Using Data Mining To Predict Hospital Admissions From The Emergency Department

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Abstract- *Crowding within emergency departments (EDs) can have significant negative consequences for patients. EDs therefore need to explore the use of innovative methods to improve patient flow and prevent overcrowding. One potential method is the use of data mining using machine learning techniques to predict ED admissions. This paper uses routinely collected administrative data (120600 records) from two major acute hospitals in Northern Ireland to compare contrasting machine learning algorithms in predicting the risk of admission from the ED. We use three algorithms to build the predictive models: 1) logistic regression; 2) decision trees; and 3) gradient boosted machines (GBM). The GBM performed better (accuracy = 80.31%, AUC-ROC = 0.859) than the decision tree (accuracy = 80.06%, AUC-ROC = 0.824) and the logistic regression model (accuracy = 79.94%, AUC-ROC = 0.849). Drawing on logistic regression, we identify several factors related to hospital admissions, including hospital site, age, arrival mode, triage category, care group, previous admission in the past month, and previous admission in the past year. This paper highlights the potential utility of three common machine learning algorithms in predicting patient admissions. Practical implementation of the models developed in this paper in decision support tools would provide a snapshot of predicted admissions from the ED at a given time, allowing for advance resource planning and the avoidance bottlenecks in patient flow, as well as comparison of predicted and actual admission rates. When interpretability is a key consideration, EDs should consider adopting logistic regression models, although GBM's will be useful where accuracy is paramount.*

Keywords- Data mining, emergency department, hospitals, machine learning, and predictive models.

I. INTRODUCTION

Emergency department (ED) crowding can have serious negative consequences for patients and staff, such as increased wait time, ambulance diversion, reduced staff morale, adverse patient outcomes such as increased mortality, and cancellation of elective procedures [1]–[6]. Previous research has shown ED crowding to be a significant international problem [7], making it crucial that innovative steps are taken to address the problem [4]. There are a range of possible causes of ED crowding depending on the context, with some of the main reasons including increased ED attendances, inappropriate attendances, a lack of alternative treatment options, a lack of inpatient beds, ED staffing shortages, and closure of other local ED departments [1], [8]. The most significant of these causes is the inability to

One mechanism that could help to reduce ED crowding and improve patient flow is the use of data mining to identify patients at high risk of an inpatient admission, therefore allowing measures to be taken to avoid bottlenecks in the system [9], [10]. For example, a model that can accurately predict hospital admissions could be used for inpatient bed management, staff planning and to facilitate specialized work streams within the ED [11]. Cameron et al. [11] also propose that the implementation of the system could help to improve patient satisfaction by providing the patient with advance notice that admission is likely. Such a model could be developed using data mining techniques, which involves examining and analyzing data to extract useful information and knowledge on which decisions can be taken [12].

Develop models to predict hospital admissions from the emergency department, and the comparison of the Performance of different approaches to model development. We trained and tested the models using data from the administrative systems of two acute hospitals in Northern Ireland.

The performance of EDs has been a particular issue for the Northern Ireland healthcare sector in recent years. EDs in Northern Ireland have been facing pressure from an increase in demand which has been accompanied by adverse levels of performance across the region compared to some other areas of the UK [14], [15]. For example, in June 2015 only one Northern Ireland ED department met the 4 hour wait time target, with over 200 patients across the region waiting over 12 hours to be admitted or sent home [15]. This can have a negative impact on patients at various stages of their journey, as presented in high profile incidents reported by the media [16], [17].

Patients attending the ED typically go through several stages between the time of arrival and discharge depending on decisions made at preceding stages. ED attenders can arrive either via the main reception area or in an ambulance. At this point, the patient's details are recorded on the main ED administration system, before the patient is either admitted, as in severe cases, or proceeds to the waiting area. The patient then waits for a target time of less than fifteen minutes before triage by a specialist nurse. The Manchester Triage scale is used by all Northern Ireland hospitals, and involves prioritizing patients based on the severity of their condition,andtoidentifypatientswhoarelikelytodeteriorateifnots een urgently and those who can safely wait to be seen [18]. Triage is an important stage in the patient journey to ensure the best use of resources, patient satisfaction, and safety [19]. Triage systems have also been found to be reliable in predicting admission to hospital, but are most reliable at extreme points of the scale, and less reliable for the majority of patients who fall in the mid points [18].

Once triaged, the patient returns to the waiting room, before assessment by a clinician, who will make a recommendation on the best course of action, which could include treatment, admission, follow up at an outpatient clinic or discharge. If there is a decision to admit the patient, the ED sends a bed request to the ward, and the patient continues to wait until the bed is available. Bottlenecks or excess demand at any point in this process can result in ED overcrowding. Routine recoding of data on hospital administrative systems takes place at each stage of this process, providing an opportunity to use machine learning to predict future stages in the process, and in particular, whether there is an admission.

This study draws on this data to achieve two objectives. The first is to create a model that accurately predicts admission to hospital from the ED department, and the second is to evaluate the performance of common machine learning algorithms in predicting hospital admissions. We also suggest use cases for the implementation of the model as a decision support and performance management tool.

