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Title

Identifying the predictors of avoidable emergency department attendance after contact with the NHS 111 phone service: Analysis of 16.6 million calls to 111 in England in 2015-17

Authors

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Abstract

Objectives: To measure the frequency of patients making avoidable emergency department (ED) attendances after contact with NHS 111, and to examine whether these attendances can be predicted reliably.

Design: Analysis of 16,563,946 calls made to 111, where each call was linked with a record of whether the patient attended ED within 24 hours.

Setting: All regions of England from March 2015 to October 2017.

Participants and data: Our main regression model used a sample of 10,954,783 calls, each with detailed patient-level information.

Main outcome: Whether patients made an unadvised, nonurgent Type 1 ED ("avoidable") attendance within 24 hours of calling 111.

Results: Of 16,563,946 calls where 111 did not advise patients to go to the ED, 12,894,561 (77.8%) were advised to either attend primary care, attend another (non-ED) healthcare service, or to self-care. Of these latter calls, 691,783 (5.4%) resulted in the patient making an avoidable ED attendance within 24 hours, incurring £65 million in tariff charges (£2.1 million per month).

Among other factors, calls were less likely to result in these attendances when they received clinical input (adjusted odds ratio [OR] 0.52, 95% CI 0.51-0.53), but were more likely when the patient was female (OR 1.07, 95% CI 1.06-1.08) or aged 0-4 (OR 1.34, 95% CI 1.33-1.35).

Conclusions: For every 20 calls where 111 did not advise people to attend the ED, 1 resulted in avoidable ED attendance within 24 hours. These avoidable attendances could be predicted, to a certain extent, based on call characteristics. It may be possible to use this information to help 111 call-handlers identify which callers are at high risk of these attendances.

Strengths and limitations of this study

- The analysis relies on a large national-level dataset containing 47% of all 111 calls in England in the study period
- It adjusts for a large set of covariates known to be predictive of avoidable ED attendances.
- However, other potentially important predictors of health behaviour, such as health history or other interactions with healthcare providers, were not available in the data.
- We conducted both a conventional (OLS and logistic) regression and a predictive (gradient-boosting) analysis.

Introduction

9.7 million (50%) of the 19.4 million attendances made at hospital emergency departments (EDs) in England in 2016-17 resulted in the patient receiving either no treatment, or advice and guidance only.[1] This incurred an estimated total cost to the NHS of over £500 million, at a time when "*pressures on the NHS are greater than they have ever been*."[2,3] The low-intensity care received by these patients suggests at least some could have been treated safely elsewhere (e.g. GP practice, pharmacy, or at home), at lower cost to the healthcare system.

One way to potentially reduce the number of nonurgent ED attendances is by encouraging greater use of the 111 service. NHS 111 is a free, non-emergency healthcare telephone line in Britain which aims to ensure that callers are seen at the "*right place, first time.*"[4] Call-handlers for the 111 service assess callers' health problems using a clinically-validated triage algorithm ('NHS Pathways'),[5] then either dispatch an ambulance or recommend the caller attend ED, or advise the caller to go to primary care, attend another healthcare service, or to self-care.

Given that 111 received 16 million calls in England in 2017-18,[6] the service is well-placed to direct large numbers of patients with nonurgent health problems to seek treatment outside the ED. However, it is not clear how often calls produce this result in practice. An evaluation of 111 in its first year of operation found it had no statistically significant impact on ED attendance rates.[7] More recent work has found that the Pathways algorithm may recommend ED attendance more often than necessary,[8] and that some 111 staff believe the service has increased the number of nonurgent calls compared to previous out-of-hours primary care services.[9]

Although there have been several big-data studies examining the predictors of nonurgent ED attendance rates in England,[10,11,12] it has only recently become possible to do large-scale analysis of linked 111/ED data (i.e. data which links individual 111 calls with a record of whether that caller went on to attend ED).[13] This linked data makes it possible to examine how often patients end up making nonurgent ED attendances after calling 111. To date, one other study has been published using this linked data: it examined a dataset of 10,356 callers across three areas of North West London and found that 15% of callers advised by 111 to manage their health needs at home attended an ED within 10 hours (this rate was lower when patients were given GP out-of-hours appointments or when the 111 call received input from a clinical supervisor).[14]

This study uses a national-level linked 111-ED dataset to examine how often 111 callers end up making unadvised, nonurgent Type 1 (henceforth 'avoidable') ED attendances within 24 hours of their call, and to examine the predictors of these attendances. We do this using a dataset of 16,563,946 calls made to 111 from March 2015 to October 2017, where each call contained patient-level information and a record of whether the patient attended ED within 24 hours.

Methods

Study design. The data initially contained 18,127,605 observations, where each row was a call made to 111 between 31 March 2015 and 31 October 2017. This represents almost half (47%) of the 38,585,200 million calls made to 111 between March 2015 and October 2017.[6] Each call was linked with a Secondary Use Services (SUS) record of whether the patient attended ED within 24 hours of the 111 call. We used logistic and OLS regressions and a gradient boosted decision tree model to assess the extent to which we could predict whether the call would result in an avoidable ED attendance within 24 hours.

Data cleaning. We excluded rows missing the date / time of the 111 call (n = 52,394), final disposition code (n = 878,461), which had disposition codes[15] indicating the call was not relevant to our research question (n = 167,182), missing patient's gender (n = 246,144), missing patient age or where age was over 110 years (n = 46,656), and calls whose duration was above the 99th percentile (more than 190 minutes) as these were presumed to be data errors (n = 172,822). Note that the following disposition codes were considered irrelevant to the research question: Dx78 ("Receive Report of Results or Tests from Laboratory"), Dx83 ("Clinician Home Management of Dying Individual (Expected)"), Dx91 ("Unexpected Death"), Dx95 ("The Call is Closed with No Further Action Required, Wrong Service Called"), Dx116 ("Speak to the Primary Care Service within 6 hours for Expected Death"), and Dx117 ("Speak to a Primary Care Service within 1 hour for Palliative Care").

This reduced the sample to 16,563,946 triaged calls, from which we produced descriptive statistics. Our main regression model used a smaller sample of 10,954,783 calls, as this retained only rows with complete information on the outcome measure and all control variables.

Outcome measure. Our outcome measure was a binary indicator of whether a patient made an avoidable ED attendance within 24 hours of calling 111. Figure 1 shows how we coded the outcome measure. We defined an ED attendance as "avoidable" if, after being told by 111 to do something other than go to the ED, the patient attended ED within 24 hours and was assigned Healthcare Resource Group (HRG) treatment codes VB07Z ("*category 2 investigation with category 2 treatment*"), VB08Z ("*category 2 investigation with category 1 treatment*"), VB09Z ("*category 1 investigation with category 1-2 treatment*"), or VB11Z ("*no investigation with no significant treatment*"),[16] and was not admitted, not referred to another healthcare specialist by the ED, and did not die in the ED department.

Figure 1. How the outcome measure was coded.

