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3825 words

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Abstract

Objectives To develop an algorithm for identifying inpatients at high risk of readmission to an NHS hospital in England within 30 days of discharge using information that can either be obtained from hospital information systems or from the patient and their notes.

Design Multivariate statistical analyses of routinely collected hospital episode statistics (HES) data using logistic regression to build the predictive model. The model's performance was calculated using bootstrapping.

Setting Hospital episode statistics data covering all NHS hospital admissions in England.

Participants NHS patients admitted to hospital between April 2008 and March 2009 (10% sample of all admissions, n=576,868)

Main outcome measures Area under the receiver operating characteristic curve for the algorithm, together with its positive predictive value and sensitivity for a range of risk score thresholds.

Results The algorithm produces a "risk score" ranging (0 to 1) for each admitted patient, and the percentage of patients with a readmission within 30 days and the mean readmission costs of all patients are provided for twenty risk bands. At a risk score threshold of 0.5, the positive predictive value (i.e. percentage of inpatients identified as high risk who were subsequently readmitted within 30 days) was 59.2% (95% CI 58.0% to 60.5%) ; representing 5.4% (95% CI 5.2% to 5.6%) of all inpatients who would be readmitted within 30 days (sensitivity). The area under the receiver operating characteristic curve was 0.70 (95% CI 0.69 to 0.70).

Conclusions – We have developed a method of identifying inpatients at high risk of unplanned readmission to NHS hospitals within 30 days of discharge. Though the models had a low sensitivity, we show how to identify subgroups of patients that contain a high proportion of patients who will be readmitted within 30 days. Additional work is necessary to validate the model in practice.

Introduction

Unplanned hospital admissions and readmissions are regarded as markers of costly, suboptimal health care[1,2] and their avoidance is currently a priority for policymakers in many countries.[3] For example in England, Department of Health (DH) guidance for the NHS proposes commissioners do not pay provider hospitals for emergency readmission within 30 days of a selected index elective (planned) admission.[4] The rate of readmissions will also play an important part in monitoring health system performance, as one of the new English public health "outcome indicators"[5].

In the five year period between 1 April 2004 and 31 March 2010, 7 per cent of patients discharged from a hospital in England were readmitted to hospital within 30 days,[6] with costs to the National Health Service (NHS) estimated at £1.6 billion each year [7]. Whilst many different interventions have been introduced with the aim of reducing unplanned admission rates[8], the evidence for their efficacy and cost-effectiveness is limited.[9]

One reason why hospital-avoidance interventions may be unsuccessful is if they are offered to patients who are at insufficiently high risk of future unplanned hospital admission.[10] A history of recent hospital admissions is not by itself an accurate predictor of future admissions,[11] and it seems that clinicians are often unable to make reliable predictions about which patients will be readmitted.[12,13] There is also some evidence to show that many readmissions may not be avoidable.[14] One recent analysis observed a strong relationship between rates of rehospitalisation and overall admission rates within specific areas [15]. In order to improve the accuracy of the "case finding" process, researchers have in recent years developed a number of predictive risk models for the NHS, with the specific aim of identifying people at highest risk of a future admission or readmission.[16,17,18,19,20,21] The models use relationships in routine data to identify patients at highest risk of unplanned admission or readmission in the next twelve months. Most of these models are not contingent on an index hospital admission but instead calculate risk scores across the population at a particular date, and are designed to be run on regular (eg monthly or quarterly) basis.

One advantage of predicting which patients are at high risk of admission in the coming twelve months is that this prolonged period may allow time for clinicians and care managers/coordinators to contact and engage with high-risk patients. Furthermore, it allows time for behavioural and treatment changes to be instigated. On the other hand, the likelihood of an unplanned admission is highest in the immediate post-discharge period,[22] so there may be advantages to predicting readmissions that occur shortly after discharge. Furthermore, there is evidence that some forms of preventive care may be more effective at reducing unplanned hospital admissions if initiated immediately after an acute illness.[23]

Outside the UK, a number of tools have been built for predicting readmissions within 15 days[24] or 30 days[25,26,27,28,29] of discharge from hospital. Until recently, NHS funding arrangements gave hospitals in England few financial inducements to predict and prevent unplanned hospital admissions. However, the 2011-12 operating framework proposed that NHS hospitals should not be reimbursed for readmissions occurring within 30 days (as well as only receiving a 30 per cent marginal rate for emergency admissions above their 2008/09 baseline).[30] In practice, the degree to which this new 30-day rule is being enforced appears to vary across the country.[31] Yet even without monetary incentives, knowledge of 30 day readmission risk could still be useful to clinicians for focussing their discharge planning efforts and post-discharge support on high-risk patients.

Predictive tools built in one setting may not necessarily be accurate when used in other health care settings.[32] So in this paper, we describe how we used English hospital episode statistics (HES) data to develop a predictive model that can identify patients at high risk of readmission to an NHS hospital in England within 30 days of discharge. The model, which we are calling "PARR-30" (Patients at Risk of Readmission within 30 Days), can be used in practice in one of two ways: either automatically, drawing variables from Secondary Uses Service (SUS) data and from a hospital's Patient Administration System (PAS);[33] or "manually" by clinicians, who can obtain the requisite information from the patient and the patient's notes and then calculate the risk using a spreadsheet or a smartphone/tablet 'app'. To facilitate this second approach, we sought to develop an algorithm that was easy to use and which relied only on a relatively small number of variables that are easily obtained from available records or from the patient. In order to justify changes in services it is often helpful to understand how the costs of the intervention may improve care and lead to lower overall costs down the line. We therefore present figures for the potential scope for savings that might accrue through reduced hospital use according to the level of risk targeted, and with assumptions about the effectiveness of interventions. We are making PARR-30 freely available for use across the NHS in England.