II. RELATED WORK

Using a range of clinical and demographic data relating to elderly patients, LaMantia *et al.* [9] used logistic regression to predict admissions to hospital, and ED re-attendance. They predicted admissions with moderate accuracy, but were unable to predict ED re-attendance accurately. The most important factors predicting admission were age, Emergency Severity Index (ESI) triage score, heart rate, diastolic blood pressure, and chief complaint [9] (pg. 255). Baumann and Strout [20] also find an association between the ESI and admission of patients aged over 65. Boyle *et al.* [2] used historical data to develop forecast models of ED presentations and admissions. Model performance was evaluated using the mean absolute percentage error (MAPE), with the best attendance model achieving a MAPE of around 7%, and the best admission model achieving a MAPE of around 2% for monthly admissions. The use of historical data by itself to predict future events has the advantage of allowing forecasts further into the future, but has the disadvantage of not incorporating data captured at arrival and through triage, which may improve the accuracy of short term forecasting of admissions.

Sun *et al.* [8] developed a logistic regression model using two years of routinely collected administrative data to predict the probability of admission at the point of triage. Risk of admission was related to age, ethnicity, arrival mode, patient acuity score, existing chronic conditions, and prior ED attendances or admission in the past three months. Although their data showed the admission of more females than males, sex was not significant in the final model. Similarly, Cameron *et al.* [11] developed a logistic regression model to predict the probability of admissions at triage, using two years of routine administration data collected from hospitals in Glasgow. The most important predictors in their model included 'triage category, age, National Early Warning Score, arrival by ambulance, referral source, and admission within the last year' (pg. 1), with an area under the curve of the receiver operating characteristic (AUC-ROC) of 0.877. Other variables including weekday, out of hour's attendances, and female gender, were significant but did not have high enough odds ratios to be included in the final models. Kim *et al.* [21] used routine administrative data to predict emergency admissions, also using a logistic regression model. However, their model was less accurate with an accuracy of 76% for their best model.
Although these models highlight the usefulness of logistic regression in predicting ED admissions, Xie [22] achieved better performance using a Coxian Phase model over logistic regression model, with the former AUC-ROC of 0.89, and the latter 0.83. Wang *et al.* [23] used a range of machine learning algorithms to predict admissions from the ED, comparing the ability of fuzzy min-max neural networks (FMM) to other standard data mining algorithms including classification and regression trees (CART), Multilayer Perceptron (MLP), random forest, and AdaBoost. Overall, MLP and Random Forest models were the most accurate, both predicting just over 80% of cases correctly, with FMM (with a genetic algorithm) predicting 77.97% of cases correctly.

Similarly, Peck *et al.* [24] developed three models to predict ED admissions using logistic regression models, naive Bayes, and expert opinion. All three techniques were useful in predicting ED admissions. Variables in the model included age, arrival mode, emergency severity index, designation, primary complaint, and ED provider. Their logistic regression model was the most accurate in predicting ED admissions, with an AUC-ROC of 0.887. Perhaps surprisingly, this model performed better than triage nurse’s opinion regarding likely admission. The use of logistic regression to predict admission was subsequently found to be generalizable to other hospitals [10]. Using simulation models, Peck *et al.* [25] have shown that the use of the predictive models to priorities discharge or treatment of patients can reduce the amount of time the patient spends in the ED department.

Qui *et al.* [26] used a relative vector machine to predict whether an ED attender would be discharged or admitted to one of three hospital words. Their model had an overall accuracy of 91.9% with an AUC of 0.825. However, the accuracy of predicting the target ward varied by ward and by the probability threshold used. Lucini *et al.* [27] used eight common machine learning algorithms to predict admissions from the ED department based on features derived from text recorded on the patients record. Six out of the eight algorithms had similar levels of performance including nusupport vector machines, support vector classification, extra trees, logistic regress, random forests, and multinomial naïve bayes, with AdaBoost and a decision tree performing worst.

Taking a different approach, Cameron *et al.* [28] compared the accuracy of nurses predictions of ED admissions with those of an objective score. They find nurses to be more accurate in cases where they are certain the patient will be admitted, but less accurate than the objective score in cases where they are uncertain about the patient’s likelihood of admission.

The literature highlights the application of a range of traditional and machine learning approaches to the prediction of ED admissions in different contexts using a variety of data. However, there are gaps in the literature to which this study contributes. Much of the previous work focuses on a narrow range of algorithms, and primarily logistic regression, with fewer studies comparing multiple approaches. This leaves open the potential for the development of more accurate predictive models using other algorithms. For example, gradient boosted machines (GBM) were not applied in any of the studies reviewed, but have been successful in predicting binary outcomes in other scenarios such as hospital transfers and mortality [29]. In addition, few studies were identified that focused on the UK context, and none that focused on Northern Ireland ED’s. This is an important gap in the literature as the structure and operation of health services varies considerably between countries and regions within countries. Most previous studies have also tended to focus on developing predictive models for one hospital site, with fewer studies building models using data from multiple sites. This study seeks to contribute to the existing body of knowledge by building machine learning models using a novel dataset and by comparing the performance of less frequently used algorithms with the more traditional logistic regression approach. Moreover, the data used in our study is routinely available at the point of triage, allowing for the potential implementation of a fully automated decision support system based on the models built here.