[figure 1]

Control measures. Our analysis used 18 control variables, shown in past research to be important predictors of ED attendance in England, which fell into five broad categories:

- *2 patient characteristics:* (i) a continuous measure of patient age and (ii) a binary measure of patient gender.
- *5 geographic characteristics:* (iii) a binary indicator of whether the patient was from a rural vs urban area,[17] (iv) a categorical variable identifying what region of England the patient was from (North, Midlands, South & East, or London), (v) the distance ratio between the patient's local area and the nearest ED relative to a GP, (vi) the deprivation of the patient's local area (measured in quintiles using 2015 indices of multiple deprivation scores), and (vii) a categorical indicator of which of the 40 different 111 sites present in the data handled the call, to account for any unobserved variation in the way different 111 sites interact with patients.[18]
- 2 *GP practice characteristics:* (viii) a variable from the GP Patient Survey which recorded the proportion of patients saying "*Yes*" or "*Yes, but I had to call back closer to or on the day I wanted the appointment*" in response to "*Were you able to get an appointment to see or speak to someone?*", and (ix) an indicator of the number of full-time-equivalent (FTE) GPs at each practice.[19]
- *3 call characteristics:* (x) duration of the 111 call in minutes, (xi) a binary variable indicating whether the call had clinical input (21% of calls did), and (xii) the NHS Pathways disposition code assigned to the patient at the end of the call.
- 6 *temporal characteristics:* Using the date and time the call was made to 111, we constructed variables for (xiii) hour of the day, (xiv) day of week, (xv) month, (xvi) year (2015, 2016, or 2017), and binary indicators for whether the day was a (xvii) bank holiday, or (xviii) spanned the December 24-26 period.

The distance ratio, i.e. variable (v) was calculated as the average travel time by public transport and/or walking to the nearest hospital relative to the nearest GP and included under the assumption that a patient's decision to see a GP or go to the ED is likely to be influenced by the relative ease of accessing these two locations).[20,21]

Deprivation, i.e. variable (vi), was measured using 2015 indices of multiple deprivation (IMD) scores, which were matched to patients' local areas using their LSOA code. While deprivation is typically measured using the aggregate IMD score compiled from 7 different subdomain measures (e.g. deprivation for income, deprivation for health, deprivation for employment, etc), it is not entirely appropriate to use this aggregate measure when predicting ED attendance. This is because the health score, which comprises 13.5% of the total IMD score, itself incorporates local ED attendance rates as a measure of local health deprivation.[22] This sort of mathematical coupling (i.e. using a score which includes ED attendances to predict ED attendances) can lead to spurious correlations in statistical assessment. We therefore followed an established procedure to construct an alternative aggregate IMD score which excluded the health domain but retained the other six deprivation domains.[23]

Ease of securing a GP appointment, i.e. variable (viii) relied on the GP Patient Survey (GPPS), which is a questionnaire sent to users of GP practices. It asks people to rate the performance of their GP practice on dimensions such as quality of care, satisfaction with opening hours, and a subjective assessment of how easy it is to get an appointment. We retained only data for GP practices who had received at least 50 responses to these questionnaires. In order to maximise sample size, we took the average score for the GP characteristic variables across the three GPPS waves published in January 2016, July 2016, and July 2017.[24]

The disposition code variable (xii) indexed 96 different disposition codes present in the data which contained at least 30 observations. These codes used the standard "Dx" coding format (e.g. "Dx14 = Speak to a Primary Care Service within 12 hours") used by the 111 services.[15] These disposition codes were the ones recorded by the call handler or clinical advisor who initially managed the 111 call, but in some cases, patients will have gone on to have further interactions with the 111 service after this disposition was assigned. For example, they may have received a call-back from another healthcare professional, who may have assigned them a different disposition.

Detailed descriptive statistics for each of the control variables can be found in table S1 in the Supplement.

Results

Descriptive statistics

Figure 2 shows the ED outcomes of 16,563,946 calls in the data, broken down by NHS Pathways disposition assigned at the end of the call, and with the original number of calls normalised to 1000 for ease of interpretation. For every 1000 callers, 779 were not advised by 111 to attend ED (i.e. they were told to attend primary care, attend another service, or self-care). Of these, 83 went on to make a Type 1 ED attendance anyway within 24 hours. Of these, 42 were classified as avoidable.

Figure 2. Outcomes of 16,563,946 calls made to 111 from March 2015 to October 2017. For ease of interpretation the total number of calls has been normalised to 1,000.

[figure 2.png]

Avoidable = Patient got Healthcare Resource Group (HRG) treatment code VB07Z ("*category 2 investigation with category 2 treatment*"), VB08Z ("*category 2 investigation with category 1 treatment*"), VB09Z ("*category 1 investigation with category 1-2 treatment*"), or VB11Z ("*no investigation with no significant treatment*"), and was not admitted, not referred to another healthcare specialist by the ED, and did not die in the ED department.

Stated differently, for calls where patients were not advised to attend ED, 5.4% resulted in avoidable ED attendances within 24 hours. Using the NHS national tariff charges present in the data for each ED attendance, we calculated that these avoidable attendances incurred tariff costs of £65 million (£2.1 million per month) over the March 2015 to October 2017 period covered in our data. If we extrapolate this 5.4% incidence rate of avoidable attendances to all 38,585,200 calls made to 111 between March 2015 and October 2017 (i.e. including calls not in our data), this implies £58.8m in tariff charges were incurred per year by avoidable ED attendances.

Regression analyses

Table 1 shows the results of our logistic and OLS regression analyses. Column 1 shows exponentiated logistic regression coefficients, which can be interpreted as odds ratios. Column 2 shows the coefficients of an ordinary least squares regression (i.e. a linear probability model) with the same specification – which, although problematic as it violates the assumption of non-negative probabilities, provides a more easily interpretable way of assessing the strength of the observed associations.

Notable results include that calls were 3.65 percentage points (95% CI -3.76, -3.54) less likely to result in avoidable attendances (relative to a baseline of 5.6%) when the call had clinical input, and 0.8 points less likely (95% CI -1.0, -0.6) when the caller was registered with a GP practice where it was easier than other practices to get an appointment. Calls were 0.34 points more likely to result in these attendances when the patient was female (95% CI 0.31-0.37), 1.72 points more likely when the patient was aged 0-4 (95% CI 1.68-1.75), and 0.17 points more likely when the patient lived in a more deprived area (95% CI 0.16-0.18).

Table 1. Summary results of the association between 111 call characteristics and the probability of making an avoidable Type 1 ED attendance within 24 hours.

	Column 1	Column 2
Variable	**Logistic regression,**	**OLS regression,**

	odds ratios (95% CI)	percentage point changes (95% CI)
Patient characteristics		
Patient aged 0-4 (vs all other ages)	1.34*** (1.33, 1.35)	1.72*** (1.68, 1.75)
Female (vs male) patient	1.07*** (1.06, 1.08)	0.34*** (0.31, 0.37)
Geographic characteristics		
Quintile of area deprivation (1 = least deprived, 5 = most deprived)	1.03*** (1.03, 1.03)	0.17*** (0.16, 0.18)
Patient's distance to hospital relative to GP	1.00 (1.00, 1.00)	0.00 (-0.01, 0.01)
Patient in rural (vs urban) area	0.91*** (0.90, 0.92)	-0.44*** (-0.48, -0.40)
GP practice characteristics		
Effect of 10 percentage point increase in % of patients saying they can typically get an appointment at GP practice	0.87*** (0.83, 0.90)	-0.79*** (-0.97, -0.61)
Effect of 10 additional FTEs at GP practice	0.99*** (0.99, 0.99)	-.03*** (-.04, -.03)
Call characteristics		
Call received clinical input (vs no input)	0.52*** (0.51, 0.53)	-3.65*** (-3.76, -3.54)
Call duration in minutes	0.99*** (0.99, 0.99)	-0.02*** (-0.02, -0.02)
Bank holiday	0.83*** (0.81, 0.84)	-0.09*** (-0.10, -0.08)
Christmas period (Dec 24-26)	1.03* (1.00, 1.06)	0.13 (-0.02, 0.27)
Additional controls?	Yes	Yes
Baseline	0.059/1	5.6%
Goodness of fit	AUC = 0.70	R^2 = 3.4%

Observations	10,954,783	10,954,783

Additional controls = hour of day, day of week, month of year, year, region of England, 111 site, and disposition code assigned to the call.
* $p < .05$, ** $p < .01$, *** $p < .001$.

