International Journal of Medical Informatics 140 (2020) 104163

Contents lists available at ScienceDirect

International Journal of Medical Informatics

journal homepage: www.elsevier.com/locate/ijmedinf

Predicting hospital admission for older emergency department patients: Insights from machine learning

Fabrice Mowbray[a,b], Manaf Zargoush[c,*], Aaron Jones[a,b], Kerstin de Wit[a,d], Andrew Costa[a,b]

[a] Department of Health Research Methods, Evidence, and Impact, McMaster University, Hamilton, Ontario, Canada
[b] Big Data and Geriatric Models of Care (BDG) Cluster, McMaster University, Hamilton, Ontario, Canada
[c] Health Policy and Management, DeGroote School of Business, McMaster University, Hamilton, Ontario, Canada
[d] Division of Emergency Medicine, Department of Medicine, McMaster University, Hamilton, Ontario, Canada

ARTICLE INFO

Keywords:
Predicting hospital admission
Older adults
Machine learning
Emergency medicine
Geriatric syndromes
Emergency disposition

ABSTRACT

Background: Emergency departments (ED) are a portal of entry into the hospital and are uniquely positioned to influence the health care trajectories of older adults seeking medical attention. Older adults present to the ED with distinct needs and complex medical histories, which can make disposition planning more challenging. Machine learning (ML) approaches have been previously used to inform decision-making surrounding ED disposition in the general population. However, little is known about the performance and utility of ML methods in predicting hospital admission among older ED patients. We applied a series of ML algorithms to predict ED admission in older adults and discuss their clinical and policy implications.

Materials and methods: We analyzed the Canadian data from the interRAI multinational ED study, the largest prospective cohort study of older ED patients to date. The data included 2274 ED patients 75 years of age and older from eight ED sites across Canada between November 2009 and April 2012. Data were extracted from the interRAI ED Contact Assessment, with predictors including a series of geriatric syndromes, functional assessments, and baseline care needs. We applied a total of five ML algorithms. Models were trained, assessed, and analyzed using 10-fold cross-validation. The performance of predictive models was measured using the area under the receiver operating characteristic curve (AUC). We also report the accuracy, sensitivity, and specificity of each model to supplement performance interpretation.

Results: Gradient boosted trees was the most accurate model to predict older ED patients who would require hospitalization (AUC = 0.80). The five most informative features include home intravenous therapy, time of ED presentation, a requirement for formal support services, independence in walking, and the presence of an unstable medical condition.

Conclusion: To the best of our knowledge, this is the first study to predict hospital admission in older ED patients using a series of geriatric syndromes and functional assessments. We were able to predict hospital admission in older ED patients with good accuracy using the items available in the interRAI ED Contact Assessment. This information can be used to inform decision-making about ED disposition and may expedite admission processes and proactive discharge planning.

1. Introduction

Health systems around the world are challenged to adapt traditional care pathways to accommodate the complex physical and psychosocial needs of the growing geriatric population. The number of adults aged 65 years and older is expected to double by 2050, reaching 1.6 billion around the world [1]. The demand for health services will continue to increase alongside this demographic shift. Emergency departments (ED) are a common access point for older adults seeking medical attention, with the number of older ED patients increasing annually [2,3]. Older adults constitute a higher percentage of ED visits than younger persons, and they are more likely to visit for an urgent reason, resulting in hospital admission [4–6]. As the portal of entry into the hospital and the first source of contact for many seniors with their health care system, EDs are uniquely positioned to influence the health care trajectories of older adults presenting to the hospital for care [7,8].

* Corresponding author at: Health Policy and Management, DeGroote School of Business, McMaster University, Hamilton, Ontario, Canada.
E-mail address: zargoush@mcmaster.ca (M. Zargoush).

https://doi.org/10.1016/j.ijmedinf.2020.104163
Received 24 December 2019; Received in revised form 26 April 2020; Accepted 28 April 2020

1.1. Challenges in caring for older emergency department patients

The task-oriented and disease-centric focus of traditional emergency care pathways limit the department's ability to attend to the multi-faceted needs of older adults [9,10]. Geriatric complexity and multi-morbidity often surpass the conventional 'one-patient, one-problem' approach to emergency care [10]. Assessing and treating older adults in the ED is often challenging for emergency clinicians [11,12], as these patients commonly present with heterogeneous symptoms, cognitive impairment, and a complex medical and social history [13]. Furthermore, the time pressures and high patient volumes seen in the ED can impede health care providers from providing comprehensive geriatric assessments and tailored treatment plans [14]. As a result, geriatric syndromes are commonly overlooked by ED clinicians [15,16], and older adults experience high rates of adverse outcomes both during their visit and following discharge [17]. Cognizant of the fact that older adults have distinct health care needs and a greater risk for adverse health events, clinical researchers and machine learning experts commonly aim to study the efficacy of clinical therapies and health services exposures in this vulnerable patient population [18–20]. Following suit, governing bodies responsible for ED accreditation and clinical practice guidelines collaborated in 2014 to create the first geriatric ED guidelines [8].