III. METHODS

The method for this study involved seven data mining tasks. These were: 1. Data extraction; 2. Data cleansing and feature engineering; 3. Data visualization and descriptive statistics;

4. Data splitting into training (80%) and test sets (20%); 5. Model tuning using the training set and 10-fold cross validation repeated 5 times; 6. Predicting admissions based on the test data set and; 7. The evaluation of model performancebasedonpredictionsmadeonthetestdata.Thesesteps helpto ensure the models are optimal and prevent against over fitting.

The study was based on administrative data, all of which was recorded on electronic systems, and subsequently warehoused for business intelligence, analytics, and reporting purposes. The data was recorded during the 2015 calendar year, and includes all ED attendances at two major acute hospitals situated within a single Northern Ireland health and social care trust. The trust itself offers a full range of acute, community, and social care services delivered in a range of settings including two major acute hospitals, which were the setting for this study. Both hospitals offer a full range of inpatient, outpatient, and emergency services and have close links to other areas of the healthcare system such as community and social services. Hospital 1 is larger, treating approximately 60000 inpatients and day cases each year and 75000 outpatients, whilst hospital 2 treats approximately 20000 inpatients and day cases and 50000 outpatients.

data used in the model building was recorded on the main administrative computer system at each stage of the patient journey at the time the event occurs. A range of variables were considered in the model building, with the final variables decided upon based on previous studies, significance in the models, and the impact of inclusion on the performance of the model. The final models consisted of variables describing whether the patient was admitted to hospital;

hospital site; date and time of attendance; age; gender; arrival model; care group; Manchester triage category; and whether the patient had a previous admission to the hospital within the last week, month, or year. The care group is a series of categories indicating the pathway a patient should take. The Manchester triage category is a scale rating the severity of the condition, and used for prioritization. Prior admissions were measured objectively by querying the hospital database. Feature engineering was also carried out on the date of attendance to disaggregate it into components relating to year, day of the week, and month of the year. The dependent variable in all models was admission to the hospital from the ED. Most of the variables included in the model are mandatory on the ED system, and recorded using of drop down menus. This led to a relatively clean dataset for analysis, with list wise deletion of cases with missing data. Patients attending direct assessment units and observation units are excluded from the analysis, as these patients follow a different pathway to those attending the main ED. Furthermore, many hospitals do not have such departments, which would limit the generalizability of the results.

The final dataset consisted of 120,600 observations, of which 10.8% had missing data, leaving 107,545 cases for building the models. To enable validation of the model, random stratified sampling was used to split the data into training (80% of cases) and test (20% of cases) datasets. Data was extracted and stored using SQL Server (2012), and the machine learning and exploratory analysis was carried out using the R software for statistical computing [32], version 3.2.1.

A. MACHINE LEARNING ALGORITHMS AND PERFORMANCE

Three machine learning algorithms were applied to the training data to build the models: (1) logistic regression, (2) a decision tree, and(3)gradient boosted machines(GBM). Logistic regression is suitable for predicting a binary dependent variable, such as positive/negative; deceased/alive; or in this study, admit/not admit. The technique uses a logit link function to enable the calculation of the odds of an outcome occurring. The second algorithm that was used was a decision tree, specifically recursive partitioning from the RPART package [33]. The RPART package is an implementation based on the model presented by Breiman and colleagues [33], [34]. This algorithm splits the data at each node based on the variable that best separates the data until either an optimal model is identified or a minimum number of observations exists in the final (terminal) nodes [33]. The resulting tree can then be pruned to prevent over fitting and to obtain the most accurate model for prediction [33], [35]. The third algorithm was a GBM, which creates multiple weakly associated decision trees that are combined to provide the final prediction [35]. This technique, known as 'boosting' can often give a more accurate prediction than a single model [35].
These algorithms were chosen to allow comparison of different commonly used techniques for predictive modelling, with the three specific algorithms being selected to allow comparison of a regression technique (logistic regression), a single decision tree (RPART), and a tree based ensemble technique (GBM). The choice of the three algorithms also allows us to compare the performance of two novel to the area machine algorithms (RPART and GBM) with the more traditional logistic regression model. The three algorithms vary in terms of how the modelling is carried out and the complexity of the final models. The possibility of practical implementation of the solution was also considered. Characteristics of the dataset were also important in the choice of model. For example, different algorithms are typically used depending on whether the problem is regression or classification, and in this case algorithms suitable for classification were used.

The model parameter associated with each algorithm were tuned using ten fold cross validation repeated five times, over a custom tuning grid. This process identifies the optimal tuning parameters, and helps to prevent against overfitting. For logistic regression there are no tuning parameters, but resampling was still performed to evaluate the performance of the model [35]. The tuning parameters commonly used for recursive partitioning are the complexity parameter and maximum node depth, and for GBM the user can tune the interaction depth, minimum observations in a node, learning rate, and number of iterations [35]. The CARET package was used to train and tune the machine learning algorithms. This library provides the user with a consistent framework to train and tune models, as well as a range of helper functions [35].