Gradient-boosting model

We next tested whether we could improve our ability to predict which 111 calls would result in avoidable ED attendances by running a gradient boosted tree model (GBM).[25] We built the GBM using a training subset of the data (a random selection of 80% of the 10,954,783 rows) and evaluated its out-of-sample predictions using a test subset (the remaining 20% of rows).

As a test of the GBM's incremental accuracy, we applied the same train-test procedure with the logistic regression model described in Table 1, and compared the predictive ability of the two models using an area-under-curve (AUC) score. We found the AUC was 0.70 for the logistic regression and 0.73 for the GBM (note that a model which randomly guesses the outcome would have an AUC of 0.5 and a model which makes perfect predictions would have an AUC of 1.0). This implies that the ability of the GBM to automatically find nonlinear relationships and interactions did result in (slightly) more accurate predictions about which 111 callers would end up making avoidable ED attendances. However, even the GBM did not reach very high levels of predictive accuracy (as would be indicated by an AUC score of 0.80 or higher).

Table 2 shows the next result from the GBM — a quantification of the relative importance of the different types of variables in our analysis, in terms of the proportion of the overall predictive power (measured in terms of deviance, a generalised notion of residual sum of squares) they explained. Of the variation which we could explain, 91% was accounted for by a combination of the call characteristics, geographic characteristics, and temporal characteristics, and the remaining 9% was explained by patient-level and GP-practice characteristics.

Table 2. Decomposition of the relative importance of different characteristics in predicting avoidable ED attendances after a 111 call.

	Proportion of explainable deviance in the outcome measure captured by variable type
Call characteristics	**51.5%**
NHS Pathways disposition assigned to 111 call	*42.7%*
Call duration	*7.7%*

Clinical input	*1.1%*
Geographic characteristics	**25.6%**
111 site	*17.1%*
Region of England	*4.4%*
Distance from caller's home to hospital	*2.7%*
Index of multiple deprivation	*1.1%*
Caller from rural (vs urban) area	*0.5%*
Temporal characteristics	**13.9%**
Hour of day	*7.4%*
Month of year	*3.4%*
Day of week	*2.0%*
Year	*0.8%*
Bank holiday	*0.2%*
Christmas	*0.1%*
Patient characteristics	**4.6%**
Patient aged 0-4 (vs all other ages)	*2.6%*
Female (vs male) patient	*2.0%*
GP practice characteristics	**4.4%**
Number of FTE employees	*2.5%*
Ease of getting appointment	*1.9%*

Finally, we used the GBM's predictions to classify the calls into different risk categories. For every 1000 triaged calls, we classified:

- 558 as low-risk (<5% predicted probability of avoidable ED attendance), of which 15 (2.6%) resulted in an avoidable ED attendance,
- 328 as medium-risk (5%–10% predicted probability of avoidable ED attendance), of which 23 (7.0%) resulted in an avoidable ED attendance, and
- 114 as high-risk (>10% predicted probability of avoidable ED attendance), of which 19 (16.2%) resulted in an avoidable ED attendance.

Using this (somewhat arbitrary) classification, high-risk calls were 6.2 times more likely than low-risk calls to result in avoidable ED attendances (although a large majority of even the high-risk calls did not result in these attendances).

Discussion

Our analysis of the largest yet published dataset of linked 111 calls and subsequent ED attendances found that, of patients not advised by 111 to go to ED, around 1 in 20 (5.4%) made an avoidable Type 1 ED attendance within 24 hours of the call. Although our analysis could not answer the counterfactual of "would overall avoidable ED attendances be higher or lower if the 111 service did not exist?", this finding does at least suggest that 111 is not causing a large fraction of callers to inappropriately seek treatment at the ED.

The key strengths of this study were: our use of a national-level dataset containing over 16 million calls to 111 (47% of the total number of 111 calls made over the study period); our use of an extensive set of covariates known to be predictive of avoidable ED attendances, and; our combination of both conventional (OLS, logistic regression) and cutting-edge (GBM) analytic techniques. One of our key findings – that calls which received clinical input were much less likely to result in avoidable ED attendance – replicated the same association found in the only other paper to date examining linked 111-ED data.[26] Key limitations included lack of controls for other characteristics likely predictive of health behaviour (e.g. patients' education, risk aversion, and health history), and the fact that the data did not record interactions patients may have had with 111 soon after their initial call (e.g. a 111 call-handler could have arranged for the patient to receive a call-back from a clinical advisor or out-of-hours GP within a few hours of their initial call, but this subsequent call would not be recorded in the data we examined).

After adjusting for the full set of covariates, which included information about the time, duration and location of the call, the age and gender of the caller, and the caller's GP practice, we classified calls into low-, medium-, and high-risk for avoidable ED attendance, and found that high-risk calls were 6 times more likely than low-risk ones to result in avoidable attendances. This suggests that it may be possible to use existing data resources to construct a tool which helps 111 call-handlers identify callers at high risk of these attendances — similar to how traffic light systems are used to identify gradations of risk in other health assessments.[27] Call handlers could then provide extra resource for these calls (e.g. spend more time providing self-care instructions or assistance securing a GP appointment).

Future research could seek to replicate and expand our analysis as more and more linked data becomes available. Given that our analysis included only 47% of 111 calls made in the examined time period, it is possible that selection effects may be distorting our own findings (e.g. perhaps 111 sites with lower avoidable attendance rates were more likely to provide their data to NHS Digital). Future work could also aim to test whether avoidable attendance rates could be reduced by providing a traffic light warning system for 111 call handlers, or by providing regular feedback to individual call-handlers or 111 sites about the avoidable attendance rate associated with their calls.

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Author contributions. HB conceived the study and designed it with help from ME. ME and FM wrote the first draft of the paper. All authors assisted in the interpretation of data and creation of the final draft. ME is the guarantor.

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Data sharing statement. The linked 111-ED data was provided by NHS England to the authors for the purposes of this study. Under this agreement the authors do not have permission to share the dataset.

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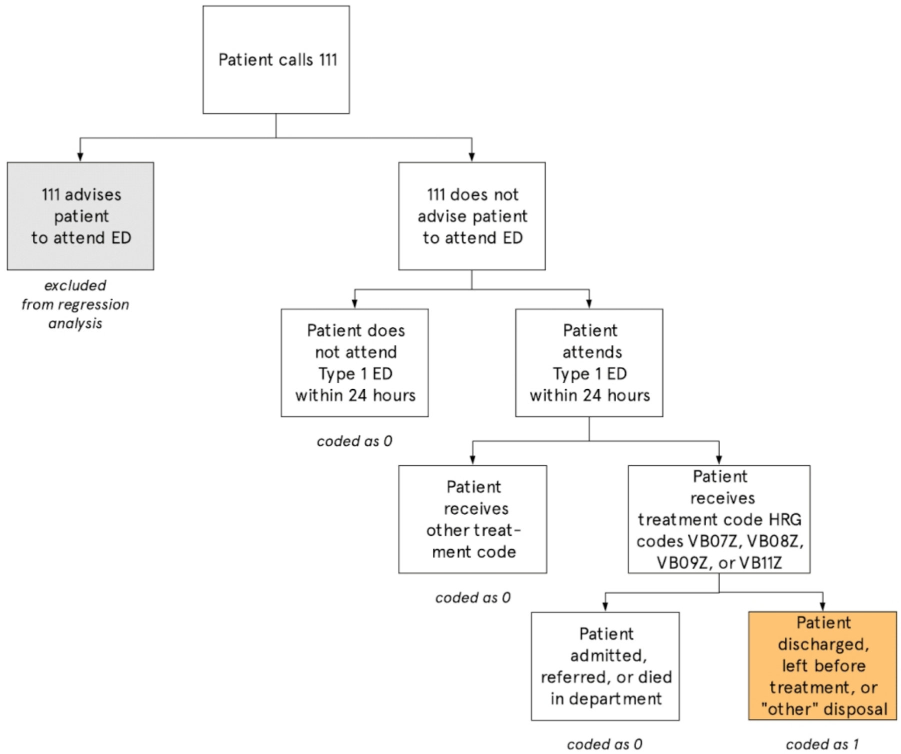

Figure 1. How the outcome measure was coded.