1.2. Predicting emergency disposition

Determining patient disposition (admission vs. discharge) is an important and sometimes difficult decision for health care providers in the ED [21]. This is especially true for older adults, as they are at greater risk for functional decline, poor outcomes, and delayed discharge during in-patient stays [22,23]. The majority of hospital admissions come through the ED and constitute a significant source of health care spending. Furthermore, many hospital admissions are deemed to be potentially avoidable. As a result, health care providers, policymakers, and key stakeholders have all taken an interest in strategies to decrease inappropriate hospital admissions and extended stays [24–26]. Early identification of ED patients who require hospitalization can expedite admission processes and in-patient treatment [27], allowing for proactive discharge planning from the first patient contact. Both departmental barriers and the hazards associated with an inappropriate ED disposition underscore the utility of clinical decision support for older ED patients.

Machine learning (ML) has previously been used to predict disease, stratify patient risk, and inform clinical decision-making around patient disposition in emergency settings [28,29]. ML approaches are flexible and better able to identify hidden patterns and interactions among predictor variables [30,31]. The heterogeneous and complex presentation of older adults seeking emergency care makes ML an ideal candidate to inform clinical decision-making surrounding hospital admission in this high-risk patient population.

1.3. Related works

To date, the majority of studies aiming to predict hospital admission in ED patients focus on the general ED population [27,32–39]. Two studies used text-mining and natural language processing to predict hospital admission [32,33], while the rest used non-linguistic methods to produce predictions. A study by Leegon et al. [40] attempted to predict hospital admission in the pediatric population. Only one study to date has attempted to predict hospital admission in older adults [41]. LaMantia and colleagues used demographic data, insurance status, chief complaint, vital signs, and triage acuity from a single hospital to fit a logistic regression model, which was moderately predictive of hospital admission in older ED patients (AUC = 0.73).

1.4. Objectives

With little known about the performance and applications of ML approaches in older ED populations, we set out to identify whether ML could accurately predict hospital admission from the ED. More specifically, the objectives of this study are two-fold. First, we aimed to predict hospital admission using several ML approaches in older patients presenting to the ED for care. Second, we aimed to identify and describe the most important clinical and patient characteristics that are associated with hospital admission in older ED patients. Our study contributes to research in medical informatics, geriatrics, and emergency medicine by reporting on the utilities of ML as well as the importance of a comprehensive set of geriatric syndromes and functional assessments. These clinical assessments are not commonly available in an emergency setting.

2. Materials and methods

2.1. Data source

We conducted a secondary data analysis of the Canadian patients in the largest prospective cohort study of older ED patients to date, the interRAI multinational ED study [42]. InterRAI is an international collaborative network that aims to improve the care of medically- or psychosocially-complex individuals. Data were collected on 2274 older adults from eight ED sites across five provinces in Canada (Ontario, Nova Scotia, Manitoba, Saskatchewan, and British Columbia) between November 2009 and April 2012. The dataset includes patients 75 years of age and older who were recruited at ED registration [43]. The age of 75 was chosen based on prior work, demonstrating that this cohort is at greatest risk for ED visitation and adverse health outcomes following discharge [44,45]. Patients were excluded if they were in severe medical distress, were expected to die within 24 hrs of arrival, or did not speak English and did not have an interpreter [43]. The majority of data were collected during daytime hrs (07:00-19:00) by research nurses or allied health professionals, based on prior work reporting higher daytime usage by older adults [46]. Ethics approval was obtained from the academic institutions and research ethics boards of all participating hospitals [43].

2.2. Predictor and outcome variables

2.2.1. Predictor variables

Patients enrolled in the original study received a formal geriatric assessment by a nurse or allied health professional using the interRAI ED Contact Assessment [42]. The ED Contact Assessment is a standardized clinical decision support tool to inform diagnostic, treatment, and discharge decision-making in the ED [47]. The items of the ED Contact Assessment have an established test content validity in acute care [48], inter-rater reliability [49,50], and predictive validity across a series of outcomes in the ED setting [42,51]. A unique feature of the ED Contact Assessment is that it collects data on baseline function and health states prior to the acute illness that resulted in the emergency presentation. This information is referred to as the premorbid condition [47]. Data pertaining to both the premorbid and acutely-ill health states were examined when items allowed. We extracted all items of the ED Contact Assessment, excluding patient identifiers. Appendix A displays a comprehensive list of all predictors utilized.