To further prevent against overfitting and to evaluate the performance of the models, predictions were made on an unseen test dataset. The performance of each machine learning algorithm was evaluated using a range of measures including accuracy, Cohens Kappa, c-statistics of the ROC, sensitivity and specificity. When interpreting the AUC-ROC, values of between 0.7 and 0.8 can be interpreted as having good discrimination ability, and models with AUC-ROC of greater than 0.8 can be interpreted as having excellent discrimination ability, with values above 0.9 indicating outstanding ability [36].

IV. RESULTS

A. DESCRIPTIVE STATISTICS

Table 1 presents the descriptive statistics for the dataset. Across both hospitals, 24% of the ED attendances resulted in an admission to hospital, with 26.5% of attendances resulting in an admission at hospital 1 and 19.81% at hospital 2. This compares similarly to other hospitals in Northern Ireland and England [37], [38]. Similar admission rates can also be observed at hospitals internationally with studies carried out in Singapore where 30.2% of ED attenders were admitted [8], in Canada where 17.9% of ED attenders were admitted [22] and in the USA where 34% were admitted [25]. However, some of these studies relied on single hospital sites or a small number of hospitals, which could be unrepresentative of national admission rates.

Whilst the admission date was disaggregated into the day, week, and month, the week of the year was not included in the final models as it reduced the performance of the model. Overall, attendances and admissions were higher on weekdays than at weekends with the highest number of admissions being on Mondays. Baker [14] observes a similar trend in England, with the highest frequency of attendances on Mondays and decreasing attendances through to Friday. However, Baker [14] also shows that attendances slightly increased at the weekend with Sunday being the second busiest day. ED attendances are lowest in the winter months and

TABLE 1. Descriptive statistics.

Variable	Top Categories	Frequency / Mean (Attendances)	Admissions	% Admitted
Admitted	Yes	29804	n/a	24.7
	No	90796	n/a	75.3
Gender	Male	61089	14210	23.3
	Female	59511	15594	26.2
Arrival day	Monday	19681	4846	24.6
	Tuesday	17596	4400	25.0
	Wednesday	17262	4349	25.2
	Thursday	17196	4240	24.7
	Friday	16857	4438	26.3
	Saturday	15699	3732	23.8
	Sunday	16339	3799	23.3
Hour of the day	11am	8791	2061	23.4
	Midday	8421	1931	22.9
	1pm	8231	1917	23.3
	3pm	8004	2063	25.8
	4pm	7912	2072	26.2
	6pm	7865	1935	24.6
Week of the year	40	2653	713	26.9
	12	2509	571	22.8
	30	2505	636	25.4
	27	2494	549	22.0
	32	2477	568	22.9
	6	2484	566	22.8
Month of the year	Oct	10608	2559	24.1
	Jun	10482	2519	24.0
	May	10384	2571	24.8
	Aug	10327	2502	24.2
	Apr	10251	2520	24.6
	Jul	10207	2495	24.4
Arrival mode	Ambulance	29386	15467	52.6
	Foot	4156	689	16.6
	Own Transport	85828	13353	15.6
	Police	508	109	21.5
	Public Transport	400	38	9.5
	St Johns Ambulance	210	111	52.9
Triage category	Non-Urgent	1465	30	2.0
	Standard	46969	3238	6.9
	Urgent	53484	117423	32.6
	Very Urgent	15247	8786	57.6
	Immediate	458	289	63.1
	Not Known	2977	38	1.3
Care group	Minors	56713	3316	5.8
	Majors	55191	23650	42.9
	Resuscitation	3457	2664	77.1
	Emergency Nurse Practitioner	1894	8	0.4
	Primary Care	1048	11	1.0
	Assessment Unit	604	13	2.2
	Triage	240	9	3.8
	Other	944	44	4.7
	Missing	1353		0.0
Admitted in past year	Yes	22281	10779	48.4
	No	98319	19025	19.4
Admitted in past month	Yes	5403	3139	58.1
	No	115197	26665	23.1
Admitted in past week	Yes	1346	725	53.9
	No	119254	29079	24.4
Hospital site	1	77069	20530	26.6
	2	43531	9274	21.3
Patient age		Mean = 43.21 Median = 41 SD=26.2	Mean = 56.49 Median = 63 SD= 26.93	

**Chi squared and ANOVA was used to examine relationships with the outcome variable. All variables were significantly correlated with the outcome variable ($p<0.001$).*

10462 VOLUME 6, 2018highest throughout spring and summer, except for a peak in attendances in October. Across the UK, Baker [14] observes higher attendances in late spring and early summer, with fewer attendances in August and January. Admissions at both hospitals were relatively consistent throughout the year, with a small increase in the summer at hospital 2, which may be due to the increase in holidaymakers in the locality during the summer months.