564x480mm (72 x 72 DPI)

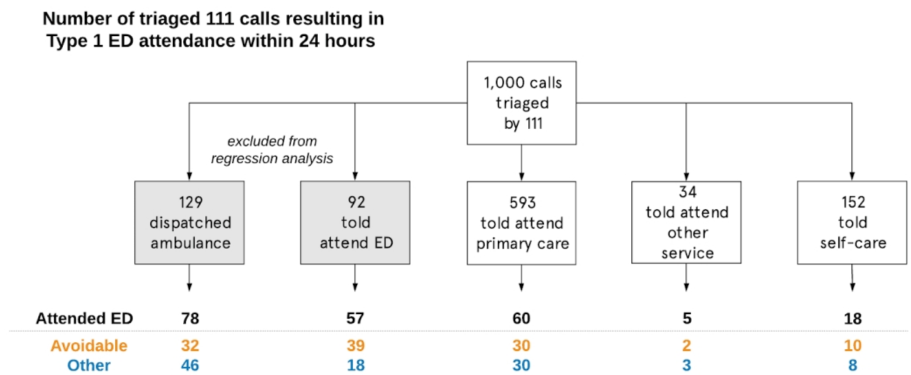

Figure 2. Outcomes of 16,563,946 calls made to 111 from March 2015 to October 2017. For ease of interpretation the total number of calls has been normalised to 1,000.

564x265mm (72 x 72 DPI)

Table S1. Descriptive statistics for selected control variables.

Variable (min-max)	Observations	Mean (SD) / %
Patient characteristics		
Age (0-110)	16,563,946	37.7 (27.9)
Gender	16,563,946	100%
Male	7,003,057	42.3%
Female	9,560,889	57.7%
IMD quintile (1-5)	15,690,550	3.2 (1.4)
Ratio distance of nearest hospital to nearest GP (0.4 - 44.6)	16,256,118	4.1 (2.4)
Type of area	15,707,810	100%
Urban	13,535,244	86.2%
Rural	2,172,566	13.8%
Region	15,690,550	100%
North	5,822,600	37.1%
South & East	2,144,612	13.7%
Midlands	5,129,125	32.7%
London	2,594,213	16.5%
GP practice characteristics		
% patients typically able to get an appointment per practice (39.9%-100%)	15,629,833	84.0%
Number of FTEs per practice (0.02-34.1)	14,877,337	5.6 (3.7)
Call characteristics		

Call had clinical input (yes=1, no=0)	16,563,946	21.6%
Call duration in minutes (0-189.7)	16,563,946	15.4 (22.6)

STROBE 2007 (v4) checklist of items to be included in reports of observational studies in epidemiology*
Checklist for cohort, case-control, and cross-sectional studies (combined)

Section/Topic	Item #	Recommendation	Reported on page #
Title and abstract	1	(*a*) Indicate the study's design with a commonly used term in the title or the abstract	1
		(*b*) Provide in the abstract an informative and balanced summary of what was done and what was found	1
Introduction			
Background/rationale	2	Explain the scientific background and rationale for the investigation being reported	2
Objectives	3	State specific objectives, including any pre-specified hypotheses	3
Methods			
Study design	4	Present key elements of study design early in the paper	3
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection	3
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	4
		(*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	
Variables	7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable	4
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	4, 5
Bias	9	Describe any efforts to address potential sources of bias	4
Study size	10	Explain how the study size was arrived at	3
Quantitative variables	11	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen and why	4, 5
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	8
		(*c*) Explain how missing data were addressed	3
		(*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	
		(*e*) Describe any sensitivity analyses	-
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	3
		(b) Give reasons for non-participation at each stage	-
		(c) Consider use of a flow diagram	4
Descriptive data	14*	(a) Give characteristics of study participants (eg demographic, clinical, social) and information on exposures and potential confounders	Table S1
		(b) Indicate number of participants with missing data for each variable of interest	Table S1
		(c) *Cohort study*—Summarise follow-up time (eg, average and total amount)	-
Outcome data	15*	*Cohort study*—Report numbers of outcome events or summary measures over time	
		Case-control study—Report numbers in each exposure category, or summary measures of exposure	
		Cross-sectional study—Report numbers of outcome events or summary measures	5, 6
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	6, 7
		(*b*) Report category boundaries when continuous variables were categorized	7
		(*c*) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period	7
Other analyses	17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses	8, 9
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	10
Interpretation	20	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence	10
Generalisability	21	Discuss the generalisability (external validity) of the study results	10
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	12

*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.

BMJ Open

Identifying the predictors of avoidable emergency department attendance after contact with the NHS 111 phone service: Analysis of 16.6 million calls to 111 in England in 2015-17

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Title

Identifying the predictors of avoidable emergency department attendance after contact with the NHS 111 phone service: Analysis of 16.6 million calls to 111 in England in 2015-17

Authors

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Abstract

Objectives: To measure the frequency of patients making avoidable emergency department (ED) attendances after contact with NHS 111, and to examine whether these attendances can be predicted reliably.

Design: Analysis of 16,563,946 calls made to 111, where each call was linked with a record of whether the patient attended ED within 24 hours.

Setting: All regions of England from March 2015 to October 2017.

Participants and data: Our main regression model used a sample of 10,954,783 calls, each with detailed patient-level information.

Main outcome: Whether patients made an unadvised, nonurgent Type 1 ED ("avoidable") attendance within 24 hours of calling 111.

Results: Of 16,563,946 calls to 111, 12,894,561 (77.8%) were not advised to go to ED (i.e. they were advised to either attend primary care, attend another non-ED healthcare service, or to self care). Of the calls where the patient was not advised to go to the ED, 691,783 (5.4%) resulted in the patient making an avoidable ED attendance within 24 hours.

Among other factors, calls were less likely to result in these attendances when they received clinical input (adjusted odds ratio [OR] 0.52, 95% CI 0.51-0.53), but were more likely when the patient was female (OR 1.07, 95% CI 1.06-1.08) or aged 0-4 (OR 1.34, 95% CI 1.33-1.35).

Conclusions: For every 20 calls where 111 did not advise people to attend the ED, 1 resulted in avoidable ED attendance within 24 hours. These avoidable attendances could be predicted, to a certain extent, based on call characteristics. It may be possible to use this information to help 111 call-handlers identify which callers are at higher risk of these attendances.

Strengths and limitations of this study

- The analysis relies on a large national-level dataset containing 47% of all 111 calls in England in the study period
- It adjusts for a large set of covariates known to be predictive of avoidable ED attendances.
- However, other potentially important predictors of health behaviour, such as health history or other interactions with healthcare providers, were not available in the data.
- We conducted both a conventional (OLS and logistic) regression and a predictive (gradient-boosting) analysis.

Introduction

9.7 million (50%) of the 19.4 million attendances made at hospital emergency departments (EDs) in England in 2016-17 resulted in the patient receiving either no treatment, or advice and guidance only. [1] This incurred a total cost to the NHS of over £500 million, at a time when "*pressures on the NHS are greater than they have ever been*" (see Supplement A for the derivation of these figures).[2,3] The low-intensity care received by these patients suggests at least some could have been treated safely elsewhere (e.g. GP practice, pharmacy, or at home), at lower cost to the healthcare system.

