0.229	-0.296	-0.298	-0.026	-0.543	-0.177	-0.225	-0.286
AE X-ray prior 91-180 days	0.227	0.117	0.120	0.346	-0.064	0.210	0.015	0.101	0.237	0.010
AE visits prior 181-365 days	0.264	0.205	0.135	0.171	0.181	0.216	0.174	0.090	0.115	0.138
AE unplanned follow-up visits prior 181-365 days	-0.251	-0.490	-0.184	-0.261	-0.203	-0.214	-0.449	-0.131	-0.175	-0.221
AE X-ray prior 181-365 days	0.262	-0.040	0.281	0.324	0.110	0.225	0.085	0.251	0.244	0.072
AE visits 2 yrs prior	0.211	0.159	0.154	0.140	0.160	0.170	0.138	0.114	0.077	0.121
AE unplanned follow-up visits 2 yrs prior	-0.307	-0.352	-0.239	-0.433	-0.339	-0.228	-0.317	-0.178	-0.262	-0.288
AE X-ray 2yrs prior	0.083	0.231	0.100	0.128	0.179	0.063	0.390	0.082	0.069	0.152
Outpatient specialty visits prior 0-90 days	0.046	0.055	0.091	0.061	0.059	0.025	0.033	0.047	0.030	0.027
Outpatient specialty visits missed prior 0-90 days	0.155	0.182	0.250		0.146	0.108	0.118	0.171		0.097
Outpatient specialty visits prior 91-180 days	0.030	0.013	0.023	0.034	0.029	0.007	0.003	-0.004	0.015	0.011
Outpatient specialty visits missed prior 91-180 days	0.113	0.239	0.168		0.193	0.087	0.184	0.113		0.159
Outpatient specialty visits prior 181-365 days	0.016	0.010	-0.005	0.019	0.031	-0.003	0.001	-0.024	0.003	0.018
Outpatient specialty visits missed prior 181-365 days	0.128	0.164	0.075		0.140	0.086	0.095	0.036		0.122
Outpatient specialty visits 2 yrs prior	0.019	0.030	0.014	0.028	0.019	0.008	0.014	-0.009	0.011	0.021

Outpatient specialty visits missed 2 yrs prior	0.142	0.162	0.140	0.190	0.082	0.097	0.090	0.085	0.129	0.057
GP DX COPD						0.218	0.174	0.112	0.287	0.295
GP - 1 long term condition						0.131	0.025	0.017	0.106	0.192
GP - 2 or more long term conditions						0.166	0.109	0.038	0.070	0.182
GP - Glomerular filtration rate group 3 last 0-365 days						-0.075	0.092	-0.017		0.050
GP - 10+ unique drugs prescribed						0.342	0.570	0.166	2.741	1.949
GP - 5-9 unique drugs prescribed						0.424	0.444	0.164	2.804	1.953
GP - 0-4 unique drugs prescribed						0.328	0.254	0.114	2.559	1.809
GP - Psychoactive substance misuse disorder						0.388	0.323	0.583	0.431	0.810
GP - 7+ distinct disorders						-0.049	0.057	0.017	-0.163	-0.062
GP - GP visits prior 0-3 months						-0.001	0.008	0.022	0.021	0.042
GP - GP visits prior 4-6 months						0.015	0.004	0.012	0.009	0.019
GP - GP visits prior 7-12 months						0.005	0.003	0.007	0.000	0.008
GP - GP visits 2yrs prior						0.000	0.002	0.004	0.006	0.002
GP - Increasing rate of GP visits during last 12 months						0.184	0.087	0.126	0.207	0.094
GP - Number of high risk BNFs						0.063	0.006	-0.036	-0.026	-0.075
GP - Any high risk						0.219	0.202	0.241	0.324	0.249
GP - Count of BNF chapters						0.066	0.053	0.059	0.066	-0.024
GP - DX Dementia						0.421	0.266	0.296	0.471	0.437
GP - Exception reported from quality indicators						0.157	0.108	0.111	0.118	0.132
GP - Health visitor or district nurse visit						0.278	0.244	0.199	0.168	0.184
GP - Record of IHD/angina						0.069	-0.048	0.110	-0.062	0.081
GP - Nebuliser used						0.113	0.315	0.207	0.191	0.448
GP - Salbutamol prescribed						0.021	0.017	0.074	0.000	-0.011
GP - Warfarin prescribed						-0.041	0.031	-0.026	-0.100	-0.244
GP - High blood pressure						-0.040	-0.001	-0.013	-0.048	-0.087
GP - Smoker						0.298	0.231	0.248	0.240	0.220
GP - BMI 30+						0.050	0.002	0.085	0.046	0.199
GP - HbA1c > 10						0.236	0.270	0.210	0.362	0.354
GD - QOF ARTF						0.176	0.064	0.095	-0.047	0.143
GP - QOF CKD						0.206	-0.003	-0.037	0.091	0.210
GP - QOF Depression						0.069	0.248	0.183	0.133	0.186
GP - Number of QOF DX categories 3+						0.003	-0.023	-0.072	-0.135	-0.009
GP - Number of phone contacts last 0-3 months						-0.004	0.046	0.004	-0.005	-0.004
Constant	-4.665	-3.262	-3.987	-4.363	-4.368	-4.381	-3.275	-4.069	-6.497	-5.939

Appendix C Regression significance levels. IPAEOP and IPAEOPGP models. Individual site runs.

	IP+AE+OP Data					IP+AE+OP+GP Data				
	NH	CW	KT	CR	RB	NH	CW	KT	CR	RB
Age	0.000	0.000	0.000	0.000	0.000	0.344	0.000	0.001	0.158	0.000
Age 65-74	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Age 75-84	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Age 85+	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Female	0.007	0.897	0.000	0.001	0.125	0.000	0.000	0.000	0.466	0.165
Practice IMD	0.008	0.036	0.000	0.000	0.000	0.015	0.010	0.000	0.000	0.000
Months registered 1 yr prior	0.002	0.006	0.085	0.247	0.047	0.009	0.011	0.387	0.026	0.255
Months registered 2 yrs prior	0.001	0.014	0.006	0.232	0.276	0.009	0.003	0.001	0.211	0.025
EM Adms prior 0-90 days	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
EL Adms prior 0-90 days	0.664	0.000	0.000	0.029	0.081	0.714	0.000	0.070	0.102	0.373
Any attender prior 0-90 days	0.002	0.000	0.955	0.006	0.004	0.001	0.000	0.489	0.005	0.008
Any day case prior 0-90 days	0.769	0.000	0.001	0.682	0.001	0.561	0.000	0.233	0.699	0.015
EM Adms prior 91-180 days	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002
EL Adms prior 91-180 days	0.000	0.000	0.068	0.022	0.528	0.000	0.001	0.437	0.016	0.680
EM Adms prior 181-365 days	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000
EL Adms prior 181-365 days	0.548	0.000	0.000	0.757	0.019	0.167	0.009	0.030	0.372	0.014
Em Adms 2 yrs prior	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Any day case 2 yrs prior	0.877	0.000	0.000	0.536	0.035	0.177	0.000	0.000	0.864	0.005
DX MI	0.366	0.134	0.049	0.611	0.000	0.076	0.966	0.002	0.216	0.017
DX CHF	0.024	0.253	0.000	0.448	0.008	0.001	0.005	0.000	0.194	0.026
DX CVD	0.015	0.000	0.446	0.610	0.571	0.013	0.002	0.977	0.179	0.504
CD CTD	0.263	0.756	0.150	0.010	0.759	0.645	0.013	0.891	0.000	0.766
DX PVD	0.230	0.061	0.097	0.567	0.665	0.079	0.462	0.661	0.270	0.982
DX Asthma	0.351	0.002	0.000	0.241	0.015	0.135	0.024	0.580	0.184	0.698
DX COPD	0.005	0.000	0.000	0.009	0.098	0.098	0.021	0.483	0.002	0.041
DX Diabetes	0.000	0.000	0.000	0.000	0.000	0.444	0.227	0.649	0.016	0.845
DX Diabetes with complications	0.478	0.025	0.540	0.363	0.013	0.674	0.073	0.347	0.973	0.083
DX Renal Disease	0.000	0.731	0.142	0.068	0.025	0.001	0.942	0.208	0.405	0.210
DX Cancer	0.753	0.751	0.271	0.001	0.421	0.727	0.104	0.862	0.009	0.721
DX Mental	0.000	0.000	0.000	0.000	0.370	0.000	0.005	0.008	0.000	0.447
DX Alcohol	0.000	0.000	0.000	0.000	0.000	0.029	0.000	0.000	0.000	0.000
DX Dementia	0.005	0.000	0.000	0.000	0.000	0.004	0.000	0.000	0.000	0.000
DX Cognitive Impairment	0.430	0.804	0.620	0.191	0.026	0.456	0.474	0.534	0.199	0.080
DX ACS Condition	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000
Charlson Index	0.012	0.000	0.000	0.000	0.212	0.042	0.000	0.006	0.000	0.160
AE visits prior 0-90 days	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AE unplanned follow-up visits prior 0-90 days	0.895	0.001	0.000	0.000	0.133	0.654	0.001	0.000	0.000	0.121
AE X-ray prior 0-90 days	0.002	0.000	0.301	0.374	0.052	0.004	0.002	0.636	0.662	0.035
AE visits prior 91-180 days	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AE unplanned follow-up visits prior 91-180 days	0.836	0.000	0.000	0.149	0.130	0.899	0.000	0.005	0.214	0.055
AE X-ray prior 91-180 days	0.070	0.582	0.045	0.002	0.672	0.062	0.946	0.090	0.009	0.985
AE visits prior 181-365 days	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AE unplanned follow-up visits prior 181-365 days	0.182	0.000	0.001	0.122	0.124	0.098	0.001	0.013	0.127	0.041
AE X-ray prior 181-365 days	0.000	0.936	0.000	0.000	0.461	0.001	0.866	0.000	0.000	0.485
AE visits 2 yrs prior	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AE unplanned follow-up visits 2 yrs prior	0.021	0.008	0.000	0.003	0.009	0.020	0.016	0.000	0.008	0.005
AE X-ray 2yrs prior	0.183	0.555	0.019	0.022	0.005	0.210	0.320	0.048	0.161	0.006
Outpatient specialty visits prior 0-90 days	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Outpatient specialty visits missed prior 0-90 days	0.000	0.000	0.000		0.002	0.000	0.000	0.000		0.008
Outpatient specialty visits prior 91-180 days	0.196	0.043	0.003	0.002	0.016	0.516	0.630	0.648	0.054	0.184
Outpatient specialty visits missed prior 91-180 days	0.027	0.000	0.000		0.000	0.039	0.000	0.002		0.000
Outpatient specialty visits prior 181-365 days	0.763	0.009	0.400	0.094	0.000	0.595	0.844	0.000	0.491	0.002
Outpatient specialty visits missed prior 181-365 days	0.000	0.000	0.009		0.000	0.001	0.002	0.206		0.000
Outpatient specialty visits 2 yrs prior	0.000	0.000	0.000	0.000	0.000	0.068	0.000	0.046	0.001	0.000