As shown in Table 1, overall, more males attended the hospitals, but a higher percentage of females were admitted. The mean age of ED attenders was 42 (SD=26.20), with the highest number of attendances being infants. The data also indicates a peak in the number of attendances for people aged in their mid-twenties. Using data from ED's in England, Baker [14] found that relative to population size in each group, older people are more likely to attend the ED department, but also observed a peak in attendances amongst working people aged between 20 and 24. The mean age of those admitted was 56 (SD=26.93), compared to an average age of 38 (SD=24.27) for attendances not resulting in an admission. This is consistent with several other studies which find that older patients are more likely to attend the ED department and to be admitted to hospital [8], [11], [39], [40]. For example, Sun *et al.* [8] find an even starker difference with patients who are admitted having an average age of 60.1 compared to 39.4 for those not admitted.

Using the Manchester triage scale, 37.9% of attendances were triaged as standard, 43.1 as urgent, and 12.3% as very urgent, with a relatively small proportion triaged as immediate non-urgent or not known. As expected, the proportion of patients admitted at each category level declined as the urgency of the triage decreased, with an admission rate of 57.6% for very urgent patients, 32.5% for urgent patients, 1.9%fornon-urgent and 6.8% for standard. However, the data also shows admissions across all triage categories.

A similar pattern can be observed based on the patients care group, with substantially more patients categorised as ‘major’ being admitted, but with 5.8% of patients categorised as ‘minor’ also being admitted. The majority of patients arrive at the ED using their own transport, with 24.4% arriving by ambulance. However, a much higher percentage of patients who arrive via ambulance end up being admitted to hospital, which can be explained by the requirement for an ambulance for more serious cases. We also constructed variables indicating whether the patient had been admitted to hospital in the past week, month, and year. The descriptive statistics shown in Table 1 indicate that 1.1 % of patients had a previous admission in the past week, 4.3% in the past month, and 17.9% in the past year. Across all three time bands for previous admissions, a higher percentage of patients were admitted compared to the percentage of patients admitted in the overall sample.

B. MULTIVARIABE RELATIONSHIPS

To gain additional insight into the data and the relationships between the variables this section discusses the multiple logistic regression model presented in Table 3 in the Appendix. Interpreting this model also assists with building more complex and less interpretable models. Logistic regression shows the relationship between each independent variable and the odds of admission, whilst holding all other variables constant. As expected, age is significantly positively associated with the probability of admission (OR=1.01 per one year increase in age). Several previous studies have also identified this relationship [9], [11]. Although the descriptive statistics indicated that females are admitted at a higher frequency than males the effect is not statistically significant in the logistic regression model. However, Cameron *et al.* [11] found that females are significantly more likely to be admitted than males, but they chose not to include gender in their final model due to a small odds ratio.

Compared to patients arriving by ambulance, admissions are significantly less likely for patients arriving by foot (OR=0.49), own transport (OR=0.51), police (OR=0.51) and public transport (OR=0.21). As expected, patients with a more urgent Manchester Triage score are also more likely to be admitted to hospital (e.g. OR for Urgent Patients = 2.28, compared with 0.38 for ‘Non Urgent’ patients). This corroborates with the results of Cameron *et al.* [11] who also find that admission is more likely with more severe triage categories. Compared to patients with a care group of ‘minor’, patients with a care group of majors (OR=5.09), assessment unit (OR=5.74), resuscitation (OR=13.81), triage (OR=3.14) and other (OR=8.61) are more likely to be admitted. Patients seen by the emergency nurse practitioner rare significantly less likely to be admitted to hospital (OR=0.288).

Focusing on the time variables, patients attending the ED department on Sundays are less likely to be admitted to hospital, compared to those attending on Fridays (OR=0.92). Patients attending between 2pm and 6pm are significantly more likely to be admitted (ORs= 1.18; 1.21; 1.23; 1.17; and 1.23), with admission less likely at 9am (OR=0.85) and 3am (OR=0.79). Patients attending in April, May, and June are significantly more likely to be admitted compared to those attending in January (ORs=1.15; 1.12; and 1.13), with patients attending in October and November being significantly less likely to be admitted (ORs= 0.91; 0.85).

Patients previously admitted in the past month (OR=1.44) or year (OR=1.70) are also significantly more likely to be admitted during the current ED visit. However, an admission in the past week does not increase the likelihood of admission. This could be because the variables relating to those admitted in the last month and year are explaining the majority of the variance in the model. Similarly, Sun *et al.* [8] found that patients previously admitted within the past three months were significantly more likely to be admitted during the current attendance.

C. MODEL PERFORMANCE

We used accuracy, kappa, AUC-ROC, sensitivity and specificity to evaluate the predictive performance of the models by making predictions on the test data. As shown in table 2, the GBM performs best across all performance measures. However, in some cases differences in performance across the models are small. Logistic regression and decision tree models show similar levels of predictive performance, with the decision tree performing only slightly better than the logistic regression model in terms of accuracy and kappa, and the logistic regression model performing better in terms of AUC-ROC and sensitivity. As a consequence of the class imbalance, specificity is considerably higher than sensitivity across all three models. These findings corroborate with those of Lucini *et al.* [27] who report similar levels of performance across the majority of models presented in their study.