One way to potentially reduce the number of nonurgent ED attendances is by encouraging greater use of the 111 service. NHS 111 is a free, non-emergency healthcare telephone line in Britain which aims to ensure that callers are seen at the "*right place, first time.*"[4] Call-handlers for the 111 service assess callers' health problems using a clinically-validated triage algorithm ('NHS Pathways'),[5] then either dispatch an ambulance or recommend the caller attend ED, or advise the caller to go to primary care, attend another healthcare service, or to self-care.

Given that 111 received 16 million calls in England in 2017-18,[6] the service is well-placed to direct large numbers of patients with nonurgent health problems to seek treatment outside the ED. However, it is not clear how often calls produce this result in practice. An evaluation of 111 in its first year of operation found it had no statistically significant impact on ED attendance rates.[7] More recent work has found that the Pathways algorithm may recommend ED attendance more often than necessary,[8] and that some 111 staff believe the service has increased the number of nonurgent calls compared to previous out-of-hours primary care services.[9]

Although there have been several big-data studies examining the predictors of nonurgent ED attendance rates in England,[10,11,12] it has only recently become possible to do large-scale analysis of linked 111/ED data (i.e. data which links individual 111 calls with a record of whether that caller went on to attend ED).[13] This linked data makes it possible to examine how often patients end up making nonurgent ED attendances after calling

111. To date, one other study has been published using this linked data: it examined a dataset of 10,356 callers across three areas of North West London and found that 15% of callers advised by 111 to manage their health needs at home attended an ED within 10 hours (this rate was lower when patients were given GP out-of-hours appointments or when the 111 call received input from a clinical supervisor).[14]

This study uses a national-level linked 111-ED dataset to examine how often 111 callers end up making unadvised, nonurgent Type 1 (henceforth 'avoidable') ED attendances within 24 hours of their call, and to examine the predictors of these attendances. We do this using a dataset of 16,563,946 calls made to 111 from March 2015 to October 2017, where each call contained patient-level information and a record of whether the patient attended ED within 24 hours.

Methods

Study design. The data initially contained 18,127,605 observations, where each row was a call made to 111 between 31 March 2015 and 31 October 2017. This represents almost half (47%) of the 38,585,200 million calls made to 111 between March 2015 and October 2017.[6] We were not able to access the full universe of calls as data from some 111 sites had not yet undergone the data linkage procedures necessary for inclusion in the analysis. For this same reason, we were not able to access calls outside the stated time period." Each call was linked with a Secondary Use Services (SUS) record of whether the patient attended ED within 24 hours of the 111 call. This linkage was conducted by researchers at NHS England and patients' NHS number was used as the matching variable. We used logistic and ordinary least squares (OLS) regressions and a gradient boosted decision tree model to assess the extent to which we could predict whether the call would result in an avoidable ED attendance within 24 hours. All analyses were performed in Stata 14 and R 3.5.0. The analysis was considered exploratory and consequently did not examine pre-specified hypotheses.

Data cleaning. We excluded rows missing the date / time of the 111 call (n = 52,394), final disposition code (n = 878,461), which had disposition codes[15] indicating the call was not relevant to our research question (n = 167,182), missing patient's gender (n = 246,144), missing patient age or where age was over 110 years (n = 46,656), and calls whose duration was above the 99th percentile (more than 190 minutes) as these were presumed to be data errors (n = 172,822). Note that the following final disposition at the end of 111 (recorded using 'Dx' codes) were considered irrelevant to the research question: Dx78 ("Receive Report of Results or Tests from Laboratory"), Dx83 ("Clinician Home Management of Dying Individual (Expected)"), Dx91 ("Unexpected Death"), Dx95 ("The Call is Closed with No Further Action Required, Wrong Service Called"), Dx116 ("Speak to the Primary Care Service within 6 hours for Expected Death"), and Dx117 ("Speak to a Primary Care Service within 1 hour for Palliative Care").

This reduced the sample to 16,563,946 triaged calls, from which we produced descriptive statistics. Our main regression model used a smaller sample of 10,954,783 calls, as this retained only rows with complete information on the outcome measure and all control variables. Comparing the former and the latter samples, we saw a slight increase in the mean value of the outcome variable (from 5.4% to 5.6%), the proportion of calls between midnight and 4 am (a 5.2% relative increase), the proportion of calls that received clinical input (a 6.1% increase), the proportion of calls that happened on a bank holiday and in the Christmas period (6.3% and 5.8%, respectively), and a decrease in the proportion of calls from patients based in London (a 12.5% decrease); all other relative changes were smaller than 3.0%. The regression sample is therefore very similar to the sample used for descriptive statistics, with a small number of notable deviations. Missing-data imputation was not performed due to computational infeasibility, given the size of the dataset.

Outcome measure. Our outcome measure was a binary indicator of whether a patient made an avoidable ED attendance within 24 hours of calling 111. Figure 1 shows how we coded the outcome measure. We defined an ED attendance as "avoidable" if, after being told by 111 to do something other than go to the ED, the patient attended ED within 24 hours and was assigned Healthcare Resource Group (HRG) treatment codes VB07Z ("*category 2 investigation with category 2 treatment*"), VB08Z ("*category 2 investigation with category 1 treatment*"), VB09Z ("*category 1 investigation with category 1-2 treatment*"), or VB11Z ("*no investigation with no significant treatment*"),[16] and was not admitted, not referred to another healthcare specialist by the ED, and did not die in the ED department. These HRG codes represent relatively low-intensity health assessments and were therefore considered more likely to capture attendances which could have been safely treated elsewhere - with the caveat that it is not certain that all these attendances should certainly not have attended the ED (e.g. some patients may have attended the ED at the explicit instruction of a healthcare professional, even though they ended up receiving low intensity treatment). This particular list of HRG codes was adapted from those used in a 2017 study by the North of England Commissioning Support Unit which also examined avoidable admissions.[17]

Figure 1. How the outcome measure was coded.

[figure 1]

Control measures. Our analysis used 18 control variables, shown in past research to be important predictors of ED attendance in England, which fell into five broad categories:

- *2 patient characteristics:* (i) a continuous measure of patient age and (ii) a binary measure of patient gender.
- *5 geographic characteristics:* (iii) a binary indicator of whether the patient was from a rural vs urban area, [18] (iv) a categorical variable identifying what region of England the patient was from (North, Midlands, South & East, or London), (v) the distance ratio between the patient's local area and the nearest ED relative to a GP (included under the assumption that a patient's decision to see a GP or go to the

ED is likely to be influenced by the relative ease of accessing these two locations), (vi) the deprivation of the patient's local area (measured in quintiles using 2015 indices of multiple deprivation scores), and (vii) a categorical indicator of which of the 40 different 111 sites present in the data handled the call, to account for any unobserved variation in the way different 111 sites interact with patients. [19]

- 2 *GP practice characteristics:* For each GP practice in the data, which was recorded at the individual-patient level, we included (viii) a variable from the GP Patient Survey which recorded the proportion of patients saying "*Yes*" or "*Yes, but I had to call back closer to or on the day I wanted the appointment*" in response to "*Were you able to get an appointment to see or speak to someone?*". We also (ix) included an indicator of the number of full-time-equivalent (FTE) GPs at each practice. [20]
- *3 call characteristics:* (x) duration of the 111 call in minutes, (xi) a binary variable indicating whether the call had clinical input from a doctor, nurse, or other clinician (21% of calls did involve the patient speaking to a healthcare professional like this), and (xii) which of the 96 NHS Pathways disposition codes the patient was assigned at the end of the call.
- 6 *temporal characteristics:* Using the date and time the call was made to 111, we constructed variables for (xiii) hour of the day, (xiv) day of week, (xv) month, (xvi) year (2015, 2016, or 2017), and binary indicators for whether the day was a (xvii) bank holiday, or (xviii) spanned the December 24-26 period.