Outpatient specialty visits missed 2 yrs prior	0.000	0.000	0.000	0.000	0.001	0.000	0.006	0.000	0.000	0.000
GP DX COPD						0.002	0.000	0.001	0.000	0.003
GP - 1 long term condition						0.000	0.229	0.310	0.000	0.000
GP - 2 or more long term conditions						0.001	0.000	0.100	0.098	0.000
GP - Glomerular filtration rate group 3 last 0-365 days						0.097	0.002	0.463		0.162
GP - 10+ unique drugs prescribed						0.000	0.000	0.000	0.000	0.000
GP - 5-9 unique drugs prescribed						0.000	0.000	0.000	0.000	0.000
GP - 0-4 unique drugs prescribed						0.000	0.000	0.000	0.000	0.000
GP - Psychoactive substance misuse disorder						0.000	0.000	0.000	0.000	0.000
GP - 7+ distinct disorders						0.311	0.290	0.523	0.002	0.263
GP visits prior 0-3 months						0.873	0.002	0.000	0.000	0.000
GP visits prior 4-6 months						0.000	0.182	0.000	0.008	0.000
GP visits prior 7-12 months						0.075	0.136	0.000	0.987	0.006
GP visits 2yrs prior						0.934	0.013	0.000	0.000	0.263
GP - Increasing rate of GP visits during last 12 months						0.000	0.001	0.000	0.000	0.010
GP - Number of high risk BNFs						0.009	0.691	0.004	0.216	0.002
GP - Any high risk						0.000	0.000	0.000	0.000	0.000
GP - Count of BNF chapters						0.000	0.000	0.000	0.000	0.000
GP - DX Dementia						0.000	0.000	0.000	0.000	0.000
GP - Exception reported from quality indicators						0.020	0.003	0.001	0.020	0.062
GP - Health visitor or district nurse visit						0.000	0.000	0.000	0.000	0.000
GP - Record of IHD/angina						0.355	0.361	0.006	0.202	0.288
GP - Nebuliser used						0.359	0.000	0.001	0.019	0.001
GP - Salbutamol prescribed						0.550	0.523	0.001	0.989	0.795
GP - Warfarin prescribed						0.643	0.423	0.440	0.106	0.001
GP - High blood pressure						0.269	0.984	0.549	0.725	0.325
GP - Smoker						0.000	0.000	0.000	0.000	0.000
GP - BMI 30+						0.074	0.956	0.000	0.074	0.000
GP - HbA1c > 10						0.000	0.000	0.000	0.000	0.000
GD - QOF ARTF						0.130	0.240	0.024	0.586	0.136
GP - QOF CKD						0.003	0.924	0.203	0.063	0.000
GP - QOF Depression						0.240	0.000	0.000	0.024	0.016
GP - Number of QOF DX categories 3+						0.974	0.717	0.123	0.342	0.948
GP - Number of phone contacts last 0-3 months						0.927	0.000	0.600	0.788	0.899
Constant	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Appendix D Further information of model variables

Variable	Variable description	Time period/Date
GP register variables		
Age	Age	End calendar year (5 months after)
Age 65-74	Age 65-74	End calendar year (5 months after)
Age 75-84	Age 75-84	End calendar year (5 months after)
Age 85+	Age 85+	End calendar year (5 months after)
Female	Sex = female	N/A
Practice IMD	Index of multiple deprivation - GP practice area	N/A
Months registered 1 yr prior	Months registered with GP prior 1-12 months	Prior 1 - 12 months (inclusive)
Months registered 2 yrs prior	Months registered with GP prior 13-24 months	Prior 13 - 24 months (inclusive)
SUS inpatient variables		
EM Adms prior 0-90 days	Number of emergency admissions - prior 1-90 days	Prior 1 to 90 days (inclusive)
EL Adms prior 0-90 days	Number of elective admissions - prior 1-90 days	Prior 1 to 90 days (inclusive)
Any attender prior 0-90 days	Any regular attendance - prior 1-90 days	Prior 1 to 90 days (inclusive)
EM Adms prior 91-180 days	Number of emergency admissions - prior 91-180 days	Prior 91 to 180 days (inclusive)
EL Adms prior 91-180 days	Number of emergency admissions - prior 181-365 days	Prior 181 to 365 days (inclusive)
Any day case prior 0-90 days	Any day case prior 1-90 days	Prior 1 to 90 days (inclusive)
Any day case prior 91-180 days	Any day case prior 91-180 days	Prior 91 to 180 days (inclusive)
Any day case prior 181-365 days	Any day case prior 181-365 days	Prior 181 to 365 days (inclusive)
Any day case 2 yrs prior	Any day case prior 366-730 days	Prior 366 to 730 days (inclusive)
Em Adms 2 yrs prior	Number of emergency admissions - prior 366-730 days	Prior 366 to 730 days (inclusive)
DX Diabetes	Any prim or sec diagnosis - Diabetes, prior 2 years	Prior 1 to 730 days (inclusive)
DX MI	Any prim or sec diagnosis - Myocardial infarction, prior 2 years	Prior 1 to 730 days (inclusive)
DX CHF	Any prim or sec diagnosis - Congestive heart failure, prior 2 years	Prior 1 to 730 days (inclusive)
DX PVD	Any prim or sec diagnosis - Peripheral vascular disease, prior 2 years	Prior 1 to 730 days (inclusive)
DX CVD	Any prim or sec diagnosis - Cereberal vascular disease, prior 2 years	Prior 1 to 730 days (inclusive)
DX Dementia	Any prim or sec diagnosis - Dementia, prior 2 years	Prior 1 to 730 days (inclusive)
CD CTD	Any prim or sec diagnosis - Connective tissue disease, prior 2 years	Prior 1 to 730 days (inclusive)
DX Cancer	Any prim or sec diagnosis - Malignant cancer, prior 2 years	Prior 1 to 730 days (inclusive)
DX Diabetes with complications	Any prim or sec diagnosis - Diabetes with complications, prior 2 years	Prior 1 to 730 days (inclusive)
DX Renal Disease	Any prim or sec diagnosis - Renal disease, prior 2 years	Prior 1 to 730 days (inclusive)
Charlson Index	Charlson Comorbidity Index, prior 2 years	Prior 1 to 730 days (inclusive)
DX Alcohol	Any prim or sec diagnosis - Alcohol abuse, prior 2 years	Prior 1 to 730 days (inclusive)
DX COPD	Any prim or sec diagnosis - Chronic obstructive pulmonary disease, prior 2 years	Prior 1 to 730 days (inclusive)
DX Mental	Any prim or sec diagnosis - Mental illness, prior 2 years	Prior 1 to 730 days (inclusive)
DX Asthma	Any prim or sec diagnosis - Asthma, prior 2 years	Prior 1 to 730 days (inclusive)
DX Cognitive Impairment	Any prim or sec diagnosis - Miscellaneous cognitive dysfunctions, prior 2 years	Prior 1 to 730 days (inclusive)
DX ACS Condition	Any prim or sec diagnosis - ACS: Any ambulatory care sensitive condition	Prior 1 to 730 days (inclusive)
SUS AE variables		
AE visits prior 0-90 days	Number of A&E visits (any) prior 1-90 days	Prior 1 to 90 days (inclusive)
AE unplanned follow-up visits prior 0-90 days	Number of A&E visits - unplanned follow-up prior 1-90 days	Prior 1 to 90 days (inclusive)
AE X-ray prior 0-90 days	Number of A&E visits with X-ray prior 1-90 days	Prior 1 to 90 days (inclusive)
AE visits prior 91-180 days	Number of A&E visits (any) prior 91-180 days	Prior 91 to 180 days (inclusive)
AE unplanned follow-up visits prior 91-180 days	Number of A&E visits - unplanned follow-up prior 91-180 days	Prior 91 to 180 days (inclusive)
AE X-ray prior 91-180 days	Number of A&E visits with X-ray prior 91-180 days	Prior 91 to 180 days (inclusive)
AE visits prior 181-365 days	Number of A&E visits (any) prior 181-365 days	Prior 91 to 180 days (inclusive)
AE unplanned follow-up visits prior 181-365 days	Number of A&E visits - unplanned follow-up prior 181-365 days	Prior 181 to 365 days (inclusive)
AE X-ray prior 181-365 days	Number of A&E visits with X-ray prior 181-365 days	Prior 181 to 365 days (inclusive)
AE visits 2 yrs prior	Number of A&E visits (any) prior 366-730 days	Prior 366 to 730 days (inclusive)
AE unplanned follow-up visits 2 yrs	Number of A&E visits - unplanned follow-up prior	Prior 366 to 730 days (inclusive)

prior	366-730 days	
AE X-ray 2yrs prior	Number of A&E visits with X-ray prior 366-730 days	Prior 366 to 730 days (inclusive)
SUS outpatient variables		
Outpatient specialty visits prior 0-90 days	Number of outpatient visits (all) prior 1-90 days	Prior 1 to 90 days (inclusive)
Outpatient specialty visits missed prior 0-90 days	Number of outpatient visits missed prior 1-90 days	Prior 1 to 90 days (inclusive)
Outpatient specialty visits prior 91-180 days	Number of outpatient visits (all) prior 91-180 days	Prior 91 to 180 days (inclusive)
Outpatient specialty visits missed prior 91-180 days	Number of outpatient visits missed prior 91-180 days	Prior 91 to 180 days (inclusive)
Outpatient specialty visits prior 181-365 days	Number of outpatient visits (all) prior 181-365 days	Prior 181 to 365 days (inclusive)
Outpatient specialty visits missed prior 181-365 days	Number of outpatient visits missed prior 181-365 days	Prior 181 to 365 days (inclusive)
Outpatient specialty visits 2 yrs prior	Number of outpatient visits (all) prior 365-730 days	Prior 366 to 730 days (inclusive)
Outpatient specialty visits missed 2 yrs prior	Number of outpatient visits missed prior 365-730 days	Prior 366 to 730 days (inclusive)
GP consultations data		
GP DX COPD	Diagnosis of COPD, prior 2 years	Prior 1 to 730 days (inclusive)
GP - 1 long term condition	Chronic conditions - 1 in prior 2 years	Prior 1 to 730 days (inclusive)
GP - 2 or more long term conditions	Chronic conditions - 2 or more in prior 2 years	Prior 1 to 730 days (inclusive)
GP - Glomerular filtration rate group 3 last 0-365 days	Glomerular Filtration Rate Group 3 in last year	Prior 1 to 365 days (inclusive)
GP - 10+ unique drugs prescribed	1-4 unique drugs - last 1 to 90 days	Prior 1 to 90 days (inclusive)
GP - 5-9 unique drugs prescribed	5-9 unique drugs - last 1 to 90 days	Prior 1 to 90 days (inclusive)
GP - 0-4 unique drugs prescribed	10+ unique drugs - last 1 to 90 days	Prior 1 to 90 days (inclusive)
GP - Psychoactive substance misuse disorder	Psychoactive substance misuse disorder, prior 2 years	Prior 1 to 730 days (inclusive)
GP - 7+ distinct disorders	7+ distinct disease disorders recorded in prior 90 days	Prior 1 to 90 days (inclusive)
GP - GP visits prior 0-3 months	Count of different BNF chapters of prescribed medicines, prior 2 years	Prior 1 to 730 days (inclusive)
GP - GP visits prior 4-6 months	Number of GP visits prior 1-3 months	Prior 1 to 3 months (inclusive)
GP - GP visits prior 7-12 months	Number of GP visits prior 13-24 months	Prior 13 to 24 months (inclusive)
GP - GP visits 2yrs prior	Number of GP visits prior 4-6 months	Prior 4 to 6 months (inclusive)
GP - Increasing rate of GP visits during last 12 months	Number of GP visits prior 7-12 months	Prior 7 to 12 months (inclusive)
GP - Number of high risk BNFs	Substantial increase in GP visits last year	
GP - Any high risk	Number of BNF codes associated with emergency admissions, prior 2 years	Prior 1 to 730 days (inclusive)
GP - Count of BNF chapters	Any BNF codes associated with emergency admissions, prior 2 years	Prior 1 to 730 days (inclusive)
GP - DX Dementia	Diagnosis of Dementia, prior 2 years	Prior 1 to 730 days (inclusive)
GP - Exception reported from quality indicators	QOF register exceptions, prior 2 years	Prior 1 to 730 days (inclusive)
GP - Health visitor or district nurse visit	Any home/district visit, prior 2 years	Prior 1 to 730 days (inclusive)
GP - Record of IHD/angina	Diagnosis of IHD/angina, prior 2 years	Prior 1 to 730 days (inclusive)
GP - Nebuliser used	Nebuliser prescribed, prior 2 years	Prior 1 to 730 days (inclusive)
GP - Salbutamol prescribed	Salbutamol prescribed, prior 2 years	Prior 1 to 730 days (inclusive)
GP - Warfarin prescribed	Warfarin prescribed, prior 2 years	Prior 1 to 730 days (inclusive)
GP - High blood pressure	High blood pressure Read code, prior 2 years	Prior 1 to 730 days (inclusive)
GP - Smoker	Smoking status, prior 2 years	Prior 1 to 730 days (inclusive)
GP - BMI 30+	BMI greater than equal to 30, prior 2 years	Prior 1 to 730 days (inclusive)
GP - HbA1c > 10	HbA1c greater than 10, prior 2 years	Prior 1 to 730 days (inclusive)
GD - QOF ARTF	QOF register: Atrial fibrillation	Prior 1 to 730 days (inclusive)
GP - QOF CKD	QOF register: Stage 3 to 5 chronic kidney disease	Prior 1 to 730 days (inclusive)
GP - QOF Depression	QOF register: Depression	Prior 1 to 730 days (inclusive)
GP - Number of QOF DX categories 3+	QOF register: number of different registers, 3 or more	Prior 1 to 730 days (inclusive)
GP - Number of phone contacts last 0-3 months	Number of GP telephone consults prior 1-3 months	Prior 1 to 3 months (inclusive)

Choosing a model to predict hospital admission. An observational study of new variants of predictive models for case finding.