2.2.2. Outcome measure

The outcome of interest in this study was hospital admission. Hospital admission was defined as the referral and in-patient admission of an older adult through the ED. Hospital admission, therefore, was measured as a binary variable.

2.3. Methods

2.3.1. Data preparation and variable selection

Prior to data analysis, all items of the ED Contact Assessment were screened for clinical relevance. Data were also screened for highly correlated features through a series of Kendal Tau analyses. A correlation coefficient of 0.9 was used as the cut-off with the most clinically-relevant feature retained. To eliminate variables with little or no variance, predictors with a ratio of 20:1 or greater between the two most common values were collapsed into fewer levels or excluded from the analysis [31]. Pre-processing was conducted within the resampling method, with features centered and scaled, and missing data imputed using the *K*-nearest neighbor (KNN) method. Categorical variables were dummy-coded only for the non-tree-based models [52].

2.3.2. Descriptive analysis

Descriptive statistics were reported using general measures of frequency and central tendency.

2.3.3. ML algorithms

Data were analyzed using R version 3.6.1, and all predictive models were built using the caret package [53]. We used 10-fold cross-validation for all analyses and performance assessments. This approach provides a more robust and reliable way of measuring model performances [31]. In doing so, we randomly split the data into a 90% training sample and 10% validation sample, and we repeat the analysis ten times. Finally, we use the average performance measure generated from the ten rounds of running the algorithm. All models were built using the same features displayed in Appendix A. We trained a series of five supervised ML classification algorithms, including (a) logistic regression (LR), (b) classification and regression tree (CART), (c) support vector machine (SVM), (d) random forests (RF), and (e) gradient boosted trees (GBT). These ML algorithms are commonly used in prior studies aiming to predict hospital admission for ED patients [27,32–41].

2.3.4. Performance measurement and variable importance

The performance of the ML algorithms was measured based on the area under the receiver operating curve (AUC) using 10-fold cross-validation. We also report the accuracy, sensitivity, and specificity of each model to supplement performance interpretation. To determine the importance of each predictor in an ML algorithm, for all models except RF, we used the accuracy-based feature importance procedure available in the caret package, which measures the average decrease in the model's AUC in the absence of the predictor [31]. For RF, we used the ranger package and the average information gain, through the mean decrease in the Gini index, to measure the variable importance. The variable importance scores are scaled to have a maximum value of 100 (for the most important predictor as the reference point). For comparative purposes, for each predictive model, we rescaled the scores, so they add up to 1. We elected to report the variable importance as determined by the most accurate ML model.

2.3.5. Hyperparameter tuning

For each model, the hyperparameters were tuned by maximizing the overall cross-validated AUC. LR was fit using the stats package. All other models were tuned in accordance with recommendations by Kuhn and Johnson [31]. In summary, an exhaustive random grid search was conducted to provide a preliminary shotgun search for eligible tuning parameter values. After plotting and scrutinizing the preliminary search

Table 1
Patient and visit characteristics.

Variable	*N* (%)
Age ˆ	82.5 (77.4–87.9)
Gender (female)	1377 (61.4)
Lives alone	806 (35.9)
Publicly funded formal support	
Community-dwelling (HC)	376 (16.5)
Long-term care home	134 (5.9)
No formal support (reference)	1764 (77.6)
Caregiver distress†	425 (18.7)
Cognitive impairment ‡	
Premorbid §	414 (18.3)
Admission ||	534 (23.7)
Potential delirium ¶	332 (14.7)
Activities of daily living (ADL)	
Difficulty with bathing	
Premorbid §	841 (37.4)
Admission ||	1318 (59.1)
Difficulty with personal hygiene	
Premorbid §	378 (16.8)
Admission ||	635 (28.1)
Difficulty with dressing lower body	
Premorbid§	568 (25.1)
Admission ||	1007 (44.5)
Difficulty with locomotion	
Premorbid §	388 (17.1)
Admission ||	970 (43.1)
Independent activities of daily living	
Difficulty with medications ‡‡	722 (31.8)
Difficulty with stairs §§	1379 (60.9)
Conditions and symptoms	
Poor self-reported health ¶¶	
Premorbid §	178 (7.8)
Admission ||	441 (19.4)
Depressive symptoms *	449 (19.7)
Anxious symptoms	870 (38.2)
Expresses anhedonia ††	822 (36.1)
Hallucinations or delusions	145 (6.4)
Any falls (last 90 days)	728 (32.5)
Traumatic injury	160 (7.3)
Daily and severe pain §§§	421 (18.5)
Dyspnea **	
Premorbid §	458 (20.1)
Admission ||	632 (27.8)
Unstable condition ¶¶¶	1080 (47.7)
Decrease food/fluids ***	666 (29.4)
Weight loss †††	194 (8.6)
ED visitation prior 90 days	930 (40.9)
Urgent triage score (CTAS 1 − 3)	1762 (80)