Methods

The model was developed using hospital episode statistics obtained from the Information Centre for Health and Social Care for the period 1st April 2006 to 30th March .[34] This analysis was based on existing data that had been anonymised and therefore did not require additional ethical approval. Records were extracted for 10% of all NHS hospital admissions in England with a discharge date between 1 April 2008 and 31 March 2009. Episodes coded as births, deaths in hospital, self-discharged patients, and patients transferred to other hospitals were excluded, leaving a total of 576,868 admissions remaining in the sample. Readmissions within 30 days were restricted according to the provisions of the 2011-12 operating framework by excluding non-emergency admission; admissions where a national tariff was not applicable; admissions for multiple trauma or transport accident, and children aged under age four. Cancer related readmissions were included since their exclusion in the operating framework is being reconsidered.[35] Patients that died after discharge were included in the development data set, reproducing what would happen if the models were applied in practice. The data set allowed patients to have more than one readmission episode, but each readmission within 30 days was linked only with the most recent prior admission

A series of logistic regressions were conducted to identify those variables that contributed most to predictions of a readmission within 30 days of discharge, creating "risk scores" of .01 to 1.00 describing the estimated probability of readmission within 30 days. The variables were restricted to those that could be formulated in way that meant they could be easily extracted from the patient or patient notes in the absence of computerised administrative data. The variables tested were based on a broad range of measures used in the PARR algorithm which predicts readmission within the following year.[14] These included: the number admissions to hospital by type (emergency vs non-emergency) according to a time interval prior to current admission (90, 180, 365, 730, 1,095 days); the number of episodes per spell in prior admissions (a proxy measure of complex health problems); number of different types of specialists consulted in the last 12 months (based on services recorded in outpatient records); a range of diagnostic categories and hierarchical diagnostic groups[36]; characteristics of the area of residence; and length of stay. A dummy variable was introduced to represent the hospital – using the largest hospital in the data as the reference point. The reduced number of variables ultimately included in this algorithm were selected based on their impact on overall model performance and ease of access to medical notes or recall by the patient.

We measured the accuracy of the predictive models in a number of ways. The positive predictive value (PPV) estimates the accuracy of the model by comparing the number of people identified by the model as being likely to experience a readmission (based on a given threshold of risk) with the number in this group who went on to experience a readmission. The PPV is defined as the percentage of those at-risk patients identified by the model who experience a readmission. The sensitivity is a related concept, which measures the percentage of those people who experienced a readmission who are correctly identified by the model as being at risk. Conversely, the specificity is defined as the proportion of people who did not experience an admission who were correctly identified as being at low risk. The sensitivity and specificity of the model can be traded off against each other by varying the threshold of risk used to define them. As well as these measures, we present estimates of the area under the receiver operating characteristic (ROC) curve, which shows the trade-off between true positives (sensitivity) and false negatives (1-specificity) at all possible thresholds. Further, we were interested in the proportion and costs of patients who experienced a readmission by risk band (twenty bands based on the level of the risk score).

Predictive models are generally "trained" on a data set consisting of dependent variables (in this case hospital readmissions) relating to many patients, together with a range of independent variables from an earlier time period. The apparent performance of the model on the training (or development) data set tends to be considerably better than its performance on another, independent data set--even if that other data set consists of similar patients. In order to ensure that the model's predictions are generalisable, it is therefore important to evaluate the performance of the model more realistically than simply by calculating its accuracy on the training sample.

To do this, we used a bootstrapping evaluation method.[37] This method involves estimating the degree of "optimism" associated with evaluating the apparent performance of the model on the training data set. The observed performance is moderated by subtracting the degree of optimism from the apparent performance. We calculated the degree of optimism by repeatedly drawing a large number of different bootstrapped samples from the training data set. Each consisted of the same number of patients as in the original sample, but each was formed by selecting patients randomly and allowing individual patients to be selected more than once. To estimate the optimism, we fitted models to each of these bootstrapped samples and calculated the difference between the performance of the model on the bootstrapped sample and its performance on the original sample. The optimism was estimated as the average of this quantity over all bootstrapped samples. One of the benefits of bootstrapping is that it allows all of the available patient data to be included in the data set. It has been shown to estimate model performance more accurately than other approaches such as those that involve setting aside data for a separate validation sample.[38]

The estimated degree of optimism was found to be very small, which we would expect given the large number of patient records available. We therefore extended the bootstrapping technique to add confidence intervals on the proportion of patients who experience a readmission by risk band, treating optimism as negligible. These confidence intervals were formed by applying the final model to a large number (we chose 200) bootstrapped samples, and estimating the range within which the proportions fell 95% of the time Confidence intervals were calculated for the ROC curve using a Bayesian bootstrap method.[39]

Developing the business case analysis

A "business" case analysis is presented to help guide providers and commissioners in designing interventions to prevent patient readmissions. For this we calculated the mean readmission costs of all patients in each risk band and at various cut-off levels. This represents the cost to NHS hospitals in terms of lost income. Various assumptions are made about the effectiveness of interventions at reducing the number of readmissions within 30 days (10%, 15%, and 20%), to estimate the maximum amount that could be expended on prevention, based on the estimated 'savings' from reduced admissions.

The costs of secondary care utilisation were estimated from HES data using 2010/11 Payment by Results (PbR) tariffs[40 41]. Activity not covered by the national tariffs was costed using the national reference costs (NRC) [42] and adjusted to ensure they were directly comparable with 2010/11 tariffs. If neither tariff nor NRC were available, the activity was costed as the average tariff for the specialty under which it was delivered in a method developed for a national study of resource allocation[43]. Therefore, costs represent income for providers rather than the actual cost of treatment for the readmission.

We established the costs of inpatient admissions by calculating the Healthcare Resource Group (HRG) for each patient's whole stay in hospital. We derived the full cost using the PbR rules[44] to combine the HRG, admission method and other details of the hospital stay. This included the unit cost of the HRG and any payments due because of an unexpectedly long stay in hospital, or for any specialist care or additional treatments and tests (so-called unbundled payments). We also calculated outpatient and A&E costs as recommended by the PbR rules.

Results

The derived model uses a small set of variable types including;

- Patient age – used as squared value,
- Index of multiple deprivation[45] for the patient's place of residence (derived from a postcode and mapped to one of five bands based on the lower super output area),
- Whether the current admission was an emergency admission (defined in HES as an admission category 21-28),
- Whether there had been an emergency hospital discharge in the past 30 days,
- The number of emergency hospital discharges in the last year (from any hospital),
- History in the prior two years (from any HES primary or secondary diagnostic field) of eleven major health conditions drawn from the Charlson co-morbidity index[46], and
- The hospital of the current admission, using a set of 150 dummy variables for the major acute hospitals in England.