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ABSTRACT

Objectives: To test the performance of new variants of models to identify people at risk of an emergency hospital admission. We compared (1) the impact of using alternative data sources (hospital inpatient, A&E, outpatient, and GP electronic medical records) (2) the effects of local calibration on the performance of the models and (3) the choice of population denominators.

Design: Multivariate logistic regressions using person level data adding each data set sequentially to test value of additional variables and denominators.

Setting: Five Primary Care Trusts within England.

Participants: 1,836,099 people aged 18-95 registered with GPs on 31 July 2009.

Main outcome measures: Models to predict hospital admission and readmission were compared in terms of positive predictive value and sensitivity for various risk strata and with receiver operating curve C statistic.

Results: The addition of each data set showed moderate improvement in number of patients identified with little or no loss of positive predictive value. However, even with inclusion of GP electronic medical record information, the algorithms identified only a small number of patients with no emergency hospital admissions in the prior two years. The model pooled across all sites performed almost as well as models calibrated to local data from just one site. Using population denominators from GP registers led to better case finding.

Conclusions: These models provide a basis for wider application in the NHS. Each of the models examined produce reasonably robust performance and offers some predictive value. The addition of more complex data add some value, but we were unable to conclude that pooled models performed less well than those in individual sites. Choices about model should be linked to the intervention design. Characteristics of patients identified by the algorithms provide useful information in the design/costing of intervention strategies to improve care coordination/outcomes for these patients.

Article focus

- The use of statistical models to predict risk of hospital admissions are increasingly used to prioritise patients for preventive care. Models exist in several different forms and use a variety of input data sets.
- This paper compared the performance of a variety of models built using different datasets.

Key messages

- The addition of more detailed data sets led to moderate improvement in number of patients identified with little or no loss of positive predictive value.
- The use of GP registry data for the denominator proved to be of significant importance. By including all patients in an area, not just those with prior hospital use, improved rates of case finding were observed.
- Models calibrated to local data sets did not show a consistent improvement over models built on pooled data.

Strengths and limitations of this study

- The analysis is based on populations from only five areas in England, however this is the largest UK population (1.8M people) used in the development of a publicly available risk tool.
- The success of a predictive model depends on many factors beyond the statistical performance of the model.

INTRODUCTION

There remains continuing interest in identifying patients at risk of future hospital admissions. Policies providing penalties[1] or non-payment[2] for hospital readmissions that put providers at risk for a share of total health expenditures have been developed for in the U.S. and in England. These create even stronger incentives to identify high risk patients to target care coordination and management strategies that may potentially reduce future inpatient expenditures.

Most predictive modelling approaches have used administrative data from claims in the U.S. or hospital data from Hospital Episode Statistics (HES) or Secondary Uses Services (SUS) in England. These data provide the information on prior utilisation and diagnostic history to develop predictive models for patients at risk of future hospitalization.[3] Payor claims data in the U.S. provide rich information on care provided in hospitals, home care services and nursing home use, as well as detailed pharmacy prescription history.[4] In England, the most commonly used models (such as in the now outdated Patient at Risk of Readmission PARR algorithm)[5,6] are based on hospital admissions data (including day case use, and regular attendances) with some use of accident and emergency (A&E) and outpatient attendance data as well.[7]

While some predictive modeling efforts in the U.K. have included information from GP electronic medical records (EMRs),[8,9] using such data presents a number of challenges. These include obtaining permissions for access to EMRs for large populations, linking the records to hospital data, and use of Read codes[10] to develop GP variables. Data from EMRs include additional elements not available in the hospital data sets such as test results (e.g. blood pressure, HbA1c levels), diagnostic history for patients without recent inpatient admissions, prescription history, GP contact patterns (GP visits and telephone contacts), and other personal health markers (e.g. body mass index, smoking status). These additional data elements have the potential to add power to predictive modeling efforts, especially for patients with no or lower levels of recent inpatient use.

Despite the challenges, a number of initiatives around the UK are demonstrating population wide access to EMR data. A common application is in the use of models that assist local clinical commissioning groups (CCGs) in identifying high risk patients.

Though the choice of data sets for a predictive model makes a big difference to the investment required to run these models – at least initially – no studies have looked at the marginal value of different data sets. In this analysis we examine the added value of including data on A&E and outpatient visits (which are readily available) to predictive modeling efforts using hospital inpatient data alone. We also assess the marginal effect of adding GP EMR information to help identify patients at risk of future hospital admissions. Most existing models in use were developed -using logistic regression techniques and we used this standard approach throughout this paper. We recognize that different modelling methods may yield different results but in this analysis we were concerned with the impact of changes in the underlying data sets. Such models will always be limited by the scope and quality of data available, the ways data are grouped and classified and the ways that users can assess up to date information. Despite these problems these models have become commonly used tools.

In addition to the depth of data used there is also a question about how generalisable models are across different sites. In many settings models are recalibrated on local data sets. Yet there is little systematic analysis of the value that this step adds and whether models built on data from one site outperform those built on a larger sample of pooled data. We therefore explore whether there is a need for development of individual site predictive models, or whether models developed from multiple sites can be applied effectively at a new individual site.

METHODS

We conducted analyses separately for five Primary Care Trust areas in England (Newham, Cornwall, Kent, Croydon, Redbridge; total adult population ranging from 209,661 to 693,089). Results are reported for the individual sites and as combined/pooled results (total population 1,836,099). Hospital data was extracted from the Secondary Users Services (SUS)[11] system which contained records of all hospital events (inpatient admissions, outpatient appointments and A&E visits) for the PCTs' registered populations between 1 August 2007 and 30 September 2010. The PCTs also extracted data from GP systems in two forms. Firstly as a register of the local adult population from 1 August 2007 and 31 July 2009, and secondly in the form of datasets recording details of GP consultations over the same time period.

Personally identifiable information was stripped out before any data were passed to the research team. Individuals' NHS numbers (the personal identifiers) were concatenated with a passcode chosen by each of the five PCT areas (and unknown to the research team) and these were pseudonymised at source using secure hash algorithm SHA-256 [12]. This ~~to~~ allowed for linkage between the hospital and the general practice data from each area, whilst preserving individuals' anonymity.

A series of variables were created from each data set that were believed to be potentially predictive of an unplanned (emergency) hospital admission in the last 12 months of the study period. These variables captured resource use, utilization patterns, diagnostic history, test results, and prescription history in the two years prior to the predictive period. They were created for all individuals aged 18+ registered with a GP in one of the five areas on 31 July 2009. To account for expected time required to obtain and process the hospital and GP EMR data, we included a two-month lag in our analyses, with data from 1 August 2007 to 31 July 2009 used to predict emergency admissions during the period 1 October 2009 to 30 September 2010.

Patient age and gender were obtained from the GP register. Patient area of residence was not available, and so GP practice attributed index of multiple deprivation (2007) was used as an area deprivation measure. The number of months the patient was registered with the PCT in the pre-period was calculated and included in the regression. Hospital inpatient data were used to capture utilization in the 0-90, 91-181, 180-365, and 366-730 days prior to the lag period. The number of emergency and elective admissions for these periods were included and dichotomous variables for any day case or regular attendance use were created.

A broad range of diagnostic variables were developed using primary and secondary diagnosis fields and a Charlson Comorbidity Index[~~12~~13] was calculated for each patient and included in the model.

A&E data were used to determine A&E visit rates for various intervals in the pre-period, both total visits and unplanned follow-up visits. A&E diagnostic information was not reliably reported across the five sites and was not included, although X-ray use was included. Outpatient data provided variables on outpatient visit rates for various intervals, as well as missed appointment rates and the number of different specialty types consulted. Diagnostic information in outpatient data was missing in more than 95% of cases and was not included.

GP EMR data were used to create proxy visit rates (these may include both actual GP visits, in addition to other events documented in a person's records) for various intervals and to capture any increase in visit rates at the end of the pre-period that may reflect increased morbidity in a patient. EMR Read codes (CTV3 version) were used to obtain test results (blood pressure, blood serum levels, HbA1c levels, etc.), body mass index, smoking history, prescription history (number and type), and a range of diagnostic variables during the pre-period.

Variables from each data set (inpatient (including day case and regular attenders), A&E, outpatient, and GP EMRs) were added and modeled sequentially using standard logistic regression in SPSS v20. Emergency admission in the next 12 months was used as the dependent variable, producing a risk score ranging from 0-100. Separate models were developed for each PCT area, and analysis was limited to patients aged 18-95 who were on the GP register in the area. Over-fitting was tested using a split sample approach, with only minor differences observed in positive predictive values (PPV), sensitivity, and specificity.

Findings provided here include both individual site results and results combined across the five sites. We also created five additional predictive models (referred to below as the 'four-site regression models'), each one combining data from four sites and applying coefficients to the fifth remaining site. With this we could compare results with individual site predictive models to help assess the value of local model development.

The full list of more than 300 potential variables was ultimately reduced to 88 by exclusion of variables with low volumes and low significance levels across the sites. The 88 variables ultimately included in the model (and regression coefficients), may be found in Appendix B and D, and a full listing of the variables

considered for inclusion and detailed specification of each variable are available at http://www.nuffieldtrust.org.uk/.

Cost variables were examined, with secondary care activity costed according to the method used in development of the person based formula for allocating commissioning funds to general practices in England.[~~13~~14] Ultimately, these were not included in the predictive models because of concerns about difficulties in constructing these variables by possible future users, however costs are included in descriptive findings to help in design of intervention strategies.

Predictive modeling performance is typically documented reporting PPV and sensitivity at the risk score threshold of 50. However, because interventions may be targeted at patients with higher or lower risk scores and interventions strategies may be calibrated differently depending on risk level and characteristics of patients at various risk score levels, we report PPV sensitivity at 20 risk score cutoff points (vigintiles) and provide detailed patient characteristics at risk score thresholds of 50 and 30 to facilitate intervention design.

RESULTS

Pooled Individual Site Results

There were 1,836,099 people aged 18 and over who were registered with a GP practice on 31 July 2009. Table 1 shows the combined results of individual site regressions including the number of patients correctly identified, PPV, and sensitivity for four models:

(i) IP based on hospital inpatient data only (including day cases and regular attendances)
(ii) IPAE using inpatient and A&E data
(iii) IPAEOP using inpatient A&E and outpatient data
(iv) IPAEOPGP using inpatient, A&E, outpatient data and GP EMR.

At the traditional risk score threshold level of 50 all four models perform respectably in terms of PPV (ranging from .523 to .538), but sensitivity remains quite low across all models (.049 to .060). Lowering the threshold to 30 increases sensitivity somewhat with a concomitant reduction in PPV (ranging from .417 to .422). The ROC area under the curve (C statistic) improved with the addition of each data set, increasing from .731 with the inpatient-only model to .780 with the full model.

Table 1 Model performance, four models: IP, IPAE, IPAEOP, IPAEOPGP. Five site individual runs combined.