The distance ratio, i.e. variable (v) was calculated as the average travel time by public transport and/or walking to the nearest hospital relative to the nearest GP and included under the assumption that a patient's decision to see a GP or go to the ED is likely to be influenced by the relative ease of accessing these two locations.[21,22]

Deprivation, i.e. variable (vi), was measured using 2015 indices of multiple deprivation (IMD) scores, which were matched to patients' local areas using their LSOA code. While deprivation is typically measured using the aggregate IMD score compiled from 7 different subdomain measures (e.g. deprivation for income, deprivation for health, deprivation for employment, etc), it is not entirely appropriate to use this aggregate measure when predicting ED attendance. This is because the health score, which comprises 13.5% of the total IMD score, itself incorporates local ED attendance rates as a measure of local health deprivation.[23] This sort of mathematical coupling (i.e. using a score which includes ED attendances to predict ED attendances) can lead to spurious correlations in statistical assessment. We therefore followed an established procedure to construct an alternative aggregate IMD score which excluded the health domain but retained the other six deprivation domains.[24]

Ease of securing a GP appointment, i.e. variable (viii) relied on the GP Patient Survey (GPPS), which is a questionnaire sent to users of GP practices. It asks people to rate the performance of their GP practice on dimensions such as quality of care, satisfaction with opening hours, and a subjective assessment of how easy it is to get an appointment. We retained only data for GP practices who had received at least 50 responses to these questionnaires. In order to maximise sample size, we took the average score for the GP characteristic variables across the three GPPS waves published in January 2016, July 2016, and July 2017.[25]

The disposition code variable (xii) indexed 96 different disposition codes present in the data which contained at least 30 observations. These codes used the standard "Dx" coding format (e.g. "Dx14 = Speak to a Primary Care Service within 12 hours") used by the 111 services.[15] These disposition codes were the ones recorded by the call handler or clinical advisor who initially managed the 111 call, but in some cases, patients will have gone on to have further interactions with the 111 service after this disposition was assigned. For example, they may have received a call-back from another healthcare professional, who may have assigned them a different disposition.

Detailed descriptive statistics for each of the control variables can be found in table S1 in Supplement B.

Our regression specification consisted of a linear combination of all the control variables and did not include any interactions or transformations.

Patient and Public Involvement. Patients were not involved in the design of this study as it involved only observational analysis of an anonymised, pre-existing, routinely-collected dataset..

Results

Descriptive statistics

Figure 2 shows the ED outcomes of 16,563,946 calls in the data, broken down by NHS Pathways disposition assigned at the end of the call, and with the original number of calls normalised to 1000 for ease of interpretation. For every 1000 callers, 779 were not advised by 111 to attend ED (i.e. they were told to attend primary care, attend another service, or self-care). Of these, 83 went on to make a Type 1 ED attendance anyway within 24 hours. Of these, 42 were classified as avoidable. Stated differently, for calls where patients were not advised to attend ED, 5.4% resulted in avoidable ED attendances within 24 hours.

Figure 2. Outcomes of 16,563,946 calls made to 111 from March 2015 to October 2017. For ease of interpretation the total number of calls has been normalised to 1,000.

[figure 2.png]

Avoidable = Patient got Healthcare Resource Group (HRG) treatment code VB07Z ("*category 2 investigation with category 2 treatment*"), VB08Z ("*category 2 investigation with category 1 treatment*"), VB09Z ("*category 1 investigation with category 1-2 treatment*"), or VB11Z ("*no investigation with no significant treatment*"), and was not admitted, not referred to another healthcare specialist by the ED, and did not die in the ED department.

Regression analyses

Table 1 shows the results of our logistic and OLS regression analyses. Column 1 shows exponentiated logistic regression coefficients, which can be interpreted as odds ratios. Column 2 shows the coefficients of an OLS regression (i.e. a linear probability model) with the same specification – although problematic, as it violates the assumption of non-negative probabilities, it provides a more easily interpretable way of assessing the strengths of the observed associations.

Notable results include that calls were 3.65 percentage points (95% CI -3.76, -3.54) less likely to result in avoidable attendances (relative to a baseline of 5.6%) when the call had clinical input, and 0.8 points less likely (95% CI -1.0, -0.6) when the caller was registered with a GP practice where it was easier than other practices to get an appointment. Calls were 0.34 points more likely to result in these attendances when the patient was female (95% CI 0.31-0.37), 1.72 points more likely when the patient was aged 0-4 (95% CI 1.68-1.75), and 0.17 points more likely when the patient lived in a more deprived area (95% CI 0.16-0.18).

Table 1. Summary results of the association between 111 call characteristics and the probability of making an avoidable Type 1 ED attendance within 24 hours.

	Column 1	Column 2
Variable	**Logistic regression, odds ratios (95% CI)**	**OLS regression, percentage point changes (95% CI)**
Patient characteristics		
Patient aged 0-4 (vs all other ages)	1.34*** (1.33, 1.35)	1.72*** (1.68, 1.75)
Female (vs male) patient	1.07*** (1.06, 1.08)	0.34*** (0.31, 0.37)
Geographic characteristics		
Quintile of area deprivation (1 = least deprived, 5 = most deprived)	1.03*** (1.03, 1.03)	0.17*** (0.16, 0.18)
Patient's distance to hospital relative to GP	1.00 (1.00, 1.00)	0.00 (-0.01, 0.01)
Patient in rural (vs urban) area	0.91*** (0.90, 0.92)	-0.44*** (-0.48, -0.40)

GP practice characteristics		
Effect of 10 percentage point increase in % of patients saying they can typically get an appointment at GP practice	0.87*** (0.83, 0.90)	-0.79*** (-0.97, -0.61)
Effect of 10 additional FTEs at GP practice	0.99*** (0.99, 0.99)	-.03*** (-.04, -.03)
Call characteristics		
Call received clinical input (vs no input)	0.52*** (0.51, 0.53)	-3.65*** (-3.76, -3.54)
Call duration in minutes	0.99*** (0.99, 0.99)	-0.02*** (-0.02, -0.02)
Bank holiday	0.83*** (0.81, 0.84)	-0.09*** (-0.10, -0.08)
Christmas period (Dec 24-26)	1.03* (1.00, 1.06)	0.13 (-0.02, 0.27)
Additional controls?	Yes	Yes
Baseline	0.059/1	5.6%
Goodness of fit	AUC = 0.70	R^2 = 3.4%
Observations	10,954,783	10,954,783

Additional controls = hour of day, day of week, month of year, year, region of England, 111 site, and disposition code assigned to the call.
* $p < .05$, ** $p < .01$, *** $p < .001$.

Predictive modelling

We next tested whether we could improve our ability to predict which 111 calls would result in avoidable ED attendances by running a gradient boosted tree model (GBM).[26] A GBM models the outcome measure as the result of a series of decision trees. Each tree attempts to identify areas where the others make poor predictions and correct for that, resulting in strong predictive performance even in the presence of complex nonlinear relationships or interactions between the predictors and the outcome (a situation in which other techniques such as OLS may not perform so well). It is one of the best-performing predictive algorithms for tabular data.[27] We built the GBM using a training subset of the data (a random selection of 80% of the 10,954,783 rows) and evaluated its out-of-sample predictions using a test subset (the remaining 20% of rows).

As a test of the GBM's incremental accuracy, we applied the same train-test procedure with the logistic regression model described in Table 1, and compared the predictive ability of the two models using an area-under-curve (AUC) score. We found the AUC was 0.70 for the logistic regression and 0.73 for the GBM (note that a model which randomly guesses the outcome would have an AUC of 0.5 and a model which makes perfect predictions would have an AUC of 1.0). This surprisingly small improvement implies that the ability of the GBM to automatically find nonlinear relationships and interactions resulted in only slightly more accurate predictions about which 111 callers would end up making avoidable ED attendances, and still felt short of reaching very high levels of predictive accuracy (as would be indicated by an AUC score of 0.80 or higher).