TABLE 2. Model performance.

	Accuracy (%)	Kappa	AUC-ROC	Specificity	Sensitivity
Logistic Regression	79.94	0.4600	0.8497	0.8995	0.5357
Decision Tree (RPART)	80.06	0.4661	0.8249	0.9015	0.5349
GBM	80.31	0.4724	0.859	0.9038	0.5379

V. DISCUSSION

This study used a data mining approach to develop and assess three machine learning algorithms to predict the probability of admission at the point of triage. Overall, the results show that the GBM performed best, although the decision tree and logistic regression models only performed slightly less well, thus making all three models potential candidates for implementation. Although the GBM was the most accurate of the three models, in scenarios where interpretability is important logistic regression model may be the most promising candidate for implementation due to its simplicity and ease of interpretation. This follows the process recommended by Kuhn and Johnson [35]. They propose three steps for identifying an implementable model: 1. Build the potentially most accurate model using complex and less interpretable models; 2. Build simpler models using more interpretable algorithms; 3. If the accuracy of the simpler model is sufficient compared to the more complex model consider this model for implementation. In this study, the simpler models (logistic regression and the decision tree) compare quite well with the more complex GBM. The logistic regression model is also straightforward to interpret and understand and clearly articulates how different factors are contributing to the prediction, which may assist with clinician buy in and confidence in the prediction. Whilst decision trees can be interpreted, they can be unstable with small changes in the data potentially drastically changing the structure of the tree [41]. Ensembles of decision trees, such as GBM's, can be similarly difficult to interpret as they combine multiple single decision trees to derive the final predictions. However, in scenarios where accuracy is paramount, the GBM would be the optimal choice for implementation.

The models presented in this study have higher levels of accuracy when compared to several other studies presented in the literature. For example, using logistic regression to model data held on the hospital administrative systems about patients aged over 75, LaMantia *et al.* [9] achieved an AUC-ROC of 0.73. They postulate that their model is not accurate enough by itself to make an individual level admission decision. Using logistic regression, Sun *et al.* [8] achieved similar accuracy to the models presented here, with an AUC-ROC of 0.849. It is notable that Sun *et al.* [8] do not achieve higher accuracy than the models presented here despite including data about pre-existing conditions. They found that admission was more likely for patients with diabetes, hypertension and dyslipidaemia.

However, Cameron *et al.* [11] achieved a slightly higher accuracy using a logistic regression model, with an AUC-ROC of 0.8774. They included two variables which were unavailable in this study: the national early warning score (NEWS), which is not used in Northern Ireland; and the referral source, which isn't always captured at the point of triage in Northern Ireland. They also covered a larger geographical area, and consequently had a larger sample, which could also have improved the accuracy of their model.
The analysis of the descriptive statistics and logistic regression model also highlights some important patterns in data. Admissions are linked to the patient's age, arrival mode, triage category, care group, previous admissions, the hospital and to a lesser extent temporal variables. Although the results show that admission is more likely with more severe triage categories, the descriptive statistics also highlight the potential for admission across the categories. Potential explanations for this could be that patients deteriorate after being triaged, or that additional information relating to their condition becomes available, resulting in an admission.

The logistic regression model also highlights that admission is more likely when patients arrive by ambulance. This may be due to the increased propensity for patients to call an ambulance for more serious conditions. This compares similarly to other studies which have also identified a positive relationship between arrival by ambulance and admission to hospital [8], [11]. Similarly, the care group and triage category are likely to be proxies for the severity of the patient's condition. It is also possible that patients with different types of conditions attend different ED's at different times, which could account for the significance of temporal and site differences. Although these relationships are interesting and useful in informing the model development process, the overall aim of the study was not to gain inference, but to develop predictive models. Further research would therefore be required to confirm any underlying causal mechanisms.

There are several practical applications of the models developed in this study. The predictions from the models can be automated and displayed in near real time in a clinical or performance management dashboard to assist with decision making. From a performance management and improvement perspective, the models can be used to compare the predicted decision to admit with the clinician's decision, thereby identifying patients who may have been admitted unnecessarily, or patients who typically would have been admitted. Auditing these cases could help to evaluate performance. At an aggregated level, predictions can be used as a performance indicator alongside other commonly used indicators such as risk adjusted mortality an length of stay. Another benefit of implementing the model developed here is that it can help to improve planning and resource allocation in hospitals [8], [10]. Bed managers in the hospital would have advance information about the number of patients in the ED department who are likely to be admitted, which can be compared to bed availability to identify any potential shortfalls, which could result in delays to admission and hence longer stays in the ED department and overcrowding. Advance warning of hospital admissions can also provide the opportunity to make bed requests and preparations in advance of the admission [26]. This is important for both the patient's experience, and from a performance management perspective. ED crowding, delays, and long waits in the ED department have been found to be associated with adverse patient outcomes such as increased morbidity and mortality [3], [22], [42]. From a performance management perspective, ED wait time is a key target which hospitals must deliver against in the UK, and one which Northern Ireland hospitals regularly fail to meet [14], [15]. One advantage of the methodological approach taken in this study, compared with much of the existing literature, is the comparison of models built using multiple machine learning algorithms. This approach allows us to compare models and to identify the most accurate approaches, whilst also taking into consideration the feasibility of implementation and use as a decision support tool. This approach is in contrast to some other studies, which have focused on a narrower range of machine learning and statistical techniques [8], [9], [11]. Moreover, no examples of the use of GBM's in this context were found in the literature. Another benefit of the model presented here is that it is simple to calculate, and uses a small number of variables usually collected and recorded on administrative systems at or before the point of triage.

Whilst the model will be useful in supporting a range of decisions, it does have a level of error and should therefore be used in conjunction with clinical judgement when making individual admission decisions. Caution should therefore be taken when implementing the model to reduce the risk of reserving a bed for a patient who ends up not being admitted [22]. In this light, the application of the model for patient level decision making can be viewed more as a decision support tool, providing clinicians with a double check automated triage scale, rather than a prescriptive decision. However, the accuracy of the model would also lend itself well for use as a planning and performance management tool.

Although the aim of this study was to use readily available routine data available at the point of triage, the incorporation of additional data could potentially increase accuracy. For example, clinical data such as pre-existing conditions, blood pressure, test results, and heart rate may be useful in improving accuracy. Similarly, the incorporation of social care data, or data collected from primary and community care may improve predictive accuracy. Some previous research has incorporated a limited range of social care data, with mixed results. Caplan *et al.* [39] find that dependence on certain daily activities is positively associated with the risk of a hospital admission. However, Cameron *et al.* [11] fail to find a significant relationship between whether the person lives alone and their probability of admission. Although electronic systems in health and social care often hold data on more clinically focused variables as well as data relating to social care, the data often resides in silos within or across the organisations involved in the provision of care. This can make accessing and combining the data difficult to achieve in practice, depending on the maturity of the organisations IT infrastructure.

The increasing digitization of textual data, such as clinical notes, could create the opportunity for future studies to incorporate textual data into the machine learning models, alongside the administrative data, which may increase predictive accuracy further. Some inroads into the use of textual data in predicting admissions has been reported in the literature [27].

Future studies should also consider whether the accuracy of the model is generalizable to other contexts. This can be investigated by applying the models presented here to data collected from other contexts, and comparing the results to models developed directly on that data. It would also be interesting for future studies to consider whether accuracy varies across different sub populations, or to what extent accuracy degrades over time.

Whilst the aims of this study focused more on the development of an implementable tool, and therefore used reliable and well-tested algorithms, future studies could also consider evaluating the use and accuracy of additional machine learning algorithms against the models presented in this study. Potential candidates for future research could include random forests, support vector machines or artificial neural networks. In particular, deep learning has been successful in several machine learning tasks [43]. Combining multiple algorithms in an ensemble may also help to increase the accuracy of the tool, as may the use of techniques such as multi-view learning. However, care should be taken in that some of these techniques are more computationally expensive, difficult to interpret and difficult to implement in production systems.

VI. CONCLUSION

This study involved the development and comparison of three machine learning models aimed at predicting hospital admissions from the ED. Each model was trained using routinely collected ED data using three different data mining algorithms, namely logistic regression, decision trees and gradient boosted machines. Overall, the GBM performed the best when compared to logistic regression and decision trees

TABLE 3. Odds ratios derived from the logistic regression model.