ˆ Data reported as the median and interquartile range (Q1–Q3).
† Primary informal helper(s) express feelings of distress, anger, or depression.
‡ Modified independent or any impairment in making decisions regarding tasks of daily living.
§Premorbid: the 3days period prior to the onset of the current acute illness or episode.
|| Admission: the past 24 hrs or time since acute illness or episode that prompted the ED visit.
¶ Acute change in mental status from a person's usual functioning.
‡‡ Difficulty remembering to take medicines, opening bottles, taking correct drug dosages, giving injections, or applying ointments.
§§ Supervision or any assistance with a full flight of stairs (12–14 stairs).
¶¶ When asked, "In general, how would you rate your health?" person responds "Poor.".
* When asked, patient reports feeling sad, depressed, or hopeless in the past three days.
†† When asked, patient reports little interest or pleasure in things they normally enjoy.
§§§ Pain that is severe or excruciating in the past three days.
** Dyspnea at rest or present when performing normal day-to-day activities.
¶¶¶ Conditions or diseases that make cognitive, ADL, mood, or behavior patterns unstable (fluctuating, precarious, or deteriorating).
*** Noticeable decrease in the amount of food usually eaten or fluids usually consumed.
††† Weight loss of 5% or more in the last 30 days, or 10% or more in the past 180 days.

results, an exhaustive, iterative, and sequential series of focused grid searches were conducted to find the optimal tuning parameters. For CART, the complexity parameter and maximum tree depth were tuned using the rpart package. SVM was tuned using a double-layered tuning grid, testing values of cost and sigma via the kernlab package. RF was trained using the ranger package, where a triple-layered tuning grid was created by examining the combinations of (a) the number of variables available at each split, (b) the splitting rule (i.e., Gini impurity index or extra trees), and (c) the minimal node size. GBT was fit using the xgboost package, with a total of six hyperparameters tuned: (a) the maximum number of iterations, (b) maximum tree depth, (c) shrinkage rate, (d) gamma, (e) the number of observations supplied to the tree, and (f) the minimum sum of instance weights required to stop splitting [31]. Appendix B provides the details and plots of the hyperparameter tuning results, and Appendix D displays the R codes we used for data analytics in this study.

3. Results

3.1. Summary results

Table 1 displays a summary of the clinical profiles of all older patients in the sample. In our data, 1119 (52%) of ED visits resulted in hospitalization. The median age of all patients was 83 (interquartile range [Q1–Q3] = 7788), and the majority of the patients were female (61%). Most older adults presented to the ED enrolled in no publicly funded formal support service (78%), with 16% receiving home care services prior to ED arrival and 6% residing in a long-term care home. Approximately 80% of all visits by older adults were deemed to be urgent, receiving a Canadian Acuity and Triage Scale (CTAS) score of three or less. Missing data was minimal and non-informative, with a range of 0–4% (mean of 0.7%) across all predictor variables, with no missing data for the outcome variable.

Table 2
Details of hyperparameter tuning, optimal parameter, and predictive accuracy of ML algorithms.

ML	Details of hyperparameter tuning		
CART	**Parameter**	**Complexity parameter (CP)**	**MTD**
	Range	0 – 0.05 by 0.0001	1 – 30
	Optimal	0.0079	8
SVM	**Parameter**	**Sigma**	**Cost**
	Range	0.001 – 0.1 by 0.001	1 – 4
	Optimal	0.003	2.8
RF*	**Parameter**	**Number of splitting variables (aka mtry)**	**Minimum node size (MNS)**
	Range	1 – 40	1 – 20
	Optimal	9	19
GBT	**Parameter**	**Maximum iterations**	**Learning rate (shrinkage)**
	Range	50 – 10,000 by 50	0.005 – 0.04 by 0.005, 0.1 – 0.4 by 0.1
	Optimal	500	0.015
	Parameter	**MTD**	**Gamma**
	Range	1 – 8	0, 0.05, 0.1, 0.5, 0.7, 0.9, 1
	Optimal	3	0.7
	Parameter	**Subsample ratio; columns (SRC)**	**Subsample ratio; training (SRT)**
	Range	0.4 –1 by 0.2	0.5, 0.75, 1
	Optimal	1	0.75
	Optimal	0.068	1
LR	Not applicable		

* **Splitting rule:** Gini index or extra trees [28].
Note: ML = machine learning; CART = classification and regression tree; SVM = support vector machine; RF = random Forest; GBT = gradient boosted trees; LR = logistic regression; MTD = max tree depth.