Table 2 shows the next result from the GBM — a quantification of the relative importance of the different types of variables in our analysis. The importance of a variable is defined as the improvement in log likelihood which is attributable to each decision (in the decision trees) made using that variable. These are then renormalised to sum to 100%, to give the relative importance. Of the variation which we could explain, 91% was accounted for by a combination of the call characteristics, geographic characteristics, and temporal characteristics, and the remaining 9% was explained by patient-level and GP-practice characteristics.

Table 2. Decomposition of the relative importance of different characteristics in predicting avoidable ED attendances after a 111 call.

	Proportion of explainable deviance in the outcome measure captured by variable type
Call characteristics	**51.5%**
NHS Pathways disposition assigned to 111 call	*42.7%*
Call duration	*7.7%*
Clinical input	*1.1%*
Geographic characteristics	**25.6%**
111 site	*17.1%*
Region of England	*4.4%*
Distance from caller's home to hospital	*2.7%*
Index of multiple deprivation	*1.1%*
Caller from rural (vs urban) area	*0.5%*
Temporal characteristics	**13.9%**
Hour of day	*7.4%*

Month of year	*3.4%*
Day of week	*2.0%*
Year	*0.8%*
Bank holiday	*0.2%*
Christmas	*0.1%*
Patient characteristics	**4.6%**
Patient aged 0-4 (vs all other ages)	*2.6%*
Female (vs male) patient	*2.0%*
GP practice characteristics	**4.4%**
Number of FTE employees	*2.5%*
Ease of getting appointment	*1.9%*

Finally, we used the GBM's predictions to classify the calls into different risk categories. For every 1000 triaged calls, we classified:

- 558 as low-risk (<5% predicted probability of avoidable ED attendance), of which 15 (2.6%) resulted in an avoidable ED attendance,
- 328 as medium-risk (5%–10% predicted probability of avoidable ED attendance), of which 23 (7.0%) resulted in an avoidable ED attendance, and
- 114 as high-risk (>10% predicted probability of avoidable ED attendance), of which 19 (16.2%) resulted in an avoidable ED attendance.

Using this (somewhat arbitrary) classification, high-risk calls were 6.2 times more likely than low-risk calls to result in avoidable ED attendances (although a large majority of even the high-risk calls did not result in these attendances).

Discussion

Our analysis of the largest yet published dataset of linked 111 calls and subsequent ED attendances found that, of patients not advised by 111 to go to ED, around 1 in 20 (5.4%) made an avoidable Type 1 ED attendance within 24 hours of the call. Using the NHS national tariff charges present in the data for each ED attendance, we estimate that these avoidable attendances incurred tariff costs of £65 million (£2.1 million per month) over the March 2015 to October 2017 period covered in our data. If we extrapolate this 5.4% incidence rate of avoidable attendances to all 38,585,200 calls made to 111 between March 2015 and October 2017 (i.e. including calls not in our data), this implies £58.8m in tariff charges were incurred per year by avoidable ED attendances. The cost to the NHS as a whole, however, is likely smaller than this, since patients who do not visit a Type 1 ED may instead attend another (albeit potentially cheaper) part of the healthcare system.

Although our analysis could not answer the counterfactual of "would overall avoidable ED attendances be higher or lower if the 111 service did not exist?", our findings do at least suggest that relatively few 111 patients end up making unadvised attendances at ED which could likely have been safely treated elsewhere. However, Figure 2 also found that a surprisingly large proportion of patients who were advised by 111 to attend the ED did nonetheless end up receiving low-intensity treatment (such that even these attendances were classified as 'avoidable' as defined in this study). Clarifying the precise nature of these 'advised and avoidable' attendances was outside the scope of this study but warrants further investigation.

The key strengths of this study were: our use of a national-level dataset containing over 16 million calls to 111 (47% of the total number of 111 calls made over the study period); our use of an extensive set of covariates known to be predictive of avoidable ED attendances, and; our combination of both conventional (OLS, logistic regression) and cutting-edge (GBM) analytic techniques. One of our key findings – that calls which received clinical input were much less likely to result in avoidable ED attendance – replicated the same association found in the only other paper to date examining linked 111-ED data.[28] Key limitations included the relatively crude criteria we used to define ED attendances as 'avoidable' (i.e. this relied principally on post-hoc ED disposition codes and did not incorporate any clinical notes which could have provided more nuanced information about the patient's health issue), our lack of controls for other characteristics likely predictive of health behaviour (e.g. patients' education, risk aversion, and health history), and the fact that the data did not record interactions patient may have had with 111 soon after their initial call (e.g. a 111 call-handler could have arranged for the patient to receive a call-back from a clinical advisor or out-of-hours GP within a few hours of their initial call, but this subsequent call would not be recorded in the data we examined).

After adjusting for the full set of covariates, which included information about the time, duration and location of the call, the age and gender of the caller, and the caller's GP practice, we classified calls into low-, medium-, and high-risk for avoidable ED attendance, and found that high-risk calls were 6 times more likely than low-risk ones to result in avoidable attendances. This suggests that it may be possible to use existing data resources to construct a tool which helps 111 call-handlers identify callers at high risk of these attendances — similar to how traffic light systems are used to identify gradations of risk in other health assessments.[29] Call handlers could then provide extra resource for these calls (e.g. spend more time providing self-care instructions or assistance securing a GP appointment).

In terms of practical implications of this research, we suggest that analysis of newer editions of the dataset examined in this report could be used to (i) provide tailored feedback to individual 111 call handlers and local leaders of 111 services regarding the proportion of their calls which result in avoidable ED attendance soon afterwards, and (ii) communicating which calls are at high-risk of an avoidable ED attendance (e.g. potentially using a traffic-light warning system where red warnings are used to identify high-risk calls) to 111 call-handlers, who could then provide extra resource for these patients (e.g. by spending extra time providing self-care instructions or guidance on how best to secure a GP appointment).

Future research could seek to replicate and expand our analysis as more and more linked data becomes available. Given that our analysis included only 47% of 111 calls made in the examined time period, it is possible that selection effects may be distorting our own findings (e.g. perhaps 111 sites with lower avoidable attendance rates were more likely to provide their data to NHS Digital). Future work could also aim to test whether avoidable attendance rates could be reduced by providing a traffic light warning system for 111 call handlers, or by providing regular feedback to individual call-handlers or 111 sites about the avoidable attendance rate associated with their calls.

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Author contributions. HB conceived the study and designed it with help from ME. ME and JL designed the analytical strategy. ME and FM performed the analysis and wrote the first draft of the paper. All authors assisted in the interpretation of data and creation of the final draft. ME is the guarantor.

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Competing interests. None.

Ethics approval. The study was approved by both the Health Research Authority's London - Fulham Research Ethics Committee (REC reference 17/LO/1569) and Confidentiality Advisory Group (CAG reference 17/CAG/0159).

Data availability statement. The data are records of 111 calls linked with Secondary Use Services (SUS) records of whether each patient attended ED within 24 hours of the call. Inquiries regarding data access should be made to the Data Services for Commissioners, Operations and Information, NHS England (england.dataservces@nhs.net).

Disclaimer. This is an independent report commissioned and funded by NHS England. The views expressed are not necessarily those of NHS England.

Word count: 4594

Keywords: 111 service, emergency department, avoidable visits, predictive analysis

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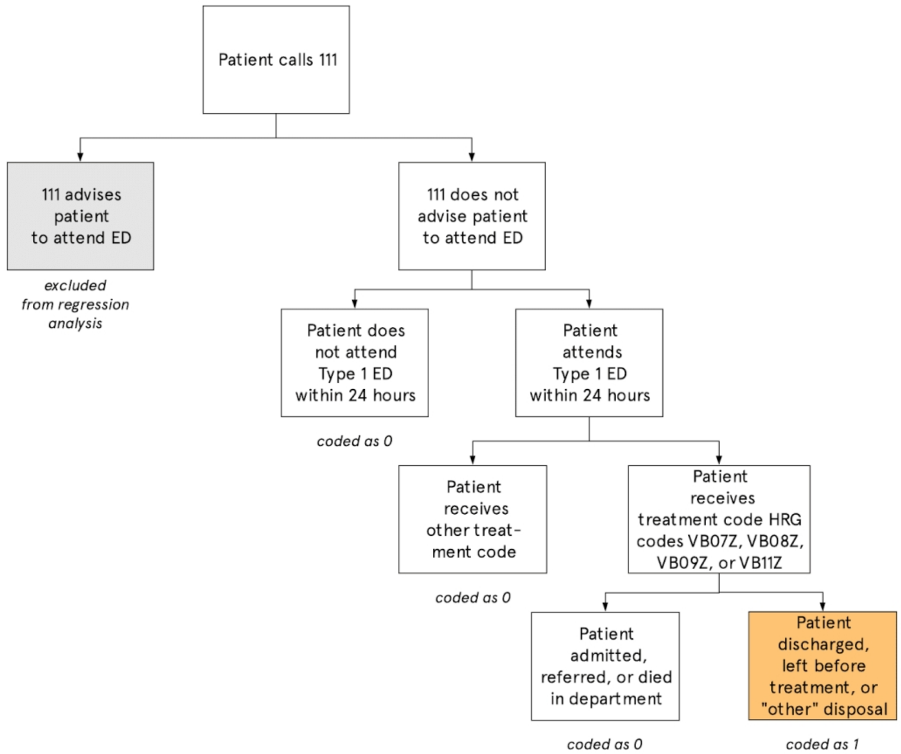

Figure 1. How the outcome measure was coded.

564x480mm (72 x 72 DPI)

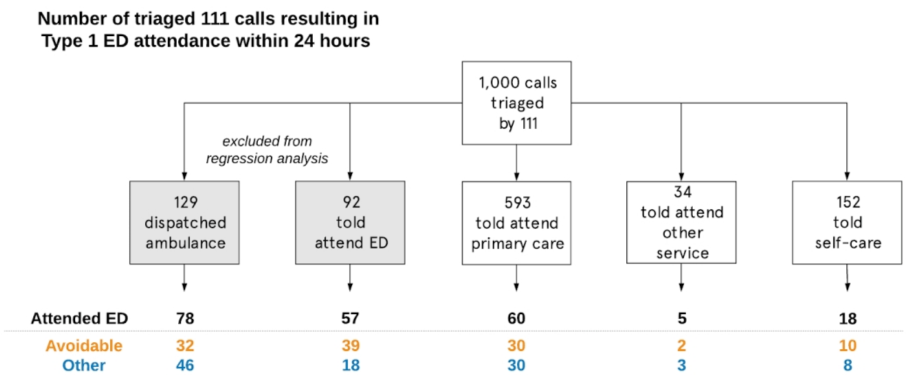

Figure 2. Outcomes of 16,563,946 calls made to 111 from March 2015 to October 2017. For ease of interpretation the total number of calls has been normalised to 1,000.

564x265mm (72 x 72 DPI)

Supplement A: Derivation of figures reported in the Introduction

The 9.7 million figure includes only attendances with valid ED treatment records and includes attendances at both major consultant-led departments (Types 1 and 2) Minor Injury Units and Walk-in Centres (Types 3 and 4). The 50% figure is calculated by summing the rows "Guidance/advice only" and "None (consider guidance/advice option)" in Table 19 in https://files.digital.nhs.uk/publication/e/7/acci-emer-atte-eng-2016-17-data.xlsx. Similarly, Table 17 in the same dataset records that, among the 19.6 million attendances in 2016-17 with valid investigation records, the first investigation recorded for 8 million of them (41%) of them was 'None'.

The '£500 million' figure was obtained thus: ED attendances requiring "No investigation with no significant treatment" cost £57 each in 2016/17. Multiplying £57 by the 9,662,456 nonurgent attendances with valid ED treatment records in 2016/17 gives us a total of £551 million. Source for £57 figure is sheet "2016-17 A&E Tariff" in file "2017-18 A and E model" in Annex B of the 2017/18 and 2018/19 National Tariff Payment System documentation, available at https://improvement.nhs.uk/resources/national-tariff-1719/

Table S1. Descriptive statistics for selected control variables.

Variable (min-max)	Observations	Mean (SD) / %
Patient characteristics		
Age (0-110)	16,563,946	37.7 (27.9)
Gender	16,563,946	100%
Male	7,003,057	42.3%
Female	9,560,889	57.7%
IMD quintile (1-5)	15,690,550	3.2 (1.4)
Ratio distance of nearest hospital to nearest GP (0.4 - 44.6)	16,256,118	4.1 (2.4)
Type of area	15,707,810	100%
Urban	13,535,244	86.2%
Rural	2,172,566	13.8%
Region	15,690,550	100%
North	5,822,600	37.1%
South & East	2,144,612	13.7%
Midlands	5,129,125	32.7%
London	2,594,213	16.5%
GP practice characteristics		
% patients typically able to get an appointment per practice (39.9%-100%)	15,629,833	84.0%
Number of FTEs per practice (0.02-34.1)	14,877,337	5.6 (3.7)
Call characteristics		
Call had clinical input (yes=1, no=0)	16,563,946	21.6%
Call duration in minutes (0-189.7)	16,563,946	15.4 (22.6)

STROBE 2007 (v4) checklist of items to be included in reports of observational studies in epidemiology*
Checklist for cohort, case-control, and cross-sectional studies (combined)

Section/Topic	Item #	Recommendation	Reported on page #
Title and abstract	1	(*a*) Indicate the study's design with a commonly used term in the title or the abstract	1
		(*b*) Provide in the abstract an informative and balanced summary of what was done and what was found	1
Introduction			
Background/rationale	2	Explain the scientific background and rationale for the investigation being reported	2
Objectives	3	State specific objectives, including any pre-specified hypotheses	3
Methods			
Study design	4	Present key elements of study design early in the paper	3
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection	3
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	4
		(*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	
Variables	7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable	4
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	5, 6
Bias	9	Describe any efforts to address potential sources of bias	4
Study size	10	Explain how the study size was arrived at	3, 4
Quantitative variables	11	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen and why	6
Statistical methods	12	(*a*) Describe all statistical methods, including those used to control for confounding	7, 9
		(*b*) Describe any methods used to examine subgroups and interactions	9
		(*c*) Explain how missing data were addressed	4
		(*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	
		(*e*) Describe any sensitivity analyses	-
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	4
		(b) Give reasons for non-participation at each stage	-
		(c) Consider use of a flow diagram	5
Descriptive data	14*	(a) Give characteristics of study participants (eg demographic, clinical, social) and information on exposures and potential confounders	Table S1
		(b) Indicate number of participants with missing data for each variable of interest	Table S1
		(c) *Cohort study*—Summarise follow-up time (eg, average and total amount)	-
Outcome data	15*	*Cohort study*—Report numbers of outcome events or summary measures over time	
		Case-control study—Report numbers in each exposure category, or summary measures of exposure	
		Cross-sectional study—Report numbers of outcome events or summary measures	7
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	7
		(*b*) Report category boundaries when continuous variables were categorized	8
		(*c*) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period	8
Other analyses	17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses	9-11
Discussion			
Key results	18	Summarise key results with reference to study objectives	11
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	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.