Table 1 summarises the coefficients for these variables – the details for the individual hospital coefficients are provided in Appendix 1. Box 1 gives an example of how a risk score for an individual patient could be calculated. Full details of the model will also be made available on the Nuffield Trust website (www.nuffieldtrust.org.uk)

The performance of the model is shown in Table 2 in terms of the percentage of patients with a 30-day readmission, and the costs of those readmissions displayed by risk band vingtiles . For the higher risk patients (risk bands 11 and above), readmission rates ranged from 47.7% to 88.7% in the highest risk band compared to an overall readmissions rate of 12.2%. However, the number of patients in these high risk bands represented only a small share (1.1%) of all patients analysed. For risk bands 1-10, the risk of readmission within 30 days dropped steadily with decreasing risk score, but the number of patients in each band increased. The two lowest risk bands cover 54.7% of patients with a risk of readmission within 30 days of 7.1% or lower.

{Table 2 about here}

The mean readmission costs tended to be lower in the lower risk bands because a smaller percentage of patients were readmitted. However those in the lower bands who had a readmission, tended to have higher costs (for example, £1,340 per admission for patients in band 20 compared with £2,143 per admission for patients in band 11).

A business case analysis is provided in Table 3, documenting the rate of readmissions and the maximum level of expenditure at each risk band (and at various risk band cut-off levels). These values indicate where the cost of the preventive intervention equals the net savings from reduced readmissions - with various assumptions about the effectiveness of interventions (10%, 15%, and 20%). With a risk band cut-off at Band 11, mean readmission costs were £1,088 (CI £1,046, £1,124 – not shown) per patient. Using an assumption of a 10% reduction in the rate of readmission, £109 per patient (CI £105, £112 – not shown) could be spent on the 6,395 patients in these bands, with the costs of the intervention equalling costs of avoided emergency admissions (breakeven).

{Table 3 about here}

The PPV for the model for all patients with a risk score above 0.50 (risk bands 11+) was 59.2% (CI 58.0%, 60.5%), with specificity of 99.5% (CI 99.5%, 99.5%) and sensitivity of 5.4% (CI 5.2%, 5.6%) See Table 4. The receiver operating characteristic curve (ROC) in Figure 1 illustrates the trade-off between true positives (sensitivity) and false negatives (1 – specificity) for the model. Overall, the area under the curve was 0.70 (CI 0.69, 0.70).

{Table4 about here}

{Figure 1 about here}

Discussion

We have built a predictive model using a limited set of variables that were generated from hospital episode statistics. The model estimates the risk and costs of readmission to an NHS hospital in England within 30 days of discharge. We have intentionally selected variables that we believe will easily translate to information available from patients' notes or from the patients themselves. Look-up tables can be built to map variables such as a patient's postcode to deprivation score. This means it is possible to build simple software tools such as a spreadsheet or 'app' to calculate scores, as well as by using data from a hospital's patient administration system.

The performance of the model was respectable, with a positive predictive value (PPV) of 59.2% and area under the ROC curve ("c-statistic") of 0.70. For example, a recent systematic review of predictive risk models for 30 day readmissions documented c-statistics ranging from 0.50 to 0.72.[47] The specificity of this model (99.5%) is high, although the sensitivity of the model is quite low with only 5.4% of all patients in the sample (Bands 11+). The performance of the model could have been improved by including more variables but this would have made the model less useful in practice. Traditional measures of performance, such as the sensitivity, mask the potential value of models in targeting preventive interventions. Knowledge of the percentage of patients in each risk score band who will have an admission in the next 30 days can be useful in titrating resources to patients, with more or different types of resources assigned for patients who are most likely to have a hospital admission. At the highest risk band, patients had a 88.7% chance of hospital readmission within 30 days and £178 could be spent per patient on interventions aimed at avoiding readmission, assuming these interventions were successful at averting 15% of all readmissions and that breakeven was required. The level and type of resources allocated to these patients should be different from those allocated to patients in the lower risk levels, such as those in Band 6 where chances of readmission were 28.0%. These data can also be used in setting an overall cut-off level/threshold for the full range of intervention strategies. For example, at a cut-off level at Band 5, almost 30% of patients who will have an admission in the next 30 days will be included, and the chance of these patients having a readmission is 31.8%. The levels and type of intervention for these patients should vary by risk band and patient characteristics, but clinicians and commissioners can use these data to select thresholds for any preventive intervention.

The model has its limitations. It was developed using HES data, but it is intended to be used by hospitals using either a combination of PAS data and SUS data or patient self-reported information on prior use and medical history from the patient's notes. While PAS/SUS data do differ from HES, the differences are minor so we believe this shortcoming is unlikely to affect the accuracy of the predictive model substantially. However, differences in patients' recall of their prior hospital use and their medical history present bigger challenges to the validity of the model. Self-recall data on health care utilisation can differ from administrative data, especially for people with high levels of health care use, older people, and people with poor health status.[48,49] We are currently testing the model to determine the extent to which patient-reported information differs from that recorded in HES.

The ability to identify patients at high risk of readmission constitutes the first step in any strategy to improve care and services for susceptible patients. The ultimate goal, however, is to couple this 'case finding' process with cost-effective interventions that mitigate the risk of readmission and ideally, uses the ensuing financial savings to help fund the intervention. Unfortunately, only a modest amount is known about what works, and for whom, in reducing readmissions.

In a recent systematic review,[50] Hansen and colleagues identified a broad range of strategies that have been employed, including pre-discharge interventions (improved discharge planning, patient education, medication reconciliation, post-discharge follow-up appointment, etc), post-discharge interventions (patient hotlines, telephone appointment reminders, home visits, etc.), and other interventions to bridge the transition from hospital to home such as nurse coaching. Many of the studies looked at were small and not well designed. Five out of 16 randomised controlled trials documented statistically significant reductions in the absolute risk of readmission, but no single intervention or bundle of strategies were found to be consistently successful in reducing risk.

The data on costs developed here also suggests additional caution. At a risk score cut-off of .50 (Band 11+), even with an optimistic assumption of a 20% reduction in the rate of readmissions, the amount available to spend on an intervention and still achieve breakeven is relatively modest (£218 per patient). Broadening the intervention to a cut-off at Band 5, this amount drops to £143 (and £71 if a more realistic reduction in readmissions of 10% is assumed). See Table 3. While improved discharge planning, arranging post-discharge follow-up visits and telephone reminders may be relatively inexpensive, other interventions such as nurse coaching and home visits can become quite costly. These data would permit targeting of interventions, with more costly strategies limited to the patients at highest risk, but the level of available resource will undoubtedly be strained if breakeven is expected.

As hospitals in England begin responding to the new financial incentives included in the 2011-12 operating framework, it will be important to gather evidence about what interventions are effective and for which patients and at what cost. Areas for future research may include determining whether and how the effectiveness of interventions differs according to the underlying level of risk. For example, it may be that patients at lower or moderate risk of readmission have conditions or circumstances where an intervention is more likely to succeed than for patients at high risk. Equally, there may be certain sub-groups of patients within a particular risk band who are more or less amenable to preventive care. The use of predictive models as case finding tools to target preventive interventions has gained considerable currency in community based settings. We believe that is it important to consider how such tools might be used in the much more immediate care environment of the hospital to improve the long term management of patients.

Box 1 . A worked example of how a risk score can be calculated

An 83 year-old woman from a relatively deprived part of London is about to be discharged from a large London teaching hospital. She received an emergency admission linked to her COPD seven days ago. Though she hasn't been in hospital within the last month, she did have two discharges following emergency admissions in the previous year. The patient also has a history of congestive heart failure and peripheral vascular disease.

The patient's risk of readmission within the next 30 days was 25.1% (24.4-25.6%).

Contributions are:

Variable	Input	Coefficient	Term
Age squared	**6889**	6E-05	0.417
Number of admissions last year	**2**	0.121	0.243
Admission in last month	**0**	0.526	0.000
Current admission is 'emergency/unplanned	**1**	0.556	0.556
Deprivation - IMD score 25 to 40	**1**	0.066	0.066
Congestive heart failure	**1**	0.095	0.095
Peripheral vascular disease	**1**	0.104	0.104
Chronic pulmonary disease	**1**	0.224	0.224
Hospital: Barts and The London NHS Trust	**1**	0.117	0.117
Constant	**1**	-2.918	-2.918
		TOTAL	-1.095
		Risk	25.1%

Table 1 Summary of variables* included in model, and their coefficients, standard error and significance

Variable	Coefficient	S.E.	Sig.
Patient age (squared)	6e-5	0	< 0.001
Number of emergency hospital discharges in the last year	0.121	0.002	< 0.001
Whether there had been a prior emergency hospital discharge in the past 30 days	0.526	0.012	< 0.001
Whether the current admission was an emergency admission	0.556	0.011	< 0.001
Index of multiple deprivation band for the place of residence (lower super output area)	0.021 to 0.102	0.013 to 0.018	<0.001 to 0.142
History in the prior two years (from any HES primary or secondary diagnostic field) of eleven major health conditions drawn from the Charlson co-morbidity index			
Congestive heart failure	0.095	0.018	< 0.001
Peripheral vascular disease	0.104	0.022	< 0.001
Chronic pulmonary disease	0.224	0.012	< 0.001
Diabetes with chronic complications	0.146	0.032	< 0.001
Renal disease	0.198	0.018	< 0.001
Metastatic cancer with solid tumour	0.276	0.024	< 0.001
Other malignant cancer	0.507	0.015	< 0.001
Moderate/severe liver disease	0.267	0.049	< 0.001
Other liver disease	0.213	0.031	< 0.001
Hemiplegia or paraplegia	0.106	0.033	0.001
Dementia	0.047	0.026	0.071
Hospital specific variable (range of values in Appendix 1)	-0.976 to 0.308	0.043 to 0.206	< 0.001 to 0.966
Constant	-2.918	0.032	0

* *Full details of the model and definitions available from www.nuffieldtrust.org.uk*

Table 2 Estimated Readmission 30 Day Rates and Costs by Risk Band. Bootstrapped Central Estimate and 95% Confidence Intervals

			% Readmitted		All Patients Readmission Costs		Patients with Readmission Readmission Costs	
Risk Band	N	% of Total	Mean	CI	Mean	CI	Mean	CI
Band 01 (0.00-0.05)	32,653	5.7%	3.9%	(3.6%, 4.0%)	£57	(£51, £60)	£1,456	(£1366, £1530)
Band 02 (0.05-0.10)	283,165	49.1%	7.1%	(7.0%, 7.2%)	£124	(£121, £126)	£1,747	(£1720, £1772)
Band 03 (0.10-0.15)	146,626	25.4%	12.7%	(12.6%, 12.9%)	£298	(£293, £306)	£2,346	(£2313, £2378)
Band 04 (0.15-0.20)	48,596	8.4%	18.9%	(18.6%, 19.3%)	£427	(£413, £440)	£2,254	(£2204, £2313)
Band 05 (0.20-0.25)	25,193	4.4%	23.7%	(23.2%, 24.3%)	£556	(£536, £576)	£2,342	(£2276, £2402)
Band 06 (0.25-0.30)	14,282	2.5%	28.0%	(27.5%, 28.9%)	£658	(£638, £686)	£2,347	(£2285, £2405)
Band 07 (0.30-0.35)	8,559	1.5%	32.0%	(31.3%, 33.0%)	£765	(£733, £802)	£2,391	(£2305, £2478)
Band 08 (0.35-0.40)	5,514	1.0%	36.3%	(35.1%, 37.9%)	£831	(£787, £884)	£2,287	(£2183, £2370)
Band 09 (0.40-0.45)	3,472	0.6%	39.0%	(37.4%, 41.0%)	£878	(£825, £928)	£2,253	(£2140, £2350)
Band 10 (0.45-0.50)	2,413	0.4%	44.9%	(43.0%, 46.9%)	£980	(£909, £1051)	£2,180	(£2071, £2296)
Band 11 (0.50-0.55)	1,543	0.3%	47.7%	(45.2%, 50.7%)	£1,023	(£935, £1122)	£2,143	(£2003, £2295)
Band 12 (0.55-0.60)	1,174	0.2%	50.6%	(48.0%, 53.3%)	£988	(£916, £1081)	£1,952	(£1817, £2094)
Band 13 (0.60-0.65)	840	0.1%	54.3%	(51.1%, 57.8%)	£1,038	(£933, £1173)	£1,912	(£1709, £2092)
Band 14 (0.65-0.70)	617	0.1%	60.6%	(56.5%, 65.1%)	£1,148	(£1014, £1269)	£1,892	(£1716, £2015)
Band 15 (0.70-0.75)	518	0.1%	63.2%	(59.8%, 67.2%)	£1,168	(£1041, £1325)	£1,847	(£1675, £2054)
Band 16 (0.75-0.80)	425	0.1%	65.0%	(60.1%, 69.3%)	£1,259	(£1075, £1423)	£1,935	(£1680, £2189)
Band 17 (0.80-0.85)	276	0.0%	66.3%	(60.4%, 72.4%)	£1,155	(£952, £1418)	£1,743	(£1444, £2073)
Band 18 (0.85-0.90)	289	0.1%	75.4%	(70.2%, 80.6%)	£1,208	(£1037, £1400)	£1,602	(£1375, £1803)
Band 19 (0.90-0.95)	263	0.0%	83.0%	(77.6%, 87.6%)	£1,137	(£985, £1305)	£1,369	(£1212, £1545)
Band 20 (0.95-1.00)	450	0.1%	88.7%	(85.3%, 91.4%)	£1,189	(£1015, £1349)	£1,340	(£1137, £1518)
All Patients	576,868	100.0%	12.2%	(12.1%, 12.3%)	£257	(£254, £260)	£2,114	(£2098, £2131)

Table 3 "Business Case" Analysis. Estimates of potential savings that could be made to fund an intervention, achieved at different risk bands and with differing assumptions about the reduction in admissions achieved

	By Risk Band Level				Cumulative at Band Cut-Off Level							
		Maximum Expenditure Per Patient for Break Even								Maximum Expenditure Per Patient for Break Even*		
		Assumed Reduction in Readmissions								Assumed Reduction in ReAdms		
Risk Band	N	10%	15%	20%	N	% of All Patients	% of Pats With Readm*	% of All Pats with Readm*	Mean Readm Cost*	10%	15%	20%
Band 01 (0.00-0.05)	32,653	£6	£9	£11	576,868	100%	12.2%	100.0%	£257	£26	£39	£51
Band 02 (0.05-0.10)	283,165	£12	£19	£25	544,215	94.3%	12.7%	98.2%	£269	£27	£40	£54
Band 03 (0.10-0.15)	146,626	£30	£45	£60	261,050	45.3%	18.7%	69.5%	£427	£43	£64	£85
Band 04 (0.15-0.20)	48,596	£43	£64	£85	114,424	19.8%	26.3%	42.9%	£591	£59	£89	£118
Band 05 (0.20-0.25)	25,193	£56	£83	£111	65,828	11.4%	31.8%	29.8%	£713	£71	£107	£143
Band 06 (0.25-0.30)	14,282	£66	£99	£132	40,635	7.0%	36.8%	21.3%	£809	£81	£121	£162
Band 07 (0.30-0.35)	8,559	£76	£115	£153	26,353	4.6%	41.6%	15.6%	£892	£89	£134	£178
Band 08 (0.35-0.40)	5,514	£83	£125	£166	17,794	3.1%	46.2%	11.7%	£953	£95	£143	£191
Band 09 (0.40-0.45)	3,472	£88	£132	£176	12,280	2.1%	50.7%	8.9%	£1,008	£101	£151	£202
Band 10 (0.45-0.50)	2,413	£98	£147	£196	8,808	1.5%	55.3%	6.9%	£1,059	£106	£159	£212
Band 11 (0.50-0.55)	1,543	£102	£153	£205	6,395	1.1%	59.2%	5.4%	£1,088	£109	£163	£218
Band 12 (0.55-0.60)	1,174	£99	£148	£198	4,852	0.8%	62.8%	4.3%	£1,109	£111	£166	£222
Band 13 (0.60-0.65)	840	£104	£156	£208	3,678	0.6%	66.7%	3.5%	£1,148	£115	£172	£230
Band 14 (0.65-0.70)	617	£115	£172	£230	2,838	0.5%	70.3%	2.8%	£1,180	£118	£177	£236
Band 15 (0.70-0.75)	518	£117	£175	£234	2,221	0.4%	73.0%	2.3%	£1,189	£119	£178	£238
Band 16 (0.75-0.80)	425	£126	£189	£252	1,703	0.3%	76.0%	1.8%	£1,196	£120	£179	£239
Band 17 (0.80-0.85)	276	£115	£173	£231	1,278	0.2%	79.7%	1.5%	£1,175	£118	£176	£235
Band 18 (0.85-0.90)	289	£121	£181	£242	1,002	0.2%	83.4%	1.2%	£1,181	£118	£177	£236
Band 19 (0.90-0.95)	263	£114	£171	£227	713	0.1%	86.6%	0.9%	£1,170	£117	£175	£234
Band 20 (0.95-1.00)	450	£119	£178	£238	450	0.1%	88.7%	0.6%	£1,189	£119	£178	£238
All Patients	576,868	£26	£39	£51								

*Confidence intervals and other details on the model are available at http://www.nuffieldtrust.org.uk/our-work/projects/predicting-risk-hospital-readmission-parr-30

Table 4 Estimated Model Performance Bootstrapped Central Estimate and 95% Confidence Intervals*

	Central Estimate	Confidence Intervals
PPV	59.2%	(58.0%, 60.5%)
Sensitivity	5.4%	(5.2%, 5.6%)
Specificity	99.5%	(99.5%, 99.5%)
Area under the ROC curve	0.70	(0.69, 0.70)

Data are for risk score threshold .50+

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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 no any non-financial interests that may be relevant to the submitted work.

Ethical approvals: 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.

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Appendix 1 Coefficients for all variable used in PARR 30model.

Variable	Coeff	S.E.	Sig.
Patient age (squared)	0.0001	0	< 0.001
Number of emergency hospital discharges in the last year	0.1215	0.002	< 0.001
Whether there had been a prior emergency hospital discharge in the past 30 days	0.5258	0.012	< 0.001
Whether the current admission was an emergency admission	0.5565	0.011	< 0.001
Index of multiple deprivation for lower super output area of residence			
IMD score 10 to 14	0.0209	0.014	0.142
IMD score 15 to 24	0.0239	0.013	0.066
IMD score 25 to 39	0.0661	0.014	< 0.001
IMD score 40 to 49	0.1017	0.018	< 0.001
IMD score 50 or over	0.0982	0.018	< 0.001
History in the prior two years (from any HES primary or secondary diagnostic field) of eleven major health conditions drawn from the Charlson co-morbidity index			
Congestive heart failure	0.0950	0.018	< 0.001
Peripheral vascular disease	0.1043	0.022	< 0.001
Chronic pulmonary disease	0.2243	0.012	< 0.001
Diabetes with chronic complications	0.1457	0.032	< 0.001
Renal disease	0.1977	0.018	< 0.001
Metastatic cancer with solid tumor	0.2762	0.024	< 0.001
Other malignant cancer	0.5069	0.015	< 0.001
Moderate/severe liver disease	0.2673	0.049	< 0.001
Other liver disease	0.2133	0.031	< 0.001
Hemiplegia or paraplegia	0.1061	0.033	0.001
Dementia	0.0467	0.026	0.071
Hospital trust specific variable			
Aintree University Hospitals NHS Foundation Trust (REM)	-0.2760	0.057	< 0.001
Airedale NHS Trust (RCF)	-0.2998	0.08	< 0.001
Ashford and St Peter's Hospitals NHS Trust (RTK)	-0.1424	0.069	0.039
Barking, Havering and Redbridge Hospitals NHS Trust (RF4)	-0.1699	0.052	0.001
Barnet and Chase Farm Hospitals NHS Trust (RVL)	0.1370	0.052	0.008
Barnsley Hospital NHS Foundation Trust (RFF)	-0.2976	0.07	< 0.001
Barts and The London NHS Trust (RNJ)	0.1171	0.052	0.024
Basildon and Thurrock University Hospitals NHS Foundation Trust (RDD)	-0.0762	0.063	0.229
Basingstoke and North Hampshire NHS Foundation Trust (RN5)	-0.2353	0.083	0.005
Bedford Hospital NHS Trust (RC1)	-0.3056	0.085	< 0.001
Blackpool, Fylde and Wyre Hospitals NHS Foundation Trust (RXL)	-0.1201	0.057	0.034
Bradford Teaching Hospitals NHS Foundation Trust (RAE)	-0.1872	0.054	0.001

Brighton and Sussex University Hospitals NHS Trust (RXH)	-0.0043	0.051	0.933
Bromley Hospitals NHS Trust (RG3)	-0.2153	0.07	0.002
Buckinghamshire Hospitals NHS Trust (RXQ)	0.0026	0.061	0.966
Burton Hospitals NHS Foundation Trust (RJF)	-0.1109	0.075	0.138
Calderdale and Huddersfield NHS Foundation Trust (RWY)	-0.2049	0.058	< 0.001
Cambridge University Hospitals NHS Foundation Trust (RGT)	-0.1115	0.055	0.041
Central Manchester University Hospitals NHS Foundation Trust (RW3)	-0.0782	0.053	0.139
Chelsea and Westminster Hospital NHS Foundation Trust (RQM)	-0.2388	0.076	0.002
Chesterfield Royal Hospital NHS Foundation Trust (RFS)	-0.3527	0.072	< 0.001
City Hospitals Sunderland NHS Foundation Trust (RLN)	-0.1949	0.054	< 0.001
Colchester Hospital University NHS Foundation Trust (RDE)	-0.3485	0.069	< 0.001
Countess of Chester Hospital NHS Foundation Trust (RJR)	-0.2975	0.068	< 0.001
County Durham and Darlington NHS Foundation Trust (RXP)	-0.0943	0.051	0.062
Dartford and Gravesham NHS Trust (RN7)	-0.1673	0.078	0.031
Derby Hospitals NHS Foundation Trust (RTG)	-0.1749	0.052	0.001
Doncaster and Bassetlaw Hospitals NHS Foundation Trust (RP5)	-0.2514	0.057	< 0.001
Dorset County Hospital NHS Foundation Trust (RBD)	-0.1666	0.077	0.031
Ealing Hospital NHS Trust (RC3)	-0.0314	0.074	0.672
East and North Hertfordshire NHS Trust (RWH)	-0.2360	0.059	< 0.001
East Cheshire NHS Trust (RJN)	-0.0539	0.082	0.512
East Kent Hospitals University NHS Foundation Trust (RVV)	-0.0078	0.046	0.866
East Lancashire Hospitals NHS Trust (RXR)	-0.3743	0.058	< 0.001
East Sussex Hospitals NHS Trust (RXC)	-0.1331	0.054	0.014
Epsom and St Helier University Hospitals NHS Trust (RVR)	-0.0332	0.057	0.558
Frimley Park Hospital NHS Foundation Trust (RDU)	-0.1811	0.067	0.007
Gateshead Health NHS Foundation Trust (RR7)	-0.0421	0.066	0.521
George Eliot Hospital NHS Trust (RLT)	-0.1241	0.086	0.15
Gloucestershire Hospitals NHS Foundation Trust (RTE)	-0.2831	0.054	< 0.001
Great Western Hospitals NHS Foundation Trust (RN3)	-0.0955	0.065	0.142
Guy's and St Thomas' NHS Foundation Trust (RJ1)	-0.2393	0.054	< 0.001
Harrogate and District NHS Foundation Trust (RCD)	-0.3723	0.1	< 0.001
Heart of England NHS Foundation Trust (RR1)	-0.0084	0.043	0.844
Heatherwood and Wexham Park Hospitals NHS Foundation Trust (RD7)	-0.1483	0.067	0.026
Hereford Hospitals NHS Trust (RLQ)	-0.2719	0.095	0.004
Hinchingbrooke Health Care NHS Trust (RQQ)	-0.2993	0.098	0.002
Homerton University Hospital NHS Foundation Trust (RQX)	-0.1506	0.083	0.069
Hull and East Yorkshire Hospitals NHS Trust (RWA)	-0.1879	0.049	< 0.001
Imperial College Healthcare NHS Trust (RYJ)	-0.1089	0.047	0.02
Ipswich Hospital NHS Trust (RGQ)	-0.2070	0.065	0.001
James Paget University Hospitals NHS Foundation Trust (RGP)	-0.2747	0.077	< 0.001
Kettering General Hospital NHS Foundation Trust (RNQ)	-0.2582	0.068	< 0.001
King's College Hospital NHS Foundation Trust (RJZ)	-0.0806	0.056	0.152
Kingston Hospital NHS Trust (RAX)	-0.1913	0.081	0.018

Lancashire Teaching Hospitals NHS Foundation Trust (RXN)	-0.1646	0.053	0.002
Liverpool Heart and Chest Hospital NHS Trust (RBQ)	-0.0228	0.114	0.841
Luton and Dunstable Hospital NHS Foundation Trust (RC9)	-0.2842	0.069	< 0.001
Maidstone and Tunbridge Wells NHS Trust (RWF)	-0.1074	0.058	0.063
Mayday Healthcare NHS Trust (RJ6)	-0.0229	0.066	0.73
Medway NHS Foundation Trust (RPA)	-0.0899	0.065	0.164
Mid Cheshire Hospitals NHS Foundation Trust (RBT)	-0.1522	0.061	0.013
Mid Essex Hospital Services NHS Trust (RQ8)	-0.0817	0.059	0.165
Mid Staffordshire NHS Foundation Trust (RJD)	-0.3216	0.083	< 0.001
Mid Yorkshire Hospitals NHS Trust (RXF)	-0.1774	0.05	< 0.001
Milton Keynes Hospital NHS Foundation Trust (RD8)	-0.0253	0.065	0.698
Newham University Hospital NHS Trust (RNH)	0.0640	0.068	0.347
Norfolk and Norwich University Hospitals NHS Foundation Trust (RM1)	-0.2619	0.053	< 0.001
North Bristol NHS Trust (RVJ)	-0.2220	0.056	< 0.001
North Cumbria University Hospitals NHS Trust (RNL)	-0.2746	0.065	< 0.001
North Middlesex University Hospital NHS Trust (RAP)	-0.1964	0.079	0.013
North Tees and Hartlepool NHS Foundation Trust (RVW)	-0.1317	0.058	0.022
North West London Hospitals NHS Trust (RV8)	-0.1428	0.057	0.012
Northampton General Hospital NHS Trust (RNS)	-0.0896	0.063	0.152
Northern Devon Healthcare NHS Trust (RBZ)	-0.2258	0.083	0.007
Northern Lincolnshire and Goole Hospitals NHS Foundation Trust (RJL)	-0.5869	0.065	< 0.001
Northumbria Healthcare NHS Foundation Trust (RTF)	-0.0188	0.049	0.702
Nottingham University Hospitals NHS Trust (RX1)	-0.0580	0.044	0.188
Nuffield Orthopaedic Centre NHS Trust (RBF)	-0.3788	0.185	0.04
Oxford Radcliffe Hospitals NHS Trust (RTH)	0.0293	0.047	0.537
Papworth Hospital NHS Foundation Trust (RGM)	-0.2873	0.101	0.005
Pennine Acute Hospitals NHS Trust (RW6)	-0.0963	0.044	0.029
Peterborough and Stamford Hospitals NHS Foundation Trust (RGN)	-0.1736	0.065	0.008
Plymouth Hospitals NHS Trust (RK9)	-0.1309	0.054	0.015
Poole Hospital NHS Foundation Trust (RD3)	-0.1420	0.064	0.026
Portsmouth Hospitals NHS Trust (RHU)	-0.2619	0.051	< 0.001
Queen Elizabeth Hospital NHS Trust (RG2)	-0.2003	0.085	0.018
Queen Mary's Sidcup NHS Trust (RGZ)	0.1977	0.074	0.008
Queen Victoria Hospital NHS Foundation Trust (RPC)	-0.7424	0.165	< 0.001
Robert Jones and Agnes Hunt Orthopaedic and District Hospital NHS Trust (RL1)	-0.9757	0.206	< 0.001
Royal Berkshire NHS Foundation Trust (RHW)	-0.0596	0.062	0.333
Royal Bolton Hospital NHS Foundation Trust (RMC)	-0.1824	0.063	0.004
Royal Brompton and Harefield NHS Trust (RT3)	-0.1868	0.088	0.033
Royal Cornwall Hospitals NHS Trust (REF)	-0.2333	0.056	< 0.001
Royal Devon and Exeter NHS Foundation Trust (RH8)	-0.4095	0.062	< 0.001
Royal Free Hampstead NHS Trust (RAL)	-0.1618	0.063	0.011

Royal Liverpool and Broadgreen University Hospitals NHS Trust (RQ6)	-0.3406	0.055	< 0.001
Royal National Orthopaedic Hospital NHS Trust (RAN)	-0.4974	0.175	0.004
Royal Surrey County Hospital NHS Trust (RA2)	-0.2396	0.077	0.002
Royal United Hospital Bath NHS Trust (RD1)	-0.1534	0.064	0.016
Royal West Sussex NHS Trust (RPR)	-0.1866	0.072	0.009
Salford Royal NHS Foundation Trust (RM3)	-0.0193	0.058	0.741
Salisbury NHS Foundation Trust (RNZ)	-0.2773	0.077	< 0.001
Sandwell and West Birmingham Hospitals NHS Trust (RXK)	-0.2114	0.052	< 0.001
Scarborough and North East Yorkshire Health Care NHS Trust (RCC)	-0.2220	0.083	0.008
Sheffield Teaching Hospitals NHS Foundation Trust (RHQ)	-0.1122	0.046	0.014
Sherwood Forest Hospitals NHS Foundation Trust (RK5)	-0.1400	0.061	0.021
Shrewsbury and Telford Hospital NHS Trust (RXW)	-0.1483	0.059	0.013
South Devon Healthcare NHS Foundation Trust (RA9)	-0.2524	0.067	< 0.001
South Tees Hospitals NHS Trust (RTR)	-0.1628	0.049	0.001
South Tyneside NHS Foundation Trust (RE9)	-0.1685	0.081	0.037
South Warwickshire General Hospitals NHS Trust (RJC)	-0.3267	0.088	< 0.001
Southampton University Hospitals NHS Trust (RHM)	-0.1075	0.05	0.033
Southend University Hospital NHS Foundation Trust (RAJ)	-0.1287	0.061	0.034
Southport and Ormskirk Hospital NHS Trust (RVY)	-0.1521	0.071	0.033
St George's Healthcare NHS Trust (RJ7)	-0.1255	0.058	0.031
St Helens and Knowsley Teaching Hospitals NHS Trust (RBN)	-0.1906	0.056	0.001
Stockport NHS Foundation Trust (RWJ)	-0.0262	0.057	0.649
Surrey and Sussex Healthcare NHS Trust (RTP)	0.0328	0.06	0.586
Tameside Hospital NHS Foundation Trust (RMP)	-0.1788	0.073	0.014
Taunton and Somerset NHS Foundation Trust (RBA)	-0.1476	0.064	0.02
The Christie NHS Foundation Trust (RBV)	0.2230	0.076	0.003
The Dudley Group of Hospitals NHS Foundation Trust (RNA)	-0.2269	0.06	< 0.001
The Hillingdon Hospital NHS Trust (RAS)	0.0248	0.067	0.713
The Lewisham Hospital NHS Trust (RJ2)	-0.1687	0.078	0.031
The Newcastle Upon Tyne Hospitals NHS Foundation Trust (RTD)	-0.1109	0.045	0.014
The Princess Alexandra Hospital NHS Trust (RQW)	-0.0683	0.072	0.344
The Queen Elizabeth Hospital King's Lynn NHS Trust (RCX)	-0.0785	0.07	0.264
The Rotherham NHS Foundation Trust (RFR)	-0.0542	0.063	0.391
The Royal Bournemouth and Christchurch Hospitals NHS Foundation Trust (RDZ)	-0.2014	0.056	< 0.001
The Royal Marsden NHS Foundation Trust (RPY)	0.3081	0.087	< 0.001
The Royal Orthopaedic Hospital NHS Foundation Trust (RRJ)	-0.3420	0.163	0.036
The Royal Wolverhampton Hospitals NHS Trust (RL4)	-0.1756	0.058	0.003
The Whittington Hospital NHS Trust (RKE)	-0.1693	0.08	0.034
Trafford Healthcare NHS Trust (RM4)	-0.6680	0.13	< 0.001
United Lincolnshire Hospitals NHS Trust (RWD)	-0.3556	0.053	< 0.001
University College London Hospitals NHS Foundation Trust (RRV)	-0.1072	0.06	0.076
University Hospital of North Staffordshire NHS Trust (RJE)	-0.1361	0.053	0.01

University Hospital of South Manchester NHS Foundation Trust (RM2)	-0.2162	0.058	< 0.001
University Hospitals Birmingham NHS Foundation Trust (RRK)	-0.0951	0.052	0.069
University Hospitals Bristol NHS Foundation Trust (RA7)	-0.1736	0.057	0.002
University Hospitals Coventry and Warwickshire NHS Trust (RKB)	-0.1415	0.053	0.008
University Hospitals of Leicester NHS Trust (RWE)	-0.0830	0.043	0.054
University Hospitals of Morecambe Bay NHS Trust (RTX)	-0.1777	0.057	0.002
Walsall Hospitals NHS Trust (RBK)	-0.0933	0.07	0.185
Warrington and Halton Hospitals NHS Foundation Trust (RWW)	-0.0641	0.057	0.26
West Hertfordshire Hospitals NHS Trust (RWG)	-0.2533	0.071	< 0.001
West Middlesex University Hospital NHS Trust (RFW)	-0.1244	0.072	0.082
West Suffolk Hospitals NHS Trust (RGR)	-0.1079	0.074	0.146
Weston Area Health NHS Trust (RA3)	-0.3588	0.092	< 0.001
Whipps Cross University Hospital NHS Trust (RGC)	-0.0757	0.063	0.229
Winchester and Eastleigh Healthcare NHS Trust (RN1)	-0.0749	0.079	0.34
Wirral University Teaching Hospital NHS Foundation Trust (RBL)	-0.1166	0.052	0.025
Worcestershire Acute Hospitals NHS Trust (RWP)	-0.1848	0.056	0.001
Worthing and Southlands Hospitals NHS Trust (RPL)	-0.0328	0.065	0.613
Wrightington, Wigan and Leigh NHS Foundation Trust (RRF)	-0.3123	0.065	< 0.001
Yeovil District Hospital NHS Foundation Trust (RA4)	-0.3096	0.088	< 0.001
York Hospitals NHS Foundation Trust (RCB)	-0.2120	0.066	0.001
Any other hospital	-0.1155	0.08	0.15
Constant	-2.9182	0.032	< 0.001

NOTE: PLEASE SAVE THIS TO YOUR HARD DRIVE UNDER A DIFFERENT FILE NAME AFTER YOU FILL IT OUT

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			
Background/rationale	2	Explain the scientific background and rationale for the investigation being reported	4
Objectives	3	State specific objectives, including any prespecified hypotheses	5
Methods			
Study design	4	Present key elements of study design early in the paper	6
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	6-7
Bias	9	Describe any efforts to address potential sources of bias	7-8
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	6-8
Statistical methods	12	(*a*) Describe all statistical methods, including those used to control for confounding	6-8
		(*b*) Describe any methods used to examine subgroups and interactions	6-8
		(*c*) Explain how missing data were addressed	6-8
		(*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	6-8
		(*e*) Describe any sensitivity analyses	9
Results			
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	6
		(b) Give reasons for non-participation at each stage	6
		(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	9
		(*b*) Report category boundaries when continuous variables were categorized	9
		(*c*) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period	9
Other analyses	17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses	9-10
Discussion			
Key results	18	Summarise key results with reference to study objectives	10
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	11-12
Interpretation	20	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence	12
Generalisability	21	Discuss the generalisability (external validity) of the study results	13
Other information			
Funding	22	Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based	14

*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.

Figure 1 Receiver Operating Characteristic Curve (ROC) for the bootstrapped central estimate (red line) and 95% confidence Intervals (shaded area)