	Estimate	Odds Ratio	Std. Error	z value	Pr(>|z|)	Sig.
(Intercept)	-3.1822393	0.041492637	0.0802	-39.679	< 2e-16	***
Hospital 1	-0.2187388	0.803531573	0.0207004	-10.567	< 2e-16	***
Patient Age	0.0148332	1.014943758	0.0003949	37.56	< 2e-16	***
Patient Gender (1=M)	-0.0276202	0.97275775	0.0188993	-1.461	0.143894	
Arrival by Foot	-0.712676	0.490330316	0.057886	-12.312	< 2e-16	***
Arrival by Own Transport	-0.6622555	0.51568689	0.0220827	-29.99	< 2e-16	***
Arrival by Police	-0.6718601	0.510757633	0.142231	-4.724	2.32E-06	***
Arrival by Public Transport	-1.4522994	0.234031537	0.2451499	-5.924	3.14E-09	***
Arrival by St Johns Ambulance	0.3551114	1.42633954	0.1876986	1.892	0.058501	.
Triage Immediate	0.8724109	2.392672399	0.1401013	6.227	4.75E-10	***
Triage Non Urgent	-0.9708113	0.378775613	0.2234201	-4.345	1.39E-05	***
Triage Not Known	0.5218526	1.685146662	0.595679	0.876	0.380996	
Triage Urgent	0.8249562	2.281780821	0.0282381	29.214	< 2e-16	***
Triage Very Urgent	1.4033001	4.068604638	0.0344092	40.783	< 2e-16	***
Care Group Other	2.1532966	8.613205941	0.4730855	4.552	5.32E-06	***
Care Group Majors	1.6265424	5.086258035	0.0266328	61.073	< 2e-16	***
Care Group Assessment	1.7475218	5.740359276	0.4478474	3.902	9.54E-05	***
Care Group ENP	-1.2443851	0.288118017	0.50865	-2.446	0.014427	*
Care Group PCC	-0.6469209	0.523655685	0.3411087	-1.897	0.057891	.
Care Group Resus	2.6253708	13.80969387	0.0609774	43.055	< 2e-16	***
Care Group Triage	1.1430994	3.136474505	0.5195744	2.2	0.027802	*
Monday	-0.0351136	0.96549573	0.0339235	-1.035	0.300631	
Tuesday	-0.0230797	0.977184599	0.0347786	-0.664	0.506934	
Wednesday	0.002019	1.00202104	0.0348537	0.058	0.953807	
Thursday	-0.0556817	0.945840149	0.0350037	-1.591	0.111668	
Saturday	-0.0261561	0.974183008	0.0361434	-0.724	0.469264	
Sunday	-0.0879773	0.915781665	0.0360014	-2.444	0.014537	*
Feb	0.0530573	1.054490066	0.0464848	1.141	0.253707	
Mar	0.0118454	1.011915835	0.0458134	0.259	0.795978	
Apr	0.1359357	1.145608229	0.0458511	2.965	0.00303	**
May	0.1091229	1.115299412	0.0456824	2.389	0.016907	*
Jun	0.1203219	1.127859851	0.0458315	2.625	0.008657	**
Jul	0.0615067	1.063437622	0.046034	1.336	0.181511	
Aug	0.050418	1.05171062	0.0460159	1.096	0.273225	
Sep	0.033209	1.033766574	0.0461039	0.72	0.471335	
Oct	-0.0985804	0.906122837	0.045454	-2.169	0.030098	*
Nov	-0.1598486	0.852272813	0.046595	-3.431	0.000602	***
Dec	-0.066517	0.93564701	0.0462649	-1.438	0.150507	
hourX1	-0.0899043	0.914018653	0.0884497	-1.016	0.309418	
hourX2	-0.1067619	0.898739637	0.0918506	-1.162	0.245096	
hourX3	-0.2381114	0.78811489	0.0959402	-2.482	0.013069	*
hourX4	-0.1322893	0.876087506	0.0990712	-1.335	0.18178	

TABLE 3. *(Continued.)* Odds ratios derived from the logistic regression model.

	Estimate	Odds Ratio	Std. Error	z value	Pr(>|z|)	Sig.
hourX5	-0.1379545	0.871138066	0.1028694	-1.341	0.179899	
hourX6	-0.0509949	0.950283517	0.1030442	-0.495	0.620682	
hourX7	-0.0222359	0.977950817	0.0970622	-0.23	0.818319	
hourX8	-0.1377259	0.871337493	0.0873248	-1.577	0.114757	
hourX9	-0.1598993	0.852229604	0.0757991	-2.11	0.0349	*
hourX10	0.0193562	1.019544746	0.0711412	0.272	0.785559	
hourX11	0.1117079	1.11818691	0.0692193	1.614	0.106565	
hourX12	0.0983965	1.102400197	0.0695661	1.414	0.157235	
hourX13	0.0643923	1.066511242	0.0697694	0.923	0.35604	
hourX14	0.1633212	1.177414865	0.0700202	2.332	0.019675	*
hourX15	0.1895516	1.208707492	0.0697502	2.718	0.006561	**
hourX16	0.2091473	1.232627167	0.0698249	2.995	0.002742	**
hourX17	0.1536451	1.166076973	0.0696961	2.205	0.027489	*
hourX18	0.2048161	1.227299344	0.0699006	2.93	0.003388	**
hourX19	0.0930663	1.097534499	0.0711064	1.309	0.190591	
hourX20	0.0851512	1.088881693	0.0740009	1.151	0.249865	
hourX21	0.098791	1.103835574	0.0735037	1.344	0.178969	
hourX22	0.0950331	1.099695251	0.0762377	1.247	0.212567	
hourX23	0.0619235	1.063880955	0.0786625	0.787	0.431162	
Prev Admission in Last Month	0.3659087	1.441823598	0.0484588	7.551	4.32E-14	***
Prev Admission in Last Week	0.1197256	1.127187509	0.0878717	1.363	0.173039	
Prev Admission in Last Year	0.5289722	1.697187043	0.0244474	21.637	<2e-16	***

Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

but the decision tree and logistic regression also performed well. The three models presented in this study yield comparable, and in some cases improved performance compared to models presented in other studies. Implementation of the models as a decision support tool could help hospital decision makers to more effectively plan and manage resources based on the expected patient inflow from the ED. This could help to improve patient flow and reduce ED crowding, therefore reducing the adverse effects of ED crowding and improving patient satisfaction. The models also have potential application in performance monitoring and audit by comparing predicted admissions against actual admissions. However, whilst the model could be used to support planning and decision making, individual level admission decisions still require clinical judgement.

APPENDIX

See Table 3.

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