Risk Score Threshold	IP Data			IP+AE Data			IP+AE+OP Data			IP+AE+OP+GP Data		
	True Positive	PPV	Sensitivity	True Positive	PPV	Sensitivity	True Positive	PPV	Sensitivity	True Positive	PPV	Sensitivity
1	94,692	0.052	1.000	94,692	0.052	1.000	94,692	0.052	1.000	94,692	0.052	1.000
5	54,450	0.126	0.575	56,117	0.128	0.593	56,438	0.131	0.596	61,498	0.133	0.649
10	33,053	0.219	0.349	34,102	0.221	0.360	35,033	0.223	0.370	39,986	0.220	0.422
15	22,898	0.285	0.242	23,166	0.293	0.245	24,261	0.290	0.256	28,697	0.283	0.303
20	16,181	0.346	0.171	16,915	0.347	0.179	17,719	0.344	0.187	21,601	0.333	0.228
25	12,670	0.385	0.134	13,182	0.386	0.139	13,754	0.383	0.145	16,672	0.378	0.176
30	10,061	0.421	0.106	10,555	0.422	0.111	11,010	0.419	0.116	13,196	0.417	0.139
35	8,130	0.449	0.086	8,600	0.450	0.091	8,986	0.448	0.095	10,516	0.450	0.111
40	6,700	0.477	0.071	7,139	0.478	0.075	7,421	0.476	0.078	8,494	0.479	0.090
45	5,535	0.501	0.058	5,976	0.504	0.063	6,167	0.499	0.065	6,921	0.510	0.073
50	4,627	0.529	0.049	5,027	0.531	0.053	5,172	0.523	0.055	5,669	0.538	0.060
55	3,862	0.551	0.041	4,222	0.551	0.045	4,359	0.543	0.046	4,581	0.562	0.048
60	3,239	0.574	0.034	3,555	0.569	0.038	3,658	0.567	0.039	3,735	0.587	0.039
65	2,711	0.593	0.029	3,012	0.590	0.032	3,041	0.587	0.032	3,034	0.618	0.032
70	2,245	0.617	0.024	2,481	0.612	0.026	2,519	0.610	0.027	2,453	0.645	0.026
75	1,816	0.634	0.019	2,049	0.639	0.022	2,064	0.631	0.022	1,921	0.666	0.020
80	1,418	0.666	0.015	1,662	0.656	0.018	1,646	0.654	0.017	1,478	0.696	0.016
85	1,064	0.679	0.011	1,293	0.674	0.014	1,276	0.679	0.013	1,114	0.711	0.012
90	769	0.710	0.008	932	0.688	0.010	935	0.702	0.010	754	0.738	0.008
95	478	0.748	0.005	592	0.725	0.006	586	0.728	0.006	437	0.771	0.005
Top 1%	8,214	0.447	0.087	8,353	0.455	0.088	8,410	0.458	0.089	8,722	0.475	0.092
Top 5%	24,873	0.271	0.263	25,355	0.276	0.268	25,712	0.280	0.272	26,991	0.294	0.285
	ROC C Statistic	0.731			0.745			0.752			0.780	

Of particular note is the finding that the addition of each data set added power, that is, correctly identified more patients with an admission in the next 12 months, with only a minor reduction in PPV. At a risk threshold of 50, the addition of A&E data resulted in increase of 400 (8.6%) correctly flagged patients, with no loss in PPV. The inclusion of outpatient data added a more modest 2.9%, but with a slight loss in PPV (.531 to .523). The addition of GP EMR data added an additional 9.6% of patients, while actually increasing the accuracy of the model (PPV increasing from .523 to .538). The added power of the A&E data set is less substantial at a risk score threshold of 30 (4.9%), but outpatient and GP EMR data sets had larger increases in correctly identified patients (4.3% and 19.9%).

There were also important differences between the models in terms of the characteristics of patients identified as high risk. For example, at a risk score cutoff of 50, patients identified using inpatient data alone had high prior emergency inpatient utilization rates with 2.62 admissions in the prior year compared to 2.43 when A&E data was added; 2.34 with addition of outpatient, and 2.20 with the addition of GP EMR data - see Table 2.

The inclusion of the additional data sets also led to a reduction in observed morbidity level of patients at the 50 threshold, with lower numbers of long term conditions, fewer patients with multiple long term conditions, lower Charlson Comorbidity Index scores, less history of alcohol abuse and mental illness, and lower emergency inpatient costs in the years prior to the predictive period. Similar, but less substantial differences were observed at the risk score threshold of 30. The addition of the A&E data set resulted in higher rates of A&E visits in the pre-period among patients identified at both risk score cutoff levels, and the addition of outpatient data resulted in higher outpatient visit and missed visit rates among identified patients.

These findings suggest inclusion of the additional data sets added some predictive power and generally tended to find additional patients who were less severely ill (more severely ill patients tended to remain high risk). Thus they potentially offer an opportunity for intervention at earlier stages in the progression of a patient's condition. However, the number of patients identified with no prior emergency inpatient utilization in the prior two years was relatively small across all models. At a risk score threshold of 50, only 0.3% of patients correctly identified by the inpatient-only model had no prior emergency admissions in the previous two years, and increasing only modestly 3.2% in the full model (Table 3). At a risk threshold of 30, the rates were higher, but only reaching 12.4% for the full model.

Table 2 Patient characteristics by risk score threshold four models: IP, IPAE, IPAEOP, IPAEOPGP. Five site individual runs combined.

	Risk Score 50+				Risk Score 30+			
	IP Data	IPAE Data	IPAEOP Data	IPAEOPGP Data	IP Data	IPAE Data	IPAEOP Data	IPAEOPGP Data
Number of patients	8,743	9,473	9,892	10,545	23,912	25,021	26,304	31,653
Patients with adm next 12 mos	4,627	5,027	5,172	5,669	10,062	10,554	11,011	13,196
Mean Age	73.9	72.3	71.2	72.2	75.3	74.0	73.4	73.9
Age 18-39	6.2%	8.4%	8.7%	7.8%	5.1%	6.8%	7.0%	6.4%
Age 40-54	8.7%	9.6%	10.9%	10.6%	7.0%	7.8%	8.6%	8.5%
Age 55-64	6.9%	7.4%	7.8%	8.1%	6.4%	6.4%	7.0%	7.3%
Age 65-74	14.4%	13.9%	15.0%	13.5%	13.9%	13.8%	14.4%	13.7%
Age 75-84	30.5%	28.9%	28.2%	27.4%	32.1%	31.1%	30.3%	29.6%
Age 85+	33.3%	31.8%	29.3%	32.6%	35.5%	34.1%	32.7%	34.4%
Female	55.2%	55.2%	54.9%	54.7%	56.9%	57.1%	56.6%	56.5%
Practice IMD	24.6	24.9	24.8	24.3	24.2	24.3	24.3	23.8
Ischaemic Heart Disease	36.2%	34.2%	33.2%	32.1%	29.8%	28.4%	27.8%	25.2%
Angina	21.7%	20.5%	19.5%	19.3%	17.3%	16.4%	15.7%	14.5%
Hypertension	64.5%	61.2%	59.9%	59.0%	59.4%	56.7%	55.1%	50.9%
CHF	19.2%	17.8%	16.9%	15.9%	14.0%	13.2%	12.5%	10.7%
CVD	21.7%	20.1%	19.3%	18.1%	16.9%	15.8%	15.2%	13.3%
COPD	23.4%	21.4%	20.6%	19.1%	17.2%	16.3%	15.7%	13.4%
Asthma	21.3%	20.9%	20.1%	18.1%	17.4%	16.6%	16.1%	13.8%
Diabetes	34.1%	32.4%	31.6%	28.8%	30.1%	28.8%	27.6%	23.6%
Renal Failure	16.5%	14.6%	14.2%	13.3%	11.2%	10.4%	10.0%	8.5%
Any long term conditions	89.8%	87.0%	85.8%	85.0%	86.6%	83.6%	81.4%	75.2%
Any cancer	15.4%	13.8%	13.4%	12.4%	13.3%	12.7%	12.2%	10.5%
Alcohol misuse	10.0%	10.0%	9.6%	9.1%	7.0%	6.7%	6.4%	5.8%
Mental illness	32.0%	30.6%	28.9%	27.2%	23.5%	22.3%	21.3%	18.6%
Number long term conditions	2.67	2.51	2.43	2.31	2.20	2.10	2.02	1.79
Charlson Index	3.96	3.69	3.55	3.28	3.09	2.95	2.82	2.43
Emerg adms 1yr prior	2.62	2.43	2.34	2.20	1.64	1.57	1.50	1.29
Emerg adms 2 yr prior	1.78	1.67	1.61	1.50	1.15	1.10	1.05	0.91
No emerg adm prior 2 yrs	0.6%	1.9%	3.3%	4.3%	4.2%	6.5%	9.2%	16.2%
Elect adms 1yr prior	0.32	0.29	0.31	0.28	0.27	0.26	0.27	0.24
Elect adms 2 yr prior	0.24	0.23	0.26	0.24	0.20	0.20	0.22	0.19
Any day case 1yr prior	31.9%	30.8%	31.6%	28.7%	31.5%	30.7%	30.4%	26.9%
Any day case 2yr prior	28.9%	27.6%	28.0%	25.7%	27.8%	26.9%	26.7%	23.7%
Emerg adm cost 1yr prior	£4,500	£4,073	£3,920	£3,688	£2,893	£2,709	£2,604	£2,231
Emerg adm cost 2yr prior	£2,932	£2,675	£2,583	£2,422	£1,962	£1,822	£1,757	£1,521
AE visits 1yr prior	2.90	3.59	3.45	3.17	1.83	2.26	2.17	1.86
AE visits 2yr prior	1.90	2.40	2.31	2.10	1.23	1.52	1.46	1.25
OP visits 1yr prior	7.27	6.94	9.65	8.23	5.65	5.63	7.39	6.16
OP visits 2yr prior	4.30	4.10	5.92	5.08	3.39	3.38	4.54	3.81
OP visits missed 1yr prior	0.47	0.48	0.74	0.65	0.35	0.36	0.53	0.44
OP visits missed 2yr prior	0.49	0.48	0.71	0.61	0.33	0.34	0.48	0.40
GP visits 1yr prior	42.9	42.7	43.3	52.5	38.5	38.4	38.8	45.4
GP visits 2yr prior	35.5	35.2	35.7	42.5	32.4	32.1	32.5	37.7
Any high risk BNFs	73.9%	71.6%	72.2%	84.0%	69.3%	67.5%	68.1%	79.8%
Num high risk BNFs	1.94	1.85	1.88	2.20	1.64	1.59	1.61	1.84
High blood pressure	9.0%	9.0%	9.0%	9.0%	10.0%	10.0%	10.0%	9.0%
Smoker	18.0%	19.0%	19.0%	23.0%	16.0%	16.0%	16.0%	20.0%
BMI 30+	16.0%	17.0%	17.0%	17.0%	15.0%	16.0%	16.0%	18.0%
HbA1c > 10	5.0%	5.0%	5.0%	7.0%	5.0%	5.0%	4.0%	6.0%
Any Em adm next 12 mos	52.9%	53.1%	52.3%	53.8%	42.1%	42.2%	41.9%	41.7%
Num Em adm next 12 mos	1.34	1.33	1.29	1.31	0.89	0.89	0.87	0.84
0 Em adm next 12 mos	47.1%	46.9%	47.7%	46.2%	57.9%	57.8%	58.1%	58.3%
1 Em adm next 12 mos	23.0%	23.0%	23.2%	23.9%	21.7%	21.9%	21.7%	22.3%
2 Em adm next 12 mos	12.5%	12.5%	12.3%	13.2%	10.0%	10.0%	10.0%	9.9%
3 Em adm next 12 mos	7.3%	7.3%	7.0%	7.1%	4.8%	4.9%	4.8%	4.6%
4+ Em adm next 12 mos	10.2%	10.2%	9.8%	9.7%	5.5%	5.5%	5.3%	4.9%
Emerg adm cost next 12 mos	£2,358	£2,266	£2,199	£2,270	£1,608	£1,575	£1,546	£1,507

AE visits next 12 mos	1.88	2.11	2.04	2.04	1.24	1.37	1.36	1.29

Table 3 Proportion of patients correctly identified, who had no emergency admissions in the prior two years. Four models: IP, IPAE, IPAEOP, IPAEOPGP. Five site individual runs combined.

Prediction threshold	IP Data	IPAE Data	IPAEOP Data	IPAEOPGP Data
Risk Score 50+	0.3%	1.2%	2.3%	3.2%
Risk Score 30+	2.7%	4.4%	6.3%	12.4%
Top 1%	1.5%	2.9%	4.2%	6.5%
Top 5%	25.9%	26.4%	26.7%	30.8%

Individual Site and 'Four-Site Regression' Model Results

Overall the performance of the models was similar at the individual site level. Only modest differences were found in PPV levels and sensitivity across the sites. For runs using non-GP data only (IPAEOP), at the risk score threshold of 50, PPVs ranged from .512 to .552 and sensitivity ranged from .047 to .071. For the model including GP EMRs, PPVs ranged from .521 to .566 and sensitivity from .053 to .073. See Appendix A. There was some variation in the magnitude of regression coefficients between sites, but in general the coefficients were comparable for models based on the non-GP data model (IPAEOP). See Appendix B. For the model including variables from GP EMRs (IPAEOPGP), the level of variation in regression coefficients (size and direction) was somewhat greater for those variables derived from GP data. We observed substantial differences in frequency of reporting of Read codes across sites which no doubt contributed to this variation. The level of significance of individual variables also varied across sites (Appendix C), but most variables were consistently strongly significant across all sites, especially variables involving prior emergency inpatient admissions. Again, higher levels of variation in levels of significance were observed for the GP variables derived from Read codes.

We compared the results for these individual site models to a pooled model combining data from four of the sites and applied coefficients to the remaining individual site. We found generally only small differences in predictive accuracy (PPV) between these two approaches (Table 4), however the individual site models identified a greater number of true positives. For example, in Cornwall at a risk

score cutoff of 50, the individual site model using hospital data identified correctly 1,041 patients while the pooled model identified only 754. In Newham however, the four-site model was more powerful, correctly identifying 858 patients compared to 734 for the individual site approach. In both cases (and in general across all sites), the model identifying larger numbers of true positives had a somewhat lower PPV, suggesting improved case finding volume came at the expense of predictive accuracy.

Table 4 Individual site and four-site regression models. Case finding and predictive accuracy.

	IPOPAE				IPOPAEGP			
	Individual Site Regression		Four Site Regression		Individual Site Regression		Four Site Regression	
	True Positives	PPV	True Positives	PPV	True Positives	PPV	True Positives	PPV
Newham								
Risk Score 50+	734	0.552	858	0.517	768	0.566	835	0.523
Risk Score 30+	1,409	0.450	1,564	0.414	1,570	0.439	1,798	0.409
Cornwall								
Risk Score 50+	1,041	0.520	754	0.548	1,176	0.545	952	0.556
Risk Score 30+	2,439	0.406	1,970	0.426	3,032	0.410	2,746	0.411
Kent								
Risk Score 50+	1,565	0.513	1,387	0.519	1,736	0.521	1,873	0.493
Risk Score 30+	3,372	0.401	3,067	0.403	4,079	0.397	4,432	0.369
Croydon								
Risk Score 50+	1,089	0.528	1,192	0.523	1,182	0.550	1,230	0.537
Risk Score 30+	2,134	0.444	2,258	0.424	2,610	0.442	2,502	0.437
Redbridge								
Risk Score 50+	743	0.512	863	0.495	807	0.522	607	0.519
Risk Score 30+	1,656	0.420	1,693	0.415	1,905	0.423	1,390	0.436

Testing alternative population denominators

Models built using inpatient data only (IP) were also built for just the subset of patients who had some inpatient care in the prior two years (to reflect typical predictive modeling efforts that may have been conducted without access to GP registry information), as well as for the group who had had an emergency admission in the prior year (to replicate analyses conducted by PARR users).

Combining the results from the five sites at a risk score threshold of 50, models using the full GP register ~~list denominator~~ correctly identified 4,627 patients compared with 3,572 patients in runs restricted to patients with prior inpatient care and 3,060 to runs limited to patients with an emergency admission in the prior year. This substantial increase in case finding was obtained with only moderate loss in PPV (.529 GP list, .559 prior inpatient and .589 emergency admissions in last year). Similar results were also found for all hospital data models (IPOPAE, though with any hospital use in prior two years, rather than just any inpatient use).

Using the full GP registry population did not result in finding substantial numbers of patients with no emergency admissions in the prior two years, but the increased numbers of patients identified included more patients with less prior use and lower levels of morbidity. For a profile of patients identified using these alternative denominators see http://www.nuffieldtrust.org.uk/.

DISCUSSION

This analysis has looked at the performance of new variants of predictive models for case finding. These models are intended to update and improve upon the established combined predictive model-like [~~14~~15] and PARR models [5] widely used in the NHS.

Each of the models examined produced reasonably robust performance, by some measures better or at least comparable to similar prior models [9]. At a risk threshold of 50, patients identified by the models had PPVs ranging from .523 to .538. While the percent of all patients with future admissions identified was relatively low (sensitivity .049 to .060), lowering the risk threshold allows the identification of more patients with relatively small loss in PPV (e.g. at a risk threshold of 30, the full model identified 14% of future admissions with a PPV of .417). Users of predictive modeling algorithms have obvious trade-offs between maximizing the number of patients identified and predictive accuracy. Lower risk score thresholds will find more patients, but these patients are increasingly less likely to have future admissions.

The implications for intervention design are important. Patients at lower risk thresholds have less prior inpatient use and lower morbidity, so an intervention here might be calibrated to be less intensive. But because the models are less accurate at lower risk scores, the amount that can be spent on an intervention is also reduced if you wish to achieve financial break-even (ie where the cost of intervention is off-set by cost savings from reduction in future admissions). As documented in Table 2,

at a risk score threshold of 50, the rate of future admission for patients identified by the full model (IPAEOPGP data) was 1.31 admissions per year with an associated cost of £2,270. If there were a 10% reduction in future admissions, £227 could be spent on an intervention to improve care coordination and still achieve break-even. However, at a lower risk threshold of 30, the lower rates of future admissions and costs means that lower intervention expenditures are required to achieve break-even (£151 with a 10% reduction in future admissions). A detailed business case analysis with mean emergency inpatient costs in the next 12 months within each risk vigintile level is available via http://www.nuffieldtrust.org.uk/.

These data also provide other information that may be useful in the development of intervention strategies. As shown in Table 2, patients identified by the models have extremely high rates of chronic disease (85-90% with long term conditions at risk threshold of 50), often with multiple long term conditions and high Charlson Comorbidity Index levels, indicating serious medical needs. However, these patients already have high use of outpatient care and very high GP visit rates. This suggests simple access to ambulatory care is not the issue, but prevention needs to look at care coordination and management of complex problems and at the ability of patients and their families to manage chronic illness. High risk patients identified by the models also have relatively high rates of mental illness (27-32% at risk threshold of 50) and moderate levels of alcohol abuse, factors that are likely to complicate any intervention strategy.

It is also important to note the limitations of these data in helping frame the design of any intervention strategy. Other studies have documented that high risk patients often have important characteristics related to care needs and patient capacity not captured by administrative data and EMRs. For example, interviews with high risk patients and their families have documented high levels of social isolation for many, as well as precarious housing status.[~~15~~16] These non-medical factors are likely to have significant impact on health status and utilization patterns. Moreover, not much is known about how/whether care coordination and management has actually failed for these patients. Are these high risk patients just very sick patients whose hospitalizations are largely not preventable/avoidable [17], or has the care delivery system failed in some important dimensions that can be corrected with improved care coordination and management? These data cannot answer this very critical question, and it is clear that the field would benefit from further study that examined the circumstances of patients identified as

high risk by predictive modeling algorithms to sort out more clearly the factors contributing to high rates of emergency admission.

This study does document the value of incorporating data sets beyond inpatient records. The addition of A&E and outpatient records resulted in identification of more high risk patients with little or no loss of predictive accuracy. These data sets are readily available and have standardized reporting formats that facilitate analysis. While the absence of useful diagnostic information in these data sets is a limiting factor, the improvement in case finding and usefulness in descriptive profiling of high risk patients to help in intervention design (e.g. high rates of A&E use rates, high rates of missed outpatient appointments) suggests their inclusion is clearly merited.

Use of GP EMRs presents significant challenges. While the lack of access to these data is unlikely to remain a problem, the variation in completeness and quality of data is problematic. The use of the unwieldy Read codes system makes analysis difficult, and we observed significant differences across sites in reporting patterns. Some of these differences may be caused by under reporting of diagnostic variables, others by differences in coding approaches. However, the potential improvement in case finding, especially among patients with lower rates of utilization in the pre-period, suggests these barriers are worth confronting. Our development of new variables beyond those included in prior predictive modeling efforts [8] contributed substantially to enhanced case finding, and further work on variable development is likely to lead to further improvements. Again, these data are also useful in providing descriptive information on high risk patients to help in intervention design (e.g. documenting potential targets of opportunity such as uncontrolled hypertension or diabetes).

This study does not provide definitive findings on the value of developing individual site models compared to simply applying coefficients from multi-site or national model coefficients to local data. Our four-site regression models generally had comparable PPVs to individual site models, but for the majority of sites- the four-site regression approach correctly identified somewhat fewer number patients with future admissions. Though it is tempting to speculate on whether differences in the health needs of the population or coding differences affect model performance, we did not observe any clear patterns between the areas. Our analysis is somewhat limited by the small number of sites involved which might cause somewhat greater variability in regression coefficients (regression coefficients for each of the five four-site models are available at http://www.nuffieldtrust.org.uk/). Development of a

national model using SUS data only is planned to further assess the need/value of locally developed models.

Finally, it is worthy of note that use of the GP registry data for the denominator also proved to be of significant importance. Many prior predictive modeling efforts have been limited to patients with utilization history in whatever data sets were included. By including all patients in an area, not just those with prior use, the impact on predictive modeling of prior use was apparently enhanced. As a result, patients with more moderate levels of prior use and morbidity were found to be of higher risk than patients with no prior use at all, and were often assigned higher risk scores than when the analysis included just patients who had prior use. Accordingly, the use of the GP registry as the denominator can improve rates of case finding and may permit identification of patients at earlier stages.

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Contributors

The preparation of data sets and input variables and costs were undertaken by TG and by IB; JB did the central modelling. MB advised on the analysis and results and managed the work of the research team at the Nuffield Trust. All authors contributed to the writing of the paper. JB is the guarantor.

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Competing interests

All authors have completed the Unified Competing Interest form at www.icmje.org/coi_disclosure.pdf and declare that no authors have any relationships with any companies that might have an interest in the submitted work in the previous 3 years; none of their spouses, partners or children have any financial relationships that may be relevant to the submitted work; and no authors have any non-financial interests that may be relevant to the submitted work.

Ethical approval

This study only involved the analysis of pseudonymous secondary data. Since there were no identifiable human subjects, ethics approval was not required for this research and informed consent was not sought.

Provenance and peer review

Not commissioned; externally peer reviewed.

Data sharing statement

Details of the derived models variables and definitions are available from the authors at the Nuffield trust at research@nuffieldtrust.org.uk.

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Appendix A. PPV and sensitivity IPAEOP and IPAEOPGP models. Individual site runs.

	IP+AE+OP Data									
Risk Score	Newham		Cornwall		Kent		Croydon		Redbridge	
Threshold	PPV	Sensitivity	PPV	Sensitivity	PPV	Sensitivity	PPV	Sensitivity	PPV	Sensitivity
1	0.049	1.000	0.061	1.000	0.052	1.000	0.046	1.000	0.047	1.000
10	0.236	0.361	0.216	0.391	0.213	0.339	0.241	0.378	0.238	0.425
20	0.368	0.201	0.328	0.188	0.326	0.158	0.377	0.210	0.357	0.236
30	0.450	0.136	0.406	0.109	0.401	0.094	0.444	0.142	0.420	0.149
40	0.506	0.098	0.477	0.072	0.457	0.062	0.486	0.100	0.475	0.098
50	0.552	0.071	0.520	0.047	0.513	0.043	0.528	0.073	0.512	0.067
60	0.585	0.052	0.560	0.030	0.569	0.031	0.580	0.055	0.532	0.044
70	0.632	0.037	0.622	0.021	0.618	0.022	0.610	0.040	0.555	0.028
80	0.678	0.024	0.655	0.013	0.673	0.014	0.659	0.028	0.571	0.016
90	0.717	0.013	0.692	0.007	0.724	0.008	0.710	0.016	0.617	0.008
Top 1%	0.501	0.102	0.470	0.077	0.417	0.080	0.482	0.106	0.474	0.101
Top 5%	0.287	0.291	0.292	0.240	0.259	0.249	0.290	0.318	0.296	0.316

	IP+AE+OP+GP Data									
Risk Score	Newham		Cornwall		Kent		Croydon		Redbridge	
Threshold	PPV	Sensitivity	PPV	Sensitivity	PPV	Sensitivity	PPV	Sensitivity	PPV	Sensitivity
1	0.049	1.000	0.061	1.000	0.052	1.000	0.046	1.000	0.047	1.000
10	0.228	0.410	0.213	0.439	0.210	0.392	0.237	0.452	0.237	0.457
20	0.360	0.235	0.323	0.232	0.314	0.194	0.358	0.267	0.348	0.272
30	0.439	0.152	0.410	0.136	0.397	0.113	0.442	0.174	0.423	0.172
40	0.499	0.103	0.481	0.084	0.459	0.072	0.494	0.114	0.482	0.113
50	0.566	0.074	0.545	0.053	0.521	0.048	0.550	0.079	0.522	0.073
60	0.606	0.052	0.602	0.033	0.580	0.032	0.589	0.052	0.563	0.047
70	0.657	0.036	0.659	0.021	0.644	0.021	0.643	0.035	0.616	0.030
80	0.723	0.021	0.714	0.013	0.694	0.013	0.694	0.021	0.651	0.018
90	0.766	0.012	0.745	0.006	0.752	0.007	0.735	0.011	0.655	0.007
Top 1%	0.504	0.102	0.490	0.081	0.438	0.084	0.502	0.110	0.487	0.104
Top 5%	0.296	0.300	0.309	0.254	0.272	0.262	0.307	0.337	0.312	0.333

Appendix B Regression coefficients. IPAEOP and IPAEOPGP models. Individual site runs.

	IP+AE+OP Data					IP+AE+OP+GP Data				
	NH	CW	KT	CR	RB	NH	CW	KT	CR	RB
Age	0.015	0.003	0.009	0.010	0.019	0.001	-0.004	0.002	0.001	0.009
Age 65-74	0.280	0.409	0.295	0.380	0.261	0.236	0.276	0.203	0.244	0.245
Age 75-84	0.738	0.905	0.731	0.847	0.734	0.721	0.672	0.605	0.708	0.749
Age 85+	1.076	1.483	1.226	1.178	1.109	1.150	1.206	1.086	1.187	1.213
Female	0.239	0.002	0.044	0.178	0.058	0.114	-0.095	-0.075	-0.014	-0.030
Practice IMD	0.013	0.003	0.016	0.018	0.012	0.008	0.004	0.017	0.010	0.015
Months registered 1 yr prior	0.014	-0.011	-0.005	-0.018	-0.013	0.011	-0.011	-0.003	-0.010	-0.006
Months registered 2 yrs prior	-0.022	-0.019	-0.016	-0.007	-0.023	-0.021	-0.024	-0.019	-0.011	-0.021
EM Adms prior 0-90 days	0.382	0.471	0.321	0.310	0.282	0.367	0.420	0.283	0.269	0.259
EL Adms prior 0-90 days	0.045	0.216	0.155	0.153	0.148	0.033	0.159	0.074	0.097	0.069
Any attender prior 0-90 days	0.115	0.027	0.001	0.041	0.073	0.135	0.026	0.010	0.042	0.064
Any day case prior 0-90 days	0.094	0.234	0.110	0.111	0.251	0.037	0.173	0.039	-0.019	0.130
EM Adms prior 91-180 days	0.215	0.310	0.351	0.282	0.185	0.217	0.262	0.297	0.243	0.160
EL Adms prior 91-180 days	0.321	0.150	0.062	0.204	0.081	0.283	0.128	0.027	0.118	0.024
EM Adms prior 181-365 days	0.113	0.345	0.350	0.248	0.146	0.124	0.289	0.292	0.227	0.129
EL Adms prior 181-365 days	0.097	0.120	0.104	0.118	0.170	0.072	0.079	0.060	0.035	0.108
Em Adms 2 yrs prior	0.102	0.269	0.307	0.181	0.143	0.116	0.216	0.250	0.178	0.149
Any day case 2 yrs prior	0.096	0.157	0.186	0.151	0.179	0.058	0.092	0.112	0.005	0.103
DX MI	-0.108	0.097	-0.105	-0.004	0.376	-0.197	-0.003	-0.163	-0.111	0.228
DX CHF	-0.348	-0.070	-0.246	-0.069	-0.337	-0.370	-0.178	-0.269	-0.110	-0.216
DX CVD	0.296	0.227	0.033	0.037	-0.040	0.269	0.166	-0.001	-0.099	-0.061
CD CTD	0.030	-0.024	0.101	-0.380	-0.029	0.071	-0.192	-0.010	-0.427	-0.039
DX PVD	-0.245	0.124	0.099	-0.100	0.021	-0.253	0.048	0.026	-0.096	0.003
DX Asthma	0.082	0.143	0.184	0.099	0.192	-0.114	-0.107	-0.023	-0.081	0.028
DX COPD	0.204	0.251	0.277	0.193	0.123	-0.169	-0.139	-0.036	-0.330	-0.269
DX Diabetes	0.240	0.303	0.285	0.253	0.276	-0.046	-0.052	-0.016	-0.124	0.011
DX Diabetes with complications	0.059	-0.221	0.062	-0.014	0.334	0.062	-0.176	0.095	0.004	0.262
DX Renal Disease	0.408	0.022	0.085	0.128	0.199	0.356	0.005	0.073	0.063	0.120
DX Cancer	-0.165	-0.019	-0.062	-0.308	0.041	0.041	0.098	-0.010	-0.207	0.034
DX Mental	0.498	0.316	0.363	0.484	0.077	0.340	0.131	0.111	0.266	-0.061
DX Alcohol	0.569	0.684	0.578	0.673	0.974	0.281	0.530	0.357	0.409	0.754
DX Dementia	-0.548	-0.589	-0.551	-0.402	-0.596	-0.530	-0.486	-0.440	-0.669	-0.641
DX Cognitive Impairment	-0.117	0.016	0.025	0.110	0.187	-0.075	0.046	0.031	0.088	0.152
DX ACS Condition	0.364	0.270	0.239	0.267	0.306	0.269	0.161	0.134	0.114	0.224
Charlson Index	0.055	0.063	0.060	0.101	0.025	0.048	0.062	0.037	0.086	0.029
AE visits prior 0-90 days	0.236	0.267	0.355	0.309	0.359	0.179	0.230	0.265	0.199	0.260
AE unplanned follow-up visits prior 0-90 days	-0.094	-0.583	-0.533	-0.874	-0.383	-0.107	-0.566	-0.452	-0.703	-0.315
AE X-ray prior 0-90 days	0.348	0.437	0.058	0.104	0.367	0.303	0.382	0.027	0.040	0.317
AE visits prior 91-180 days	0.265	0.262	0.220	0.225	0.277	0.197	0.225	0.165	0.142	0.210
AE unplanned follow-up visits prior 91-180 days	-0.023	-0.560	-0.229	-0.296	-0.298	-0.026	-0.543	-0.177	-0.225	-0.286
AE X-ray prior 91-180 days	0.227	0.117	0.120	0.346	-0.064	0.210	0.015	0.101	0.237	0.010
AE visits prior 181-365 days	0.264	0.205	0.135	0.171	0.181	0.216	0.174	0.090	0.115	0.138
AE unplanned follow-up visits prior 181-365 days	-0.251	-0.490	-0.184	-0.261	-0.203	-0.214	-0.449	-0.131	-0.175	-0.221
AE X-ray prior 181-365 days	0.262	-0.040	0.281	0.324	0.110	0.225	0.085	0.251	0.244	0.072
AE visits 2 yrs prior	0.211	0.159	0.154	0.140	0.160	0.170	0.138	0.114	0.077	0.121
AE unplanned follow-up visits 2 yrs prior	-0.307	-0.352	-0.239	-0.433	-0.339	-0.228	-0.317	-0.178	-0.262	-0.288
AE X-ray 2yrs prior	0.083	0.231	0.100	0.128	0.179	0.063	0.390	0.082	0.069	0.152
Outpatient specialty visits prior 0-90 days	0.046	0.055	0.091	0.061	0.059	0.025	0.033	0.047	0.030	0.027
Outpatient specialty visits missed prior 0-90 days	0.155	0.182	0.250		0.146	0.108	0.118	0.171		0.097
Outpatient specialty visits prior 91-180 days	0.030	0.013	0.023	0.034	0.029	0.007	0.003	-0.004	0.015	0.011
Outpatient specialty visits missed prior 91-180 days	0.113	0.239	0.168		0.193	0.087	0.184	0.113		0.159
Outpatient specialty visits prior 181-365 days	0.016	0.010	-0.005	0.019	0.031	-0.003	0.001	-0.024	0.003	0.018
Outpatient specialty visits missed prior 181-365 days	0.128	0.164	0.075		0.140	0.086	0.095	0.036		0.122
Outpatient specialty visits 2 yrs prior	0.019	0.030	0.014	0.028	0.019	0.008	0.014	-0.009	0.011	0.021

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Outpatient specialty visits missed 2 yrs prior	0.142	0.162	0.140	0.190	0.082	0.097	0.090	0.085	0.129	0.057
GP DX COPD						0.218	0.174	0.112	0.287	0.295
GP - 1 long term condition						0.131	0.025	0.017	0.106	0.192
GP - 2 or more long term conditions						0.166	0.109	0.038	0.070	0.182
GP - Glomerular filtration rate group 3 last 0-365 days						-0.075	0.092	-0.017		0.050
GP - 10+ unique drugs prescribed						0.342	0.570	0.166	2.741	1.949
GP - 5-9 unique drugs prescribed						0.424	0.444	0.164	2.804	1.953
GP - 0-4 unique drugs prescribed						0.328	0.254	0.114	2.559	1.809
GP - Psychoactive substance misuse disorder						0.388	0.323	0.583	0.431	0.810
GP - 7+ distinct disorders						-0.049	0.057	0.017	-0.163	-0.062
GP - GP visits prior 0-3 months						-0.001	0.008	0.022	0.021	0.042
GP - GP visits prior 4-6 months						0.015	0.004	0.012	0.009	0.019
GP - GP visits prior 7-12 months						0.005	0.003	0.007	0.000	0.008
GP - GP visits 2yrs prior						0.000	0.002	0.004	0.006	0.002
GP - Increasing rate of GP visits during last 12 months						0.184	0.087	0.126	0.207	0.094
GP - Number of high risk BNFs						0.063	0.006	-0.036	-0.026	-0.075
GP - Any high risk						0.219	0.202	0.241	0.324	0.249
GP - Count of BNF chapters						0.066	0.053	0.059	0.066	-0.024
GP - DX Dementia						0.421	0.266	0.296	0.471	0.437
GP - Exception reported from quality indicators						0.157	0.108	0.111	0.118	0.132
GP - Health visitor or district nurse visit						0.278	0.244	0.199	0.168	0.184
GP - Record of IHD/angina						0.069	-0.048	0.110	-0.062	0.081
GP - Nebuliser used						0.113	0.315	0.207	0.191	0.448
GP - Salbutamol prescribed						0.021	0.017	0.074	0.000	-0.011
GP - Warfarin prescribed						-0.041	0.031	-0.026	-0.100	-0.244
GP - High blood pressure						-0.040	-0.001	-0.013	-0.048	-0.087
GP - Smoker						0.298	0.231	0.248	0.240	0.220
GP - BMI 30+						0.050	0.002	0.085	0.046	0.199
GP - HbA1c > 10						0.236	0.270	0.210	0.362	0.354
GD - QOF ARTF						0.176	0.064	0.095	-0.047	0.143
GP - QOF CKD						0.206	-0.003	-0.037	0.091	0.210
GP - QOF Depression						0.069	0.248	0.183	0.133	0.186
GP - Number of QOF DX categories 3+						0.003	-0.023	-0.072	-0.135	-0.009
GP - Number of phone contacts last 0-3 months						-0.004	0.046	0.004	-0.005	-0.004
Constant	-4.665	-3.262	-3.987	-4.363	-4.368	-4.381	-3.275	-4.069	-6.497	-5.939

Appendix C Regression significance levels. IPAEOP and IPAEOPGP models. Individual site runs.

	IP+AE+OP Data					IP+AE+OP+GP Data				
	NH	CW	KT	CR	RB	NH	CW	KT	CR	RB
Age	0.000	0.000	0.000	0.000	0.000	0.344	0.000	0.001	0.158	0.000
Age 65-74	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Age 75-84	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Age 85+	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Female	0.007	0.897	0.000	0.001	0.125	0.000	0.000	0.000	0.466	0.165
Practice IMD	0.008	0.036	0.000	0.000	0.000	0.015	0.010	0.000	0.000	0.000
Months registered 1 yr prior	0.002	0.006	0.085	0.247	0.047	0.009	0.011	0.387	0.026	0.255
Months registered 2 yrs prior	0.001	0.014	0.006	0.232	0.276	0.009	0.003	0.001	0.211	0.025
EM Adms prior 0-90 days	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
EL Adms prior 0-90 days	0.664	0.000	0.000	0.029	0.081	0.714	0.000	0.070	0.102	0.373
Any attender prior 0-90 days	0.002	0.000	0.955	0.006	0.004	0.001	0.000	0.489	0.005	0.008
Any day case prior 0-90 days	0.769	0.000	0.001	0.682	0.001	0.561	0.000	0.233	0.699	0.015
EM Adms prior 91-180 days	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002
EL Adms prior 91-180 days	0.000	0.000	0.068	0.022	0.528	0.000	0.001	0.437	0.016	0.680
EM Adms prior 181-365 days	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000
EL Adms prior 181-365 days	0.548	0.000	0.000	0.757	0.019	0.167	0.009	0.030	0.372	0.014
Em Adms 2 yrs prior	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Any day case 2 yrs prior	0.877	0.000	0.000	0.536	0.035	0.177	0.000	0.000	0.864	0.005
DX MI	0.366	0.134	0.049	0.611	0.000	0.076	0.966	0.002	0.216	0.017
DX CHF	0.024	0.253	0.000	0.448	0.008	0.001	0.005	0.000	0.194	0.026
DX CVD	0.015	0.000	0.446	0.610	0.571	0.013	0.002	0.977	0.179	0.504
CD CTD	0.263	0.756	0.150	0.010	0.759	0.645	0.013	0.891	0.000	0.766
DX PVD	0.230	0.061	0.097	0.567	0.665	0.079	0.462	0.661	0.270	0.982
DX Asthma	0.351	0.002	0.000	0.241	0.015	0.135	0.024	0.580	0.184	0.698
DX COPD	0.005	0.000	0.000	0.009	0.098	0.098	0.021	0.483	0.002	0.041
DX Diabetes	0.000	0.000	0.000	0.000	0.000	0.444	0.227	0.649	0.016	0.845
DX Diabetes with complications	0.478	0.025	0.540	0.363	0.013	0.674	0.073	0.347	0.973	0.083
DX Renal Disease	0.000	0.731	0.142	0.068	0.025	0.001	0.942	0.208	0.405	0.210
DX Cancer	0.753	0.751	0.271	0.001	0.421	0.727	0.104	0.862	0.009	0.721
DX Mental	0.000	0.000	0.000	0.000	0.370	0.000	0.005	0.008	0.000	0.447
DX Alcohol	0.000	0.000	0.000	0.000	0.000	0.029	0.000	0.000	0.000	0.000
DX Dementia	0.005	0.000	0.000	0.000	0.000	0.004	0.000	0.000	0.000	0.000
DX Cognitive Impairment	0.430	0.804	0.620	0.191	0.026	0.456	0.474	0.534	0.199	0.080
DX ACS Condition	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000
Charlson Index	0.012	0.000	0.000	0.000	0.212	0.042	0.000	0.006	0.000	0.160
AE visits prior 0-90 days	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AE unplanned follow-up visits prior 0-90 days	0.895	0.001	0.000	0.000	0.133	0.654	0.001	0.000	0.000	0.121
AE X-ray prior 0-90 days	0.002	0.000	0.301	0.374	0.052	0.004	0.002	0.636	0.662	0.035
AE visits prior 91-180 days	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AE unplanned follow-up visits prior 91-180 days	0.836	0.000	0.000	0.149	0.130	0.899	0.000	0.005	0.214	0.055
AE X-ray prior 91-180 days	0.070	0.582	0.045	0.002	0.672	0.062	0.946	0.090	0.009	0.985
AE visits prior 181-365 days	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AE unplanned follow-up visits prior 181-365 days	0.182	0.000	0.001	0.122	0.124	0.098	0.001	0.013	0.127	0.041
AE X-ray prior 181-365 days	0.000	0.936	0.000	0.000	0.461	0.001	0.866	0.000	0.000	0.485
AE visits 2 yrs prior	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AE unplanned follow-up visits 2 yrs prior	0.021	0.008	0.000	0.003	0.009	0.020	0.016	0.000	0.008	0.005
AE X-ray 2yrs prior	0.183	0.555	0.019	0.022	0.005	0.210	0.320	0.048	0.161	0.006
Outpatient specialty visits prior 0-90 days	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Outpatient specialty visits missed prior 0-90 days	0.000	0.000	0.000		0.002	0.000	0.000	0.000		0.008
Outpatient specialty visits prior 91-180 days	0.196	0.043	0.003	0.002	0.016	0.516	0.630	0.648	0.054	0.184
Outpatient specialty visits missed prior 91-180 days	0.027	0.000	0.000		0.000	0.039	0.000	0.002		0.000
Outpatient specialty visits prior 181-365 days	0.763	0.009	0.400	0.094	0.000	0.595	0.844	0.000	0.491	0.002
Outpatient specialty visits missed prior 181-365 days	0.000	0.000	0.009		0.000	0.001	0.002	0.206		0.000
Outpatient specialty visits 2 yrs prior	0.000	0.000	0.000	0.000	0.000	0.068	0.000	0.046	0.001	0.000

Outpatient specialty visits missed 2 yrs prior	0.000	0.000	0.000	0.000	0.001	0.000	0.006	0.000	0.000	0.000
GP DX COPD						0.002	0.000	0.001	0.000	0.003
GP - 1 long term condition						0.000	0.229	0.310	0.000	0.000
GP - 2 or more long term conditions						0.001	0.000	0.100	0.098	0.000
GP - Glomerular filtration rate group 3 last 0-365 days						0.097	0.002	0.463		0.162
GP - 10+ unique drugs prescribed						0.000	0.000	0.000	0.000	0.000
GP - 5-9 unique drugs prescribed						0.000	0.000	0.000	0.000	0.000
GP - 0-4 unique drugs prescribed						0.000	0.000	0.000	0.000	0.000
GP - Psychoactive substance misuse disorder						0.000	0.000	0.000	0.000	0.000
GP - 7+ distinct disorders						0.311	0.290	0.523	0.002	0.263
GP visits prior 0-3 months						0.873	0.002	0.000	0.000	0.000
GP visits prior 4-6 months						0.000	0.182	0.000	0.008	0.000
GP visits prior 7-12 months						0.075	0.136	0.000	0.987	0.006
GP visits 2yrs prior						0.934	0.013	0.000	0.000	0.263
GP - Increasing rate of GP visits during last 12 months						0.000	0.001	0.000	0.000	0.010
GP - Number of high risk BNFs						0.009	0.691	0.004	0.216	0.002
GP - Any high risk						0.000	0.000	0.000	0.000	0.000
GP - Count of BNF chapters						0.000	0.000	0.000	0.000	0.000
GP - DX Dementia						0.000	0.000	0.000	0.000	0.000
GP - Exception reported from quality indicators						0.020	0.003	0.001	0.020	0.062
GP - Health visitor or district nurse visit						0.000	0.000	0.000	0.000	0.000
GP - Record of IHD/angina						0.355	0.361	0.006	0.202	0.288
GP - Nebuliser used						0.359	0.000	0.001	0.019	0.001
GP - Salbutamol prescribed						0.550	0.523	0.001	0.989	0.795
GP - Warfarin prescribed						0.643	0.423	0.440	0.106	0.001
GP - High blood pressure						0.269	0.984	0.549	0.725	0.325
GP - Smoker						0.000	0.000	0.000	0.000	0.000
GP - BMI 30+						0.074	0.956	0.000	0.074	0.000
GP - HbA1c > 10						0.000	0.000	0.000	0.000	0.000
GD - QOF ARTF						0.130	0.240	0.024	0.586	0.136
GP - QOF CKD						0.003	0.924	0.203	0.063	0.000
GP - QOF Depression						0.240	0.000	0.000	0.024	0.016
GP - Number of QOF DX categories 3+						0.974	0.717	0.123	0.342	0.948
GP - Number of phone contacts last 0-3 months						0.927	0.000	0.600	0.788	0.899
Constant	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Appendix D Further information of model variables

Variable	Variable description	Time period/Date
GP register variables		
Age	Age	End calendar year (5 months after)
Age 65-74	Age 65-74	End calendar year (5 months after)
Age 75-84	Age 75-84	End calendar year (5 months after)
Age 85+	Age 85+	End calendar year (5 months after)
Female	Sex = female	N/A
Practice IMD	Index of multiple deprivation - GP practice area	N/A
Months registered 1 yr prior	Months registered with GP prior 1-12 months	Prior 1 - 12 months (inclusive)
Months registered 2 yrs prior	Months registered with GP prior 13-24 months	Prior 13 - 24 months (inclusive)
SUS inpatient variables		
EM Adms prior 0-90 days	Number of emergency admissions - prior 1-90 days	Prior 1 to 90 days (inclusive)
EL Adms prior 0-90 days	Number of elective admissions - prior 1-90 days	Prior 1 to 90 days (inclusive)
Any attender prior 0-90 days	Any regular attendance - prior 1-90 days	Prior 1 to 90 days (inclusive)
EM Adms prior 91-180 days	Number of emergency admissions - prior 91-180 days	Prior 91 to 180 days (inclusive)
EL Adms prior 91-180 days	Number of emergency admissions - prior 181-365 days	Prior 181 to 365 days (inclusive)
Any day case prior 0-90 days	Any day case prior 1-90 days	Prior 1 to 90 days (inclusive)
Any day case prior 91-180 days	Any day case prior 91-180 days	Prior 91 to 180 days (inclusive)
Any day case prior 181-365 days	Any day case prior 181-365 days	Prior 181 to 365 days (inclusive)
Any day case 2 yrs prior	Any day case prior 366-730 days	Prior 366 to 730 days (inclusive)
Em Adms 2 yrs prior	Number of emergency admissions - prior 366-730 days	Prior 366 to 730 days (inclusive)
DX Diabetes	Any prim or sec diagnosis - Diabetes, prior 2 years	Prior 1 to 730 days (inclusive)
DX MI	Any prim or sec diagnosis - Myocardial infarction, prior 2 years	Prior 1 to 730 days (inclusive)
DX CHF	Any prim or sec diagnosis - Congestive heart failure, prior 2 years	Prior 1 to 730 days (inclusive)
DX PVD	Any prim or sec diagnosis - Peripheral vascular disease, prior 2 years	Prior 1 to 730 days (inclusive)
DX CVD	Any prim or sec diagnosis - Cereberal vascular disease, prior 2 years	Prior 1 to 730 days (inclusive)
DX Dementia	Any prim or sec diagnosis - Dementia, prior 2 years	Prior 1 to 730 days (inclusive)
CD CTD	Any prim or sec diagnosis - Connective tissue disease, prior 2 years	Prior 1 to 730 days (inclusive)
DX Cancer	Any prim or sec diagnosis - Malignant cancer, prior 2 years	Prior 1 to 730 days (inclusive)
DX Diabetes with complications	Any prim or sec diagnosis - Diabetes with complications, prior 2 years	Prior 1 to 730 days (inclusive)
DX Renal Disease	Any prim or sec diagnosis - Renal disease, prior 2 years	Prior 1 to 730 days (inclusive)
Charlson Index	Charlson Comorbidity Index, prior 2 years	Prior 1 to 730 days (inclusive)
DX Alcohol	Any prim or sec diagnosis - Alcohol abuse, prior 2 years	Prior 1 to 730 days (inclusive)
DX COPD	Any prim or sec diagnosis - Chronic obstructive pulmonary disease, prior 2 years	Prior 1 to 730 days (inclusive)
DX Mental	Any prim or sec diagnosis - Mental illness, prior 2 years	Prior 1 to 730 days (inclusive)
DX Asthma	Any prim or sec diagnosis - Asthma, prior 2 years	Prior 1 to 730 days (inclusive)
DX Cognitive Impairment	Any prim or sec diagnosis - Miscellaneous cognitive dysfunctions, prior 2 years	Prior 1 to 730 days (inclusive)
DX ACS Condition	Any prim or sec diagnosis - ACS: Any ambulatory care sensitive condition	Prior 1 to 730 days (inclusive)
SUS AE variables		
AE visits prior 0-90 days	Number of A&E visits (any) prior 1-90 days	Prior 1 to 90 days (inclusive)
AE unplanned follow-up visits prior 0-90 days	Number of A&E visits - unplanned follow-up prior 1-90 days	Prior 1 to 90 days (inclusive)
AE X-ray prior 0-90 days	Number of A&E visits with X-ray prior 1-90 days	Prior 1 to 90 days (inclusive)
AE visits prior 91-180 days	Number of A&E visits (any) prior 91-180 days	Prior 91 to 180 days (inclusive)
AE unplanned follow-up visits prior 91-180 days	Number of A&E visits - unplanned follow-up prior 91-180 days	Prior 91 to 180 days (inclusive)
AE X-ray prior 91-180 days	Number of A&E visits with X-ray prior 91-180 days	Prior 91 to 180 days (inclusive)
AE visits prior 181-365 days	Number of A&E visits (any) prior 181-365 days	Prior 91 to 180 days (inclusive)
AE unplanned follow-up visits prior 181-365 days	Number of A&E visits - unplanned follow-up prior 181-365 days	Prior 181 to 365 days (inclusive)
AE X-ray prior 181-365 days	Number of A&E visits with X-ray prior 181-365 days	Prior 181 to 365 days (inclusive)
AE visits 2 yrs prior	Number of A&E visits (any) prior 366-730 days	Prior 366 to 730 days (inclusive)
AE unplanned follow-up visits 2 yrs	Number of A&E visits - unplanned follow-up prior	Prior 366 to 730 days (inclusive)

prior	366-730 days	
AE X-ray 2yrs prior	Number of A&E visits with X-ray prior 366-730 days	Prior 366 to 730 days (inclusive)
SUS outpatient variables		
Outpatient specialty visits prior 0-90 days	Number of outpatient visits (all) prior 1-90 days	Prior 1 to 90 days (inclusive)
Outpatient specialty visits missed prior 0-90 days	Number of outpatient visits missed prior 1-90 days	Prior 1 to 90 days (inclusive)
Outpatient specialty visits prior 91-180 days	Number of outpatient visits (all) prior 91-180 days	Prior 91 to 180 days (inclusive)
Outpatient specialty visits missed prior 91-180 days	Number of outpatient visits missed prior 91-180 days	Prior 91 to 180 days (inclusive)
Outpatient specialty visits prior 181-365 days	Number of outpatient visits (all) prior 181-365 days	Prior 181 to 365 days (inclusive)
Outpatient specialty visits missed prior 181-365 days	Number of outpatient visits missed prior 181-365 days	Prior 181 to 365 days (inclusive)
Outpatient specialty visits 2 yrs prior	Number of outpatient visits (all) prior 365-730 days	Prior 366 to 730 days (inclusive)
Outpatient specialty visits missed 2 yrs prior	Number of outpatient visits missed prior 365-730 days	Prior 366 to 730 days (inclusive)
GP consultations data		
GP DX COPD	Diagnosis of COPD, prior 2 years	Prior 1 to 730 days (inclusive)
GP - 1 long term condition	Chronic conditions - 1 in prior 2 years	Prior 1 to 730 days (inclusive)
GP - 2 or more long term conditions	Chronic conditions - 2 or more in prior 2 years	Prior 1 to 730 days (inclusive)
GP - Glomerular filtration rate group 3 last 0-365 days	Glomerular Filtration Rate Group 3 in last year	Prior 1 to 365 days (inclusive)
GP - 10+ unique drugs prescribed	1-4 unique drugs - last 1 to 90 days	Prior 1 to 90 days (inclusive)
GP - 5-9 unique drugs prescribed	5-9 unique drugs - last 1 to 90 days	Prior 1 to 90 days (inclusive)
GP - 0-4 unique drugs prescribed	10+ unique drugs - last 1 to 90 days	Prior 1 to 90 days (inclusive)
GP - Psychoactive substance misuse disorder	Psychoactive substance misuse disorder, prior 2 years	Prior 1 to 730 days (inclusive)
GP - 7+ distinct disorders	7+ distinct disease disorders recorded in prior 90 days	Prior 1 to 90 days (inclusive)
GP - GP visits prior 0-3 months	Count of different BNF chapters of prescribed medicines, prior 2 years	Prior 1 to 730 days (inclusive)
GP - GP visits prior 4-6 months	Number of GP visits prior 1-3 months	Prior 1 to 3 months (inclusive)
GP - GP visits prior 7-12 months	Number of GP visits prior 13-24 months	Prior 13 to 24 months (inclusive)
GP - GP visits 2yrs prior	Number of GP visits prior 4-6 months	Prior 4 to 6 months (inclusive)
GP - Increasing rate of GP visits during last 12 months	Number of GP visits prior 7-12 months	Prior 7 to 12 months (inclusive)
GP - Number of high risk BNFs	Substantial increase in GP visits last year	
GP - Any high risk	Number of BNF codes associated with emergency admissions, prior 2 years	Prior 1 to 730 days (inclusive)
GP - Count of BNF chapters	Any BNF codes associated with emergency admissions, prior 2 years	Prior 1 to 730 days (inclusive)
GP - DX Dementia	Diagnosis of Dementia, prior 2 years	Prior 1 to 730 days (inclusive)
GP - Exception reported from quality indicators	QOF register exceptions, prior 2 years	Prior 1 to 730 days (inclusive)
GP - Health visitor or district nurse visit	Any home/district visit, prior 2 years	Prior 1 to 730 days (inclusive)
GP - Record of IHD/angina	Diagnosis of IHD/angina, prior 2 years	Prior 1 to 730 days (inclusive)
GP - Nebuliser used	Nebuliser prescribed, prior 2 years	Prior 1 to 730 days (inclusive)
GP - Salbutamol prescribed	Salbutamol prescribed, prior 2 years	Prior 1 to 730 days (inclusive)
GP - Warfarin prescribed	Warfarin prescribed, prior 2 years	Prior 1 to 730 days (inclusive)
GP - High blood pressure	High blood pressure Read code, prior 2 years	Prior 1 to 730 days (inclusive)
GP - Smoker	Smoking status, prior 2 years	Prior 1 to 730 days (inclusive)
GP - BMI 30+	BMI greater than equal to 30, prior 2 years	Prior 1 to 730 days (inclusive)
GP - HbA1c > 10	HbA1c greater than 10, prior 2 years	Prior 1 to 730 days (inclusive)
GD - QOF ARTF	QOF register: Atrial fibrillation	Prior 1 to 730 days (inclusive)
GP - QOF CKD	QOF register: Stage 3 to 5 chronic kidney disease	Prior 1 to 730 days (inclusive)
GP - QOF Depression	QOF register: Depression	Prior 1 to 730 days (inclusive)
GP - Number of QOF DX categories 3+	QOF register: number of different registers, 3 or more	Prior 1 to 730 days (inclusive)
GP - Number of phone contacts last 0-3 months	Number of GP telephone consults prior 1-3 months	Prior 1 to 3 months (inclusive)

STROBE Statement—checklist of items that should be included in reports of observational studies

Please fill out the page numbers on this form and upload the file as a supplemental file when you submit your revision

Manuscript Number_____

	Item No	Recommendation	Indicate page number ↓ (Or n/a if not applicable)
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	2
Introduction			4-5
Background/rationale	2	Explain the scientific background and rationale for the investigation being reported	4-5
Objectives	3	State specific objectives, including any prespecified hypotheses	5
Methods			6-8
Study design	4	Present key elements of study design early in the paper	6-7
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection	6
Participants	6	(*a*) *Cohort study*—Give the eligibility criteria, and the sources and methods of selection of participants. Describe methods of follow-up *Case-control study*—Give the eligibility criteria, and the sources and methods of case ascertainment and control selection. Give the rationale for the choice of cases and controls *Cross-sectional study*—Give the eligibility criteria, and the sources and methods of selection of participants	6
		(*b*) *Cohort study*—For matched studies, give matching criteria and number of exposed and unexposed *Case-control study*—For matched studies, give matching criteria and the number of controls per case	n/a
Variables	7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable	6-7
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	6-8
Bias	9	Describe any efforts to address potential sources of bias	7
Study size	10	Explain how the study size was arrived at	6
Quantitative variables	11	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen and why	7-8
Statistical methods	12	(*a*) Describe all statistical methods, including those used to control for confounding	7-8
		(*b*) Describe any methods used to examine subgroups and interactions	7-8
		(*c*) Explain how missing data were addressed	n/a
		(*d*) *Cohort study*—If applicable, explain how loss to follow-up was addressed *Case-control study*—If applicable, explain how matching of cases and controls was addressed *Cross-sectional study*—If applicable, describe analytical methods taking account of sampling strategy	n/a
		(*e*) Describe any sensitivity analyses	7
Results			8-14
Participants	13*	(a) Report numbers of individuals at each stage of study—eg numbers potentially eligible, examined for eligibility, confirmed eligible, included in the study, completing follow-up, and analysed	8
		(b) Give reasons for non-participation at each stage	n/a
		(c) Consider use of a flow diagram	n/a
Descriptive data	14*	(a) Give characteristics of study participants (eg demographic, clinical, social) and information on exposures and potential confounders	9
		(b) Indicate number of participants with missing data for each variable of interest	n/a
		(c) *Cohort study*—Summarise follow-up time (eg, average and total amount)	9
Outcome data	15*	*Cohort study*—Report numbers of outcome events or summary measures over time	n/a
		Case-control study—Report numbers in each exposure category, or summary measures of exposure	n/a
		Cross-sectional study—Report numbers of outcome events or summary measures	n/a
Main results	16	(*a*) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision (eg, 95%	

		confidence interval). Make clear which confounders were adjusted for and why they were included	8-10
		(*b*) Report category boundaries when continuous variables were categorized	9,11
		(*c*) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period	n/a
Other analyses	17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses	12-13
Discussion			14-17
Key results	18	Summarise key results with reference to study objectives	14-17
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	15
Interpretation	20	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence	15-16
Generalisability	21	Discuss the generalisability (external validity) of the study results	16
Other information			18
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	18

*Give information separately for cases and controls in case-control studies and, if applicable, for exposed and unexposed groups in cohort and cross-sectional studies.

Note: An Explanation and Elaboration article discusses each checklist item and gives methodological background and published examples of transparent reporting. The STROBE checklist is best used in conjunction with this article (freely available on the Web sites of PLoS Medicine at http://www.plosmedicine.org/, Annals of Internal Medicine at http://www.annals.org/, and Epidemiology at http://www.epidem.com/). Information on the STROBE Initiative is available at www.strobe-statement.org.