3.2. Hyperparameter tuning and predictive model performance

Table 2 summarizes the details of the hyperparameters tuning procedure and the optimal values utilized in the final models.

Fig. 1 illustrates various measures of predictive performance for each ML algorithm in our study, and Fig. 2 illustrates the 95% confidence intervals of all AUCs. There was a significant overlap in the AUC confidence intervals of all models except for CART, which had the worst overall performance. Overall, GBT achieved the best performance in classifying older adults who were hospitalized through the ED, achieving an AUC of 0.8 and an accuracy of 0.76.

3.3. Variable importance

Fig. 3 depicts the relative importance of the top 15 variables for GBT. Appendix C provides the details of the relative importance of the predictors across all ML models. In the interest of space, we will discuss the top five most predictive features of the hospital admission in older ED patients based on the GBT algorithm, which are (1) an order for home intravenous therapy, (2) time of ED presentation, (3) the level of formal support required in the community to facilitate healthy aging (e.g., home care, long-term care), (4) independence in walking or wheeling between locations at the time of ED presentation, and (5) presenting to the ED with a baseline medical disease or condition that makes cognitive, ADL, mood, or behavior patterns unstable.

4. Discussion

Without knowledge of the presenting complaint, emergency diagnosis, or clinical therapies employed in the ED, we were able to predict hospital admission with good predictive accuracy. The GBT was best able to classify patients, producing an AUC of 0.8 and an accuracy of 0.76. Both the sensitivity and specificity of this model are relatively close (0.73 and 0.74, respectively), demonstrating that this algorithm can be used to both rule-in and rule-out older adults who may require hospitalization. A similar balance of sensitivity and specificity was found across all models.

4.1. Comparison of findings with prior medical literature

A plethora of literature has examined the use of predictive modeling and ML approaches to predict hospital admission and ED visitation in the general ED patient population [27,32–39]. To our knowledge, only one other study has attempted to predict hospital admission in older ED patients; however, they did not have access to geriatric syndromes and functional assessments when creating their predictive model. In this study, LaMantia and colleagues fit a logistic regression model, which was moderately predictive of hospital admission (AUC = 0.73) [41]. Despite having a smaller sample size and no knowledge of the chief complaint or triage vital signs, we were able to outperform the previous model.

Our GBT model determined that the most informative predictor of hospital admission was an order for home intravenous therapies prior to presenting to the ED. Our findings could be interpreted in several ways. These patients are already receiving high-level medical care in the community, and there may be no option to further escalate intravenous therapy while staying at home. The use of intravenous therapies is generally reserved for patients with severe medical conditions such as end-stage disease, cancer, and systemic infection. These patients may be less able to cope with an additional acute health problem. Furthermore, hospital admission may be required for the same medical condition, in the case of failed community management. The second most informative predictor was the time of ED presentation. More specifically, older adults who presented to the ED during the early morning hrs (i.e., before 09:00) were most likely to be admitted for in-patient care. This finding is to be expected, considering that those who seek medical

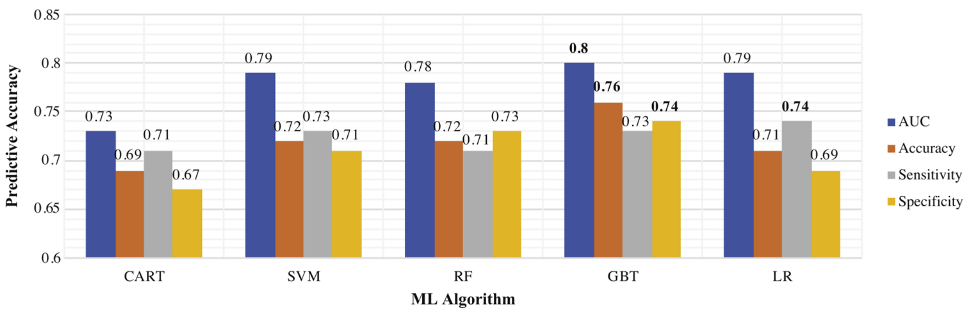

Fig. 1. Various measures of predictive accuracy across all ML algorithms.
Notes:
1. For each measure of predictive accuracy, the highest value is boldfaced.
2. Sensitivity and specificity, respectