



**Development of a predictive model to identify inpatients at risk of readmission within 30 days of discharge (PARR-30)**

Journal:	<i>BMJ Open</i>
Manuscript ID:	bmjopen-2012-001667
Article Type:	Research
Date Submitted by the Author:	14-Jun-2012
Complete List of Authors:	Billings, John; New York University, Blunt, Ian; Nuffield Trust, Georghiou, Theo; Nuffield Trust, Lewis, Geraint; Walgreen Co., Clinical Outcomes & Analytics Bardsley, Martin; Nuffield Trust,
<b>Primary Subject Heading</b>:	Health services research
Secondary Subject Heading:	Emergency medicine, Health informatics, Health policy
Keywords:	STATISTICS & RESEARCH METHODS, HEALTH SERVICES ADMINISTRATION & MANAGEMENT, HEALTH ECONOMICS

SCHOLARONE™  
Manuscripts

Peer Review Only

# *Development of a predictive model to identify inpatients at risk of readmission within 30 days of discharge (PARR-30)*

John Billings<sup>1</sup>, Associate Professor of Health Policy  
Ian Blunt<sup>2</sup>, Senior Research Analyst  
Adam Steventon<sup>2</sup>, Senior Research Analyst  
Theo Georghiou<sup>2</sup>, Senior Research Analyst  
Geraint Lewis<sup>3</sup>, Senior Director, Clinical Outcomes & Analytics\*  
Martin Bardsley<sup>2</sup>, Head of Research

<sup>1</sup> Robert F. Wagner Graduate School of Public Service, New York University, 295 Lafayette Street, Room 3010, New York, NY 10012-9604, USA

<sup>2</sup> Nuffield Trust, 59 New Cavendish Street, London W1G 7LP, UK

<sup>3</sup> Walgreen Co., 1415 Lake Cook Road, Deerfield, IL 60015, USA

\*Geraint Lewis was Senior Fellow, Nuffield Trust when this research was conducted.

Correspondence to: [martin.bardsley@nuffieldtrust.org.uk](mailto:martin.bardsley@nuffieldtrust.org.uk)

Key words: Readmission, Predictive risk; Risk model;

3825 words

## Development of a predictive model to identify inpatients at risk of readmission within 30 days of discharge (PARR-30)

### *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).

1  
2  
3  
4  
5  
6 **Conclusions** – We have developed a method of identifying inpatients at high risk of unplanned  
7  
8 readmission to NHS hospitals within 30 days of discharge. Though the models had a low sensitivity,  
9  
10 we show how to identify subgroups of patients that contain a high proportion of patients who will  
11  
12 be readmitted within 30 days. Additional work is necessary to validate the model in practice.  
13  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23  
24  
25  
26  
27  
28  
29  
30  
31  
32  
33  
34  
35  
36  
37  
38  
39  
40  
41  
42  
43  
44  
45  
46  
47  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60

For peer review only

## Introduction

Unplanned hospital admissions and readmissions are regarded as markers of costly, suboptimal health care<sup>1,2</sup> and their avoidance is currently a priority for policymakers in many countries.<sup>3</sup> 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.<sup>4</sup> 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”<sup>5</sup>.

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,<sup>6</sup> with costs to the National Health Service (NHS) estimated at £1.6 billion each year<sup>7</sup>. Whilst many different interventions have been introduced with the aim of reducing unplanned admission rates<sup>8</sup>, the evidence for their efficacy and cost-effectiveness is limited.<sup>9</sup>

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.<sup>10</sup> A history of recent hospital admissions is not by itself an accurate predictor of future admissions,<sup>11</sup> and it seems that clinicians are often unable to make reliable predictions about which patients will be readmitted.<sup>12,13</sup> There is also some evidence to show that many readmissions may not be avoidable.<sup>14</sup> One recent analysis observed a strong relationship between rates of rehospitalisation and overall admission rates within specific areas<sup>15</sup>. 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

1  
2  
3 readmission.<sup>16,17,18,19,20,21</sup> The models use relationships in routine data to identify patients at highest  
4  
5 risk of unplanned admission or readmission in the next twelve months. Most of these models are  
6  
7 not contingent on an index hospital admission but instead calculate risk scores across the population  
8  
9 at a particular date, and are designed to be run on regular (eg monthly or quarterly) basis.  
10

11  
12 One advantage of predicting which patients are at high risk of admission in the coming twelve  
13  
14 months is that this prolonged period may allow time for clinicians and care managers/coordinators  
15  
16 to contact and engage with high-risk patients. Furthermore, it allows time for behavioural and  
17  
18 treatment changes to be instigated. On the other hand, the likelihood of an unplanned admission is  
19  
20 highest in the immediate post-discharge period,<sup>22</sup> so there may be advantages to predicting  
21  
22 readmissions that occur shortly after discharge. Furthermore, there is evidence that some forms of  
23  
24 preventive care may be more effective at reducing unplanned hospital admissions if initiated  
25  
26 immediately after an acute illness.<sup>23</sup>  
27  
28  
29

30  
31 Outside the UK, a number of tools have been built for predicting readmissions within 15 days<sup>24</sup>  
32  
33 or 30 days<sup>25,26,27,28,29</sup> of discharge from hospital. Until recently, NHS funding arrangements gave  
34  
35 hospitals in England few financial inducements to predict and prevent unplanned hospital  
36  
37 admissions. However, the 2011-12 operating framework proposed that NHS hospitals should not be  
38  
39 reimbursed for readmissions occurring within 30 days (as well as only receiving a 30 per cent  
40  
41 marginal rate for emergency admissions above their 2008/09 baseline).<sup>30</sup> In practice, the degree to  
42  
43 which this new 30-day rule is being enforced appears to vary across the country.<sup>31</sup> Yet even without  
44  
45 monetary incentives, knowledge of 30 day readmission risk could still be useful to clinicians for  
46  
47 focussing their discharge planning efforts and post-discharge support on high-risk patients.  
48  
49

50  
51 Predictive tools built in one setting may not necessarily be accurate when used in other health  
52  
53 care settings.<sup>32</sup> So in this paper, we describe how we used English hospital episode statistics (HES)  
54  
55 data to develop a predictive model that can identify patients at high risk of readmission to an NHS  
56  
57  
58  
59  
60

1  
2  
3 hospital in England within 30 days of discharge. The model, which we are calling “PARR-30”  
4  
5 (Patients at Risk of Readmission within 30 Days), can be used in practice in one of two ways: either  
6  
7 automatically, drawing variables from Secondary Uses Service (SUS) data and from a hospital’s  
8  
9 Patient Administration System (PAS);<sup>33</sup> or “manually” by clinicians, who can obtain the requisite  
10  
11 information from the patient and the patient's notes and then calculate the risk using a spreadsheet  
12  
13 or a smartphone/tablet ‘app’. To facilitate this second approach, we sought to develop an algorithm  
14  
15 that was easy to use and which relied only on a relatively small number of variables that are easily  
16  
17 obtained from available records or from the patient. In order to justify changes in services it is often  
18  
19 helpful to understand how the costs of the intervention may improve care and lead to lower overall  
20  
21 costs down the line. We therefore present figures for the potential scope for savings that might  
22  
23 accrue through reduced hospital use according to the level of risk targeted, and with assumptions  
24  
25 about the effectiveness of interventions. We are making PARR-30 freely available for use across the  
26  
27 NHS in England.  
28  
29  
30  
31

## 32 **Methods**

33  
34  
35 The model was developed using hospital episode statistics obtained from the Information Centre  
36  
37 for Health and Social Care for the period 1st April 2006 to 30th March .<sup>34</sup> This analysis was based on  
38  
39 existing data that had been anonymised and therefore did not require additional ethical approval.  
40  
41 Records were extracted for 10% of all NHS hospital admissions in England with a discharge date  
42  
43 between 1 April 2008 and 31 March 2009. Episodes coded as births, deaths in hospital, self-  
44  
45 discharged patients, and patients transferred to other hospitals were excluded, leaving a total of  
46  
47 576,868 admissions remaining in the sample. Readmissions within 30 days were restricted according  
48  
49 to the provisions of the 2011-12 operating framework by excluding non-emergency admission;  
50  
51 admissions where a national tariff was not applicable; admissions for multiple trauma or transport  
52  
53 accident, and children aged under age four. Cancer related readmissions were included since their  
54  
55 exclusion in the operating framework is being reconsidered.<sup>35</sup> Patients that died after discharge  
56  
57  
58  
59  
60

1  
2  
3 were included in the development data set, reproducing what would happen if the models were  
4 applied in practice. The data set allowed patients to have more than one readmission episode, but  
5 each readmission within 30 days was linked only with the most recent prior admission  
6  
7  
8  
9

10  
11  
12  
13 A series of logistic regressions were conducted to identify those variables that contributed most  
14 to predictions of a readmission within 30 days of discharge, creating “risk scores” of .01 to 1.00  
15 describing the estimated probability of readmission within 30 days. The variables were restricted to  
16 those that could be formulated in way that meant they could be easily extracted from the patient or  
17 patient notes in the absence of computerised administrative data. The variables tested were based  
18 on a broad range of measures used in the PARR algorithm which predicts readmission within the  
19 following year.<sup>14</sup> These included: the number admissions to hospital by type (emergency vs non-  
20 emergency) according to a time interval prior to current admission (90, 180, 365, 730, 1,095 days);  
21 the number of episodes per spell in prior admissions (a proxy measure of complex health problems);  
22 number of different types of specialists consulted in the last 12 months (based on services recorded  
23 in outpatient records); a range of diagnostic categories and hierarchical diagnostic groups<sup>36</sup>;  
24 characteristics of the area of residence; and length of stay. A dummy variable was introduced to  
25 represent the hospital – using the largest hospital in the data as the reference point. The reduced  
26 number of variables ultimately included in this algorithm were selected based on their impact on  
27 overall model performance and ease of access to medical notes or recall by the patient.  
28  
29  
30  
31  
32  
33  
34  
35  
36  
37  
38  
39  
40  
41  
42  
43  
44  
45  
46  
47

48 We measured the accuracy of the predictive models in a number of ways. The positive  
49 predictive value (PPV) estimates the accuracy of the model by comparing the number of people  
50 identified by the model as being likely to experience a readmission (based on a given threshold of  
51 risk) with the number in this group who went on to experience a readmission. The PPV is defined as  
52  
53  
54  
55  
56  
57  
58  
59  
60



1  
2  
3 the percentage of those at-risk patients identified by the model who experience a readmission. The  
4  
5 sensitivity is a related concept, which measures the percentage of those people who experienced a  
6  
7 readmission who are correctly identified by the model as being at risk. Conversely, the specificity is  
8  
9 defined as the proportion of people who did not experience an admission who were correctly  
10  
11 identified as being at low risk. The sensitivity and specificity of the model can be traded off against  
12  
13 each other by varying the threshold of risk used to define them. As well as these measures, we  
14  
15 present estimates of the area under the receiver operating characteristic (ROC) curve, which shows  
16  
17 the trade-off between true positives (sensitivity) and false negatives (1-specificity) at all possible  
18  
19 thresholds. Further, we were interested in the proportion and costs of patients who experienced a  
20  
21 readmission by risk band (twenty bands based on the level of the risk score).  
22  
23

24  
25 Predictive models are generally "trained" on a data set consisting of dependent variables (in this  
26  
27 case hospital readmissions) relating to many patients, together with a range of independent  
28  
29 variables from an earlier time period. The apparent performance of the model on the training (or  
30  
31 development) data set tends to be considerably better than its performance on another,  
32  
33 independent data set--even if that other data set consists of similar patients. In order to ensure that  
34  
35 the model's predictions are generalisable, it is therefore important to evaluate the performance of  
36  
37 the model more realistically than simply by calculating its accuracy on the training sample.  
38  
39

40  
41 To do this, we used a bootstrapping evaluation method.<sup>37</sup> This method involves estimating the  
42  
43 degree of "optimism" associated with evaluating the apparent performance of the model on the  
44  
45 training data set. The observed performance is moderated by subtracting the degree of optimism  
46  
47 from the apparent performance. We calculated the degree of optimism by repeatedly drawing a  
48  
49 large number of different bootstrapped samples from the training data set. Each consisted of the  
50  
51 same number of patients as in the original sample, but each was formed by selecting patients  
52  
53 randomly and allowing individual patients to be selected more than once. To estimate the optimism,  
54  
55 we fitted models to each of these bootstrapped samples and calculated the difference between the  
56  
57  
58  
59  
60

1  
2  
3 performance of the model on the bootstrapped sample and its performance on the original sample.  
4  
5 The optimism was estimated as the average of this quantity over all bootstrapped samples. One of  
6  
7 the benefits of bootstrapping is that it allows all of the available patient data to be included in the  
8  
9 data set. It has been shown to estimate model performance more accurately than other approaches  
10  
11 such as those that involve setting aside data for a separate validation sample.<sup>38</sup>  
12  
13

14  
15 The estimated degree of optimism was found to be very small, which we would expect given the  
16  
17 large number of patient records available. We therefore extended the bootstrapping technique to  
18  
19 add confidence intervals on the proportion of patients who experience a readmission by risk band,  
20  
21 treating optimism as negligible. These confidence intervals were formed by applying the final model  
22  
23 to a large number (we chose 200) bootstrapped samples, and estimating the range within which the  
24  
25 proportions fell 95% of the time. Confidence intervals were calculated for the ROC curve using a  
26  
27 Bayesian bootstrap method.<sup>39</sup>  
28  
29

### 30 31 **Developing the business case analysis**

32  
33  
34 A “business” case analysis is presented to help guide providers and commissioners in designing  
35  
36 interventions to prevent patient readmissions. For this we calculated the mean readmission costs of  
37  
38 all patients in each risk band and at various cut-off levels. This represents the cost to NHS hospitals  
39  
40 in terms of lost income. Various assumptions are made about the effectiveness of interventions at  
41  
42 reducing the number of readmissions within 30 days (10%, 15%, and 20%), to estimate the maximum  
43  
44 amount that could be expended on prevention, based on the estimated ‘savings’ from reduced  
45  
46 admissions.  
47  
48

49  
50 The costs of secondary care utilisation were estimated from HES data using 2010/11 Payment by  
51  
52 Results (PbR) tariffs<sup>40 41</sup>. Activity not covered by the national tariffs was costed using the national  
53  
54 reference costs (NRC)<sup>42</sup> and adjusted to ensure they were directly comparable with 2010/11 tariffs.  
55  
56 If neither tariff nor NRC were available, the activity was costed as the average tariff for the specialty  
57  
58

1  
2  
3 under which it was delivered in a method developed for a national study of resource allocation<sup>43</sup>.  
4  
5 Therefore, costs represent income for providers rather than the actual cost of treatment for the  
6  
7 readmission.  
8  
9

10 We established the costs of inpatient admissions by calculating the Healthcare Resource Group  
11 (HRG) for each patient's whole stay in hospital. We derived the full cost using the PbR rules<sup>44</sup> to  
12 combine the HRG, admission method and other details of the hospital stay. This included the unit  
13 cost of the HRG and any payments due because of an unexpectedly long stay in hospital, or for any  
14 specialist care or additional treatments and tests (so-called unbundled payments). We also  
15  
16 calculated outpatient and A&E costs as recommended by the PbR rules.  
17  
18  
19  
20  
21  
22  
23  
24

## 25 Results

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

- 27 • Patient age – used as squared value,
- 28 • Index of multiple deprivation<sup>45</sup> for the patient's place of residence (derived from a
- 29 postcode and mapped to one of five bands based on the lower super output area),
- 30 • Whether the current admission was an emergency admission (defined in HES as an
- 31 admission category 21-28),
- 32 • Whether there had been an emergency hospital discharge in the past 30 days,
- 33 • The number of emergency hospital discharges in the last year (from any hospital),
- 34 • History in the prior two years (from any HES primary or secondary diagnostic field) of
- 35 eleven major health conditions drawn from the Charlson co-morbidity index<sup>46</sup>, and
- 36 • The hospital of the current admission, using a set of 150 dummy variables for the major
- 37 acute hospitals in England.
- 38
- 39
- 40
- 41
- 42
- 43
- 44
- 45
- 46

47 Table 1 summarises the coefficients for these variables – the details for the individual hospital  
48 coefficients are provided in Appendix 1. Box 1 gives an example of how a risk score for an individual  
49 patient could be calculated. Full details of the model will also be made available on the Nuffield  
50 Trust website ([www.nuffieldtrust.org.uk](http://www.nuffieldtrust.org.uk))  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60

1  
2  
3 The performance of the model is shown in Table 2 in terms of the percentage of patients with a  
4 30-day readmission, and the costs of those readmissions displayed by risk band vignettes. For the  
5 higher risk patients (risk bands 11 and above), readmission rates ranged from 47.7% to 88.7% in the  
6 highest risk band compared to an overall readmissions rate of 12.2%. However, the number of  
7 patients in these high risk bands represented only a small share (1.1%) of all patients analysed. For  
8 risk bands 1-10, the risk of readmission within 30 days dropped steadily with decreasing risk score,  
9 but the number of patients in each band increased. The two lowest risk bands cover 54.7% of  
10 patients with a risk of readmission within 30 days of 7.1% or lower.  
11  
12  
13  
14  
15  
16  
17  
18  
19

20  
21 *{Table 2 about here}*  
22  
23

24 The mean readmission costs tended to be lower in the lower risk bands because a smaller  
25 percentage of patients were readmitted. However those in the lower bands who had a readmission,  
26 tended to have higher costs (for example, £1,340 per admission for patients in band 20 compared  
27 with £2,143 per admission for patients in band 11).  
28  
29  
30  
31  
32  
33  
34

35 A business case analysis is provided in Table 3, documenting the rate of readmissions and the  
36 maximum level of expenditure at each risk band (and at various risk band cut-off levels). These  
37 values indicate where the cost of the preventive intervention equals the net savings from reduced  
38 readmissions - with various assumptions about the effectiveness of interventions (10%, 15%, and  
39 20%). With a risk band cut-off at Band 11, mean readmission costs were £1,088 (CI £1,046, £1,124 –  
40 not shown) per patient. Using an assumption of a 10% reduction in the rate of readmission, £109 per  
41 patient (CI £105, £112 – not shown) could be spent on the 6,395 patients in these bands, with the  
42 costs of the intervention equalling costs of avoided emergency admissions (breakeven).  
43  
44  
45  
46  
47  
48  
49  
50  
51

52  
53 *{Table 3 about here}*  
54  
55  
56  
57  
58  
59  
60

1  
2  
3 The PPV for the model for all patients with a risk score above 0.50 (risk bands 11+) was 59.2% (CI  
4 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  
5 Table 4. The receiver operating characteristic curve (ROC) in Figure 1 illustrates the trade-off  
6  
7 between true positives (sensitivity) and false negatives (1 – specificity) for the model. Overall, the  
8  
9 area under the curve was 0.70 (CI 0.69, 0.70).  
10  
11  
12

13  
14  
15 *{Table 4 about here}*

16  
17 *{Figure 1 about here}*  
18  
19

## 20 21 22 23 24 Discussion

25  
26 We have built a predictive model using a limited set of variables that were generated from  
27  
28 hospital episode statistics. The model estimates the risk and costs of readmission to an NHS hospital  
29  
30 in England within 30 days of discharge. We have intentionally selected variables that we believe will  
31  
32 easily translate to information available from patients' notes or from the patients themselves. Look-  
33  
34 up tables can be built to map variables such as a patient's postcode to deprivation score. This means  
35  
36 it is possible to build simple software tools such as a spreadsheet or 'app' to calculate scores, as well  
37  
38 as by using data from a hospital's patient administration system.  
39  
40

41  
42 The performance of the model was respectable, with a positive predictive value (PPV) of 59.2%  
43  
44 and area under the ROC curve ("c-statistic") of 0.70. For example, a recent systematic review of  
45  
46 predictive risk models for 30 day readmissions documented c-statistics ranging from 0.50 to 0.72.<sup>47</sup>  
47  
48 The specificity of this model (99.5%) is high, although the sensitivity of the model is quite low with  
49  
50 only 5.4% of all patients in the sample (Bands 11+). The performance of the model could have been  
51  
52 improved by including more variables but this would have made the model less useful in practice.  
53  
54 Traditional measures of performance, such as the sensitivity, mask the potential value of models in  
55  
56  
57  
58  
59  
60

1  
2  
3 targeting preventive interventions. Knowledge of the percentage of patients in each risk score band  
4  
5 who will have an admission in the next 30 days can be useful in titrating resources to patients, with  
6  
7 more or different types of resources assigned for patients who are most likely to have a hospital  
8  
9 admission. At the highest risk band, patients had a 88.7% chance of hospital readmission within 30  
10  
11 days and £178 could be spent per patient on interventions aimed at avoiding readmission, assuming  
12  
13 these interventions were successful at averting 15% of all readmissions and that breakeven was  
14  
15 required. The level and type of resources allocated to these patients should be different from those  
16  
17 allocated to patients in the lower risk levels, such as those in Band 6 where chances of readmission  
18  
19 were 28.0%. These data can also be used in setting an overall cut-off level/threshold for the full  
20  
21 range of intervention strategies. For example, at a cut-off level at Band 5, almost 30% of patients  
22  
23 who will have an admission in the next 30 days will be included, and the chance of these patients  
24  
25 having a readmission is 31.8%. The levels and type of intervention for these patients should vary by  
26  
27 risk band and patient characteristics, but clinicians and commissioners can use these data to select  
28  
29 thresholds for any preventive intervention.  
30  
31  
32

33  
34 The model has its limitations. It was developed using HES data, but it is intended to be used by  
35  
36 hospitals using either a combination of PAS data and SUS data or patient self-reported information  
37  
38 on prior use and medical history from the patient's notes. While PAS/SUS data do differ from HES,  
39  
40 the differences are minor so we believe this shortcoming is unlikely to affect the accuracy of the  
41  
42 predictive model substantially. However, differences in patients' recall of their prior hospital use  
43  
44 and their medical history present bigger challenges to the validity of the model. Self-recall data on  
45  
46 health care utilisation can differ from administrative data, especially for people with high levels of  
47  
48 health care use, older people, and people with poor health status.<sup>48,49</sup> We are currently testing the  
49  
50 model to determine the extent to which patient-reported information differs from that recorded in  
51  
52 HES.  
53  
54  
55  
56  
57  
58  
59  
60

1  
2  
3 The ability to identify patients at high risk of readmission constitutes the first step in any  
4 strategy to improve care and services for susceptible patients. The ultimate goal, however, is to  
5 couple this 'case finding' process with cost-effective interventions that mitigate the risk of  
6 readmission and ideally, uses the ensuing financial savings to help fund the intervention.  
7  
8 Unfortunately, only a modest amount is known about what works, and for whom, in reducing  
9 readmissions.  
10

11  
12  
13 In a recent systematic review,<sup>50</sup> Hansen and colleagues identified a broad range of strategies  
14 that have been employed, including pre-discharge interventions (improved discharge planning,  
15 patient education, medication reconciliation, post-discharge follow-up appointment, etc), post-  
16 discharge interventions (patient hotlines, telephone appointment reminders, home visits, etc.), and  
17 other interventions to bridge the transition from hospital to home such as nurse coaching. Many of  
18 the studies looked at were small and not well designed. Five out of 16 randomised controlled trials  
19 documented statistically significant reductions in the absolute risk of readmission, but no single  
20 intervention or bundle of strategies were found to be consistently successful in reducing risk.  
21  
22  
23  
24  
25  
26  
27  
28  
29  
30  
31  
32  
33  
34

35 The data on costs developed here also suggests additional caution. At a risk score cut-off of .50  
36 (Band 11+), even with an optimistic assumption of a 20% reduction in the rate of readmissions, the  
37 amount available to spend on an intervention and still achieve breakeven is relatively modest (£218  
38 per patient). Broadening the intervention to a cut-off at Band 5, this amount drops to £143 (and £71  
39 if a more realistic reduction in readmissions of 10% is assumed). See Table 3. While improved  
40 discharge planning, arranging post-discharge follow-up visits and telephone reminders may be  
41 relatively inexpensive, other interventions such as nurse coaching and home visits can become quite  
42 costly. These data would permit targeting of interventions, with more costly strategies limited to  
43 the patients at highest risk, but the level of available resource will undoubtedly be strained if  
44 breakeven is expected.  
45  
46  
47  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60

1  
2  
3 As hospitals in England begin responding to the new financial incentives included in the 2011-12  
4 operating framework, it will be important to gather evidence about what interventions are effective  
5 and for which patients and at what cost. Areas for future research may include determining  
6 whether and how the effectiveness of interventions differs according to the underlying level of risk.  
7 For example, it may be that patients at lower or moderate risk of readmission have conditions or  
8 circumstances where an intervention is more likely to succeed than for patients at high risk. Equally,  
9 there may be certain sub-groups of patients within a particular risk band who are more or less  
10 amenable to preventive care. The use of predictive models as case finding tools to target  
11 preventive interventions has gained considerable currency in community based settings. We believe  
12 that it is important to consider how such tools might be used in the much more immediate care  
13 environment of the hospital to improve the long term management of patients.  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23  
24  
25  
26  
27  
28  
29  
30  
31  
32  
33  
34  
35  
36  
37  
38  
39  
40  
41  
42  
43  
44  
45  
46  
47  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60



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

**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](http://www.nuffieldtrust.org.uk)

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

Risk Band	N	% of Total	% Readmitted		All Patients Readmission Costs		Patients with Readmission Readmission Costs	
			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

Risk Band	By Risk Band Level				Cumulative at Band Cut-Off Level							
	N	Maximum Expenditure Per Patient for Break Even			N	% of All Patients	% of Pats With Readm*	% of All Pats with Readm*	Mean Readm Cost*	Maximum Expenditure Per Patient for Break Even*		
		Assumed Reduction in Readmissions								Assumed Reduction in ReAdms		
		10%	15%	20%						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+

For peer review only

1  
2  
3  
4  
5  
6  
7  
8  
9  
10  
11  
12  
13  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23  
24  
25  
26  
27  
28  
29  
30  
31  
32  
33  
34  
35  
36  
37  
38  
39  
40  
41  
42  
43  
44  
45  
46  
47  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60

***Acknowledgements***

This work was funded by the Nuffield Trust. We are grateful to the staff at Chelsea & Westminster Hospital and the Royal Berkshire Hospital for their support and guidance as we developed the PARR-30 model.

For peer review only

1  
2  
3  
4  
5  
6  
7  
8  
9  
10  
11  
12  
13  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23  
24  
25  
26  
27  
28  
29  
30  
31  
32  
33  
34  
35  
36  
37  
38  
39  
40  
41  
42  
43  
44  
45  
46  
47  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60

*Contributions:* The preparation of data sets and input variables and costs were undertaken by Theo Georghiou and Ian Blunt, John Billings did the central modelling and reporting whilst Adam Steventon undertook work on bootstrapping and testing derived models. Geraint Lewis wrote the first draft of the paper and coordinated advice from local sites. Martin Bardsley advised on the analysis and results and managed the work of the research team at Nuffield. All authors contributed to the writing of the paper. Geraint Lewis was employed as a Senior Fellow at the Nuffield Trust at the time this work was undertaken. John Billings is the guarantor.

*Copyright/Licence for publication:* The Corresponding Author has the right to grant on behalf of all authors and does grant on behalf of all authors, an exclusive licence (or non exclusive for government employees) on a worldwide basis to the BMJ Publishing Group Ltd and its licensees , to permit this article (if accepted) to be published in BMJ editions and any other BMJPG products and to exploit all subsidiary rights, as set out in our licence (<http://resources.bmj.com/bmj/authors/checklists-forms/licence-for-publication>)

*Competing interests:* All authors have completed the Unified Competing Interest form at [www.icmje.org/coi\\_disclosure.pdf](http://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.

*Funding and disclaimer:* This research was funded by the Nuffield Trust. The study sponsor was the Chairman of the Nuffield Trust. The sponsor had no role in and the collection, analysis, and interpretation of data, in the writing of the article nor in the decision to submit it for publication.

1  
2  
3  
4  
5  
6  
7  
8  
9  
10  
11  
12  
13  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23  
24  
25  
26  
27  
28  
29  
30  
31  
32  
33  
34  
35  
36  
37  
38  
39  
40  
41  
42  
43  
44  
45  
46  
47  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60

For peer review only



## References

- 1 McKee M, Nolte E. Chronic care. In: Smith PC, Mossialos E, Papanicolas I, Leatherman S (eds.). *Performance measurement for health system improvement: experiences, challenges and prospects*. Cambridge: Cambridge University Press, 2009
- 2 Billings J, Zeitel L, Lukomnik J, et al. Impact of socioeconomic status on hospital use in New York City. *Health Affairs* 1993;12(1):162-73.
- 3 Health system priorities in the aftermath of the crisis. Paris: OECD, 2010. Available at <http://www.oecd.org/dataoecd/14/36/46098360.pdf> (accessed 10 September 2011)
- 4 Department of Health. *Payment by Results Guidance for 2011-12*. London: Department of Health 2011
- 5 Department of Health. *Healthy Lives, Healthy People: transparency in outcomes, proposals for a public health outcomes framework*. London: Department of Health, 2010.
- 6 Blunt I, Bardsley M, Clarke A. Analysis of emergency 30-day readmissions in England using routine hospital data 2004-2010. Is there scope for reduction? (Forthcoming)
- 7 Robinson P. Hospitals readmissions and the 30 day threshold London: CHKS 2010  
[http://www.chks.co.uk/assets/files/Hospital\\_readmissions\\_and\\_the\\_30\\_day\\_threshold\\_final.pdf](http://www.chks.co.uk/assets/files/Hospital_readmissions_and_the_30_day_threshold_final.pdf) (accessed 2 December 2011)
- 8 Purdy S. Avoiding hospital admissions: what does the research evidence say? London: King's Fund, 2011. Available at [http://www.kingsfund.org.uk/publications/avoiding\\_hospital.html](http://www.kingsfund.org.uk/publications/avoiding_hospital.html) (accessed 10 September 2011)
- 9 Hansen LO, Young RS, Hinami K, et al. Interventions to reduce 30-day rehospitalization: a systematic review. *Ann Intern Med*. 2011 Oct 18;155(8):520-8.
- 10 Steventon A, Bardsley M, Billings J, et al. An evaluation of the impact of community-based interventions on hospital use. London: Nuffield Trust, 2011. Available at [http://www.nuffieldtrust.org.uk/sites/files/nuffield/an-evaluation-of-the-impact-of-community-based-interventions-on-hospital-use-full\\_report.pdf](http://www.nuffieldtrust.org.uk/sites/files/nuffield/an-evaluation-of-the-impact-of-community-based-interventions-on-hospital-use-full_report.pdf) (accessed 11 September 2011)
- 11 Roland M, Dusheiko M, Gravelle H, et al. Follow up of people aged 65 and over with a history of emergency admissions: analysis of routine admission data. *BMJ*. 2005;330(7486):289-92.
- 12 Curry N, Billings J, Darin B, et al. Predictive risk Project Literature Review. London: King's Fund, 2005. Available at [www.kingsfund.org.uk/document.rm?id=6196](http://www.kingsfund.org.uk/document.rm?id=6196)
- 13 Allaudeen N, Schnipper JL, Orav EJ, et al. Inability of providers to predict unplanned readmissions. *J Gen Intern Med*. 2011;26(7):771-6.
- 14 van Walraven C, Bennett C, Jennings A, et al. Proportion of hospital readmissions deemed avoidable: a systematic review *CMAJ* 2011;183(7):E391-402).
- 15 Epstein AM, Jha AK, Orav EJ. The relationship between hospital admission rates and rehospitalizations. *N Engl J Med* 2011;365:2287-95
- 16 Billings J, Dixon J, Mijanovich T, et al. Case finding for patients at risk of readmission to hospital: development of algorithm to identify high risk patients. *British Medical Journal* 2006; 333(7563):327.

- 1  
2  
3  
4  
5  
6  
7  
8  
9  
10  
11  
12  
13  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23  
24  
25  
26  
27  
28  
29  
30  
31  
32  
33  
34  
35  
36  
37  
38  
39  
40  
41  
42  
43  
44  
45  
46  
47  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60
- 
- <sup>17</sup> Wennberg D, Siegel M, Darin B, et al. Combined predictive model: final report and technical documentation. London: Health Dialog/King's Fund/New York University; 2006. Available from: <http://www.kingsfund.org.uk/document.rm?id=8248> (accessed 10 September 2011)
- <sup>18</sup> SPARRA: Scottish Patients At Risk of Readmission and Admission. Edinburgh: NHS National Services Scotland 2006. Available from [www.isdscotland.org/isd/files/SPARRA\\_Report.pdf](http://www.isdscotland.org/isd/files/SPARRA_Report.pdf) (accessed 10 September 2011)
- <sup>19</sup> NHS Scotland Information Services Division. *SPARRA Mental Health: Scottish Patients at Risk of Readmission and Admission (to psychiatric hospitals or units)*. Edinburgh: NHS Scotland Information Services Division 2009. <http://www.isdscotland.org/Health-Topics/Health-and-Social-Community-Care/SPARRA/SPARRA-History/SPARRA-MH-report-final.doc> (accessed 10 September 2011)
- <sup>20</sup> Donnan PT, Dorward DW, Mutch B, et al. Development and validation of a model for predicting emergency admissions over the next year (PEONY): a UK historical cohort study. *Arch Intern Med*. 2008;168(13):1416-22.
- <sup>21</sup> NHS Wales Informatics Service. *Reducing Emergency Risk: The Prism tool*. NHS Wales Informatics Service. Available at <http://www.wales.nhs.uk/nwis/page/52558>
- <sup>22</sup> Jencks SF, Williams MV, Coleman EA. Rehospitalizations among patients in the Medicare fee-for-service program. *N Engl J Med*. 2009;360(14):1418-28.
- <sup>23</sup> Puhan MA, Scharplatz M, Troosters T, et al. Respiratory rehabilitation after acute exacerbation of COPD may reduce risk for readmission and mortality: a systematic review. *Respir Res*. 2005;6:54.
- <sup>24</sup> Rowland K, Maitra AK, Richardson DA, et al. The discharge of elderly patients from an accident and emergency department: functional changes and risk of readmission. *Age and Ageing* 1990;19(6):415-8.
- <sup>25</sup> Hasan O, Meltzer DO, Shaykevich SA, et al. Hospital Readmission in General Medicine Patients: A Prediction Model. *J Gen Intern Med*. 2010 March; 25(3): 211-219
- <sup>26</sup> Novotny NL, Anderson MA. Prediction of early readmission in medical inpatients using the Probability of Repeated Admission instrument. *Nurs Res*. 2008;57(6):406-415.
- <sup>27</sup> van Walraven C, Dhalla IA, Bell C, et al. Derivation and validation of an index to predict early death or unplanned readmission after discharge from hospital to the community. *CMAJ*. 2010;182(6):551-7
- <sup>28</sup> Salvi F, Morichi V, Grilli A, et al. Predictive validity of the Identification of Seniors At Risk (ISAR) screening tool in elderly patients presenting to two Italian Emergency Departments. *Aging Clin Exp Res*. 2009;21(1):69-75
- <sup>29</sup> Meldon SW, Mion LC, Palmer RM, et al. A brief risk-stratification tool to predict repeat emergency department visits and hospitalizations in older patients discharged from the emergency department. *Acad Emerg Med*. 2003;10(3):224-32.
- <sup>30</sup> Department of Health. *The Operating Framework for the NHS in England 2011/12*. London: Department of Health, 2010.
- <sup>31</sup> Dowler C. Emergency readmissions payment ban being ignored. *Health Service Journal* 21 July, 2011. Available at <http://www.hsj.co.uk/news/finance/emergency-readmissions-payment-ban-being-ignored/5032666.article> (accessed 11 September 2011)
- <sup>32</sup> Fan J, Worster A, Fernandes CM. Predictive validity of the triage risk screening tool for elderly patients in a Canadian emergency department. *Am J Emerg Med*. 2006 Sep;24(5):540-4.

- 1  
2  
3  
4  
5  
6  
7  
8  
9  
10  
11  
12  
13  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23  
24  
25  
26  
27  
28  
29  
30  
31  
32  
33  
34  
35  
36  
37  
38  
39  
40  
41  
42  
43  
44  
45  
46  
47  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60
- 
- <sup>33</sup> NHS Information Centre for Health and Social Care . *The SUS programme*. Leeds: NHS Information Centre for Health and Social Care, 2011. Available from <http://www.connectingforhealth.nhs.uk/systemsandservices/sus> (accessed 12 September 2011)
- <sup>34</sup> Information Centre for Health and Social Care . *Hospital Episode Statistics*. Leeds: Information Centre, 2009
- <sup>35</sup> Payment by Results Guidance for 2011-12. London: Department of Health, 2011. Available at [http://www.dh.gov.uk/prod\\_consum\\_dh/groups/dh\\_digitalassets/documents/digitalasset/dh\\_126157.pdf](http://www.dh.gov.uk/prod_consum_dh/groups/dh_digitalassets/documents/digitalasset/dh_126157.pdf)
- <sup>36</sup> Pope GC, Kautter J, Ellis RP, et al. Risk adjustment of Medicare capitation payments using the CMS-HCC model. *Health Care Financ Rev*. 2004 Summer;25(4):119-41.
- <sup>38</sup> Steyerberg EW, Harrell Jr FE, Borsboom GJJM, et al. Internal validation of predictive models: Efficiency of some procedures for logistic regression analysis. *Journal of Clinical Epidemiology*. 2001;54:774-781.
- <sup>39</sup> Gu J, Ghosal S, Roy A. Bayesian bootstrap estimation of ROC curve. *Statistics in Medicine*. 2008;27:5407-20.
- <sup>40</sup> Department of Health. *Payment by Results Guidance for 2010-11*. London: Department of Health, 2010
- <sup>41</sup> PBRA3 team. Updating and enhancing a resource allocation formula at general practice level based on individual level characteristics (person-based resource allocation) (Forthcoming)
- <sup>42</sup> Department of Health. *NHS reference costs 2007-08*. London: Department of Health, 2009
- <sup>43</sup> Dixon J, Smith P, Gravelle H, et al. A person based formula for allocating commissioning funds to general practices in England: development of a statistical model *BMJ* 2011;343:d6608 doi: 10.1136/bmj.d6608 (Published 22 November 2011)
- <sup>44</sup> Department of Health (2010b) *Payment by Results Guidance for 2010-11*. London: Department of Health
- <sup>45</sup> Department for Communities and Local Government. The English Indices of Deprivation 2010 <http://www.communities.gov.uk/publications/corporate/statistics/indices2010>
- <sup>46</sup> Charlson ME, Popei P, Ales KL, et al. A new method of classifying prognostic comorbidity in longitudinal studies: development and validation. *Journal of Chronic Disease*. 1987;40:373-383.
- <sup>47</sup> Kansagara D, Englander H, Salanitro A, et al. Risk Prediction Models for Hospital Readmission: A Systematic Review. *JAMA*. 2011;306(15):1688-1698
- <sup>48</sup> Bellón J.A., P. Lardelli, L.J. de Dios, A, et al. "Validity of self reported utilisation of primary health care services in an urban population in Spain." *Journal of Epidemiology and Community Health* 54:544-51.
- <sup>49</sup> Cleary P.D., A.M. Jette. 1984. "The validity of self-reported physician utilization measures." *Medical Care* 22:796-803.
- <sup>50</sup> Hansen LO, Young RS, Hinami K, et al. Interventions to reduce 30-day rehospitalisation: a systematic review. *Ann Intern Med* 2011;155:520-528

## 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
<b>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</b>			
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
<b>Hospital trust specific variable</b>			
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

1				
2				
3	Brighton and Sussex University Hospitals NHS Trust (RXH)	-0.0043	0.051	0.933
4	Bromley Hospitals NHS Trust (RG3)	-0.2153	0.07	0.002
5	Buckinghamshire Hospitals NHS Trust (RXQ)	0.0026	0.061	0.966
6	Burton Hospitals NHS Foundation Trust (RJF)	-0.1109	0.075	0.138
7	Calderdale and Huddersfield NHS Foundation Trust (RWY)	-0.2049	0.058	< 0.001
8	Cambridge University Hospitals NHS Foundation Trust (RGT)	-0.1115	0.055	0.041
9				
10	Central Manchester University Hospitals NHS Foundation Trust (RW3)	-0.0782	0.053	0.139
11	Chelsea and Westminster Hospital NHS Foundation Trust (RQM)	-0.2388	0.076	0.002
12	Chesterfield Royal Hospital NHS Foundation Trust (RFS)	-0.3527	0.072	< 0.001
13	City Hospitals Sunderland NHS Foundation Trust (RLN)	-0.1949	0.054	< 0.001
14	Colchester Hospital University NHS Foundation Trust (RDE)	-0.3485	0.069	< 0.001
15	Countess of Chester Hospital NHS Foundation Trust (RJR)	-0.2975	0.068	< 0.001
16	County Durham and Darlington NHS Foundation Trust (RXP)	-0.0943	0.051	0.062
17	Dartford and Gravesham NHS Trust (RN7)	-0.1673	0.078	0.031
18	Derby Hospitals NHS Foundation Trust (RTG)	-0.1749	0.052	0.001
19	Doncaster and Bassetlaw Hospitals NHS Foundation Trust (RP5)	-0.2514	0.057	< 0.001
20	Dorset County Hospital NHS Foundation Trust (RBD)	-0.1666	0.077	0.031
21	Ealing Hospital NHS Trust (RC3)	-0.0314	0.074	0.672
22	East and North Hertfordshire NHS Trust (RWH)	-0.2360	0.059	< 0.001
23	East Cheshire NHS Trust (RJN)	-0.0539	0.082	0.512
24	East Kent Hospitals University NHS Foundation Trust (RVV)	-0.0078	0.046	0.866
25	East Lancashire Hospitals NHS Trust (RXR)	-0.3743	0.058	< 0.001
26	East Sussex Hospitals NHS Trust (RXC)	-0.1331	0.054	0.014
27	Epsom and St Helier University Hospitals NHS Trust (RVR)	-0.0332	0.057	0.558
28	Frimley Park Hospital NHS Foundation Trust (RDU)	-0.1811	0.067	0.007
29	Gateshead Health NHS Foundation Trust (RR7)	-0.0421	0.066	0.521
30	George Eliot Hospital NHS Trust (RLT)	-0.1241	0.086	0.15
31	Gloucestershire Hospitals NHS Foundation Trust (RTE)	-0.2831	0.054	< 0.001
32	Great Western Hospitals NHS Foundation Trust (RN3)	-0.0955	0.065	0.142
33	Guy's and St Thomas' NHS Foundation Trust (RJ1)	-0.2393	0.054	< 0.001
34	Harrogate and District NHS Foundation Trust (RCD)	-0.3723	0.1	< 0.001
35	Heart of England NHS Foundation Trust (RR1)	-0.0084	0.043	0.844
36				
37	Heatherwood and Wexham Park Hospitals NHS Foundation Trust (RD7)	-0.1483	0.067	0.026
38	Hereford Hospitals NHS Trust (RLQ)	-0.2719	0.095	0.004
39	Hinchingbrooke Health Care NHS Trust (RQQ)	-0.2993	0.098	0.002
40	Homerton University Hospital NHS Foundation Trust (RQX)	-0.1506	0.083	0.069
41	Hull and East Yorkshire Hospitals NHS Trust (RWA)	-0.1879	0.049	< 0.001
42	Imperial College Healthcare NHS Trust (RYJ)	-0.1089	0.047	0.02
43	Ipswich Hospital NHS Trust (RGQ)	-0.2070	0.065	0.001
44	James Paget University Hospitals NHS Foundation Trust (RGP)	-0.2747	0.077	< 0.001
45	Kettering General Hospital NHS Foundation Trust (RNQ)	-0.2582	0.068	< 0.001
46	King's College Hospital NHS Foundation Trust (RJZ)	-0.0806	0.056	0.152
47	Kingston Hospital NHS Trust (RAX)	-0.1913	0.081	0.018
48				
49				
50				
51				
52				
53				
54				
55				
56				
57				
58				
59				
60				

1				
2				
3				
4	Lancashire Teaching Hospitals NHS Foundation Trust (RXN)	-0.1646	0.053	0.002
5	Liverpool Heart and Chest Hospital NHS Trust (RBQ)	-0.0228	0.114	0.841
6	Luton and Dunstable Hospital NHS Foundation Trust (RC9)	-0.2842	0.069	< 0.001
7	Maidstone and Tunbridge Wells NHS Trust (RWF)	-0.1074	0.058	0.063
8	Mayday Healthcare NHS Trust (RJ6)	-0.0229	0.066	0.73
9	Medway NHS Foundation Trust (RPA)	-0.0899	0.065	0.164
10	Mid Cheshire Hospitals NHS Foundation Trust (RBT)	-0.1522	0.061	0.013
11	Mid Essex Hospital Services NHS Trust (RQ8)	-0.0817	0.059	0.165
12	Mid Staffordshire NHS Foundation Trust (RJD)	-0.3216	0.083	< 0.001
13	Mid Yorkshire Hospitals NHS Trust (RXF)	-0.1774	0.05	< 0.001
14	Milton Keynes Hospital NHS Foundation Trust (RD8)	-0.0253	0.065	0.698
15	Newham University Hospital NHS Trust (RNH)	0.0640	0.068	0.347
16				
17	Norfolk and Norwich University Hospitals NHS Foundation Trust (RM1)	-0.2619	0.053	< 0.001
18				
19	North Bristol NHS Trust (RVJ)	-0.2220	0.056	< 0.001
20				
21	North Cumbria University Hospitals NHS Trust (RNL)	-0.2746	0.065	< 0.001
22				
23	North Middlesex University Hospital NHS Trust (RAP)	-0.1964	0.079	0.013
24				
25	North Tees and Hartlepool NHS Foundation Trust (RVW)	-0.1317	0.058	0.022
26				
27	North West London Hospitals NHS Trust (RV8)	-0.1428	0.057	0.012
28				
29	Northampton General Hospital NHS Trust (RNS)	-0.0896	0.063	0.152
30				
31	Northern Devon Healthcare NHS Trust (RBZ)	-0.2258	0.083	0.007
32				
33	Northern Lincolnshire and Goole Hospitals NHS Foundation Trust (RNL)	-0.5869	0.065	< 0.001
34				
35	Northumbria Healthcare NHS Foundation Trust (RTF)	-0.0188	0.049	0.702
36				
37	Nottingham University Hospitals NHS Trust (RX1)	-0.0580	0.044	0.188
38				
39	Nuffield Orthopaedic Centre NHS Trust (RBF)	-0.3788	0.185	0.04
40				
41	Oxford Radcliffe Hospitals NHS Trust (RTH)	0.0293	0.047	0.537
42				
43	Papworth Hospital NHS Foundation Trust (RGM)	-0.2873	0.101	0.005
44				
45	Pennine Acute Hospitals NHS Trust (RW6)	-0.0963	0.044	0.029
46				
47	Peterborough and Stamford Hospitals NHS Foundation Trust (RGN)	-0.1736	0.065	0.008
48				
49	Plymouth Hospitals NHS Trust (RK9)	-0.1309	0.054	0.015
50				
51	Poole Hospital NHS Foundation Trust (RD3)	-0.1420	0.064	0.026
52				
53	Portsmouth Hospitals NHS Trust (RHU)	-0.2619	0.051	< 0.001
54				
55	Queen Elizabeth Hospital NHS Trust (RG2)	-0.2003	0.085	0.018
56				
57	Queen Mary's Sidcup NHS Trust (RGZ)	0.1977	0.074	0.008
58				
59	Queen Victoria Hospital NHS Foundation Trust (RPC)	-0.7424	0.165	< 0.001
60				
	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



**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 \_\_\_\_\_

Indicate page number ↓  
(Or n/a if not applicable)

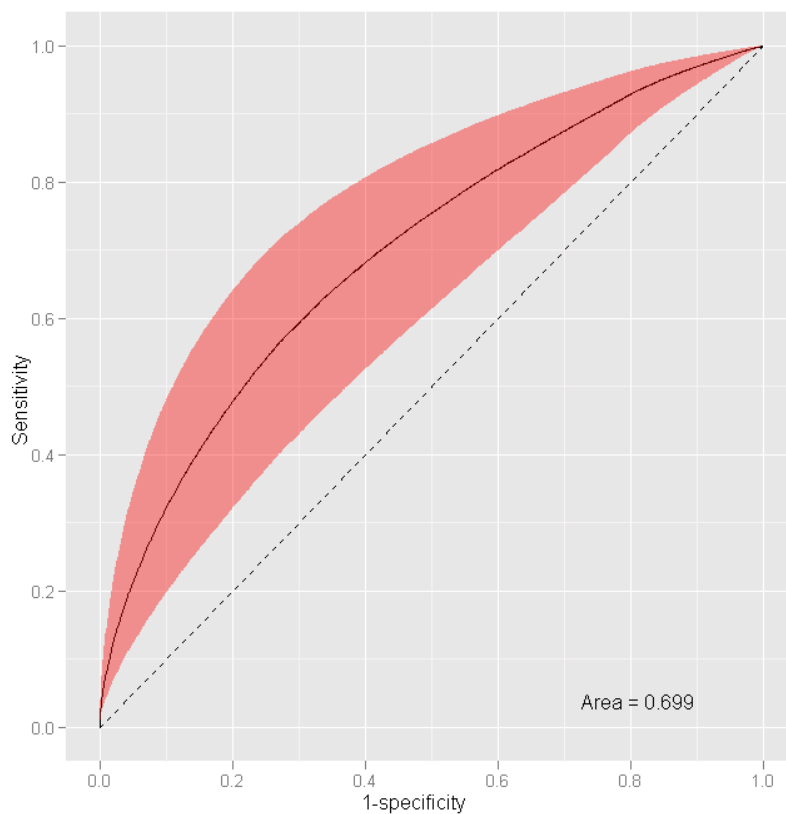
	Item No	Recommendation	
Title and abstract	1	(a) Indicate the study's design with a commonly used term in the title or the abstract	
		(b) Provide in the abstract an informative and balanced summary of what was done and what was found	
<b>Introduction</b>			
Background/rationale	2	Explain the scientific background and rationale for the investigation being reported	
Objectives	3	State specific objectives, including any prespecified hypotheses	
<b>Methods</b>			
Study design	4	Present key elements of study design early in the paper	
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection	
Participants	6	(a) <i>Cohort study</i> —Give the eligibility criteria, and the sources and methods of selection of participants. Describe methods of follow-up <i>Case-control study</i> —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 <i>Cross-sectional study</i> —Give the eligibility criteria, and the sources and methods of selection of participants	
		(b) <i>Cohort study</i> —For matched studies, give matching criteria and number of exposed and unexposed <i>Case-control study</i> —For matched studies, give matching criteria and the number of controls per case	
Variables	7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable	
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	
Bias	9	Describe any efforts to address potential sources of bias	
Study size	10	Explain how the study size was arrived at	
Quantitative variables	11	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen and why	
Statistical methods	12	(a) Describe all statistical methods, including those used to control for confounding	
		(b) Describe any methods used to examine subgroups and interactions	
		(c) Explain how missing data were addressed	
		(d) <i>Cohort study</i> —If applicable, explain how loss to follow-up was addressed <i>Case-control study</i> —If applicable, explain how matching of cases and controls was addressed <i>Cross-sectional study</i> —If applicable, describe analytical methods taking account of sampling strategy	
		(e) Describe any sensitivity analyses	
<b>Results</b>			
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	
		(b) Give reasons for non-participation at each stage	
		(c) Consider use of a flow diagram	
Descriptive data	14*	(a) Give characteristics of study participants (eg demographic, clinical, social) and information on exposures and potential confounders	
		(b) Indicate number of participants with missing data for each variable of interest	
		(c) <i>Cohort study</i> —Summarise follow-up time (eg, average and total amount)	
Outcome data	15*	<i>Cohort study</i> —Report numbers of outcome events or summary measures over time	
		<i>Case-control study</i> —Report numbers in each exposure category, or summary measures of exposure	
		<i>Cross-sectional study</i> —Report numbers of outcome events or summary measures	
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	
		(b) Report category boundaries when continuous variables were categorized	
		(c) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period	
Other analyses	17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses	
<b>Discussion</b>			
Key results	18	Summarise key results with reference to study objectives	
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	
Interpretation	20	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence	
Generalisability	21	Discuss the generalisability (external validity) of the study results	
<b>Other information</b>			
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	

\*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](http://www.strobe-statement.org).

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



ew only

1  
2  
3  
4  
5  
6  
7  
8  
9  
10  
11  
12  
13  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23  
24  
25  
26  
27  
28  
29  
30  
31  
32  
33  
34  
35  
36  
37  
38  
39  
40  
41  
42  
43  
44  
45  
46  
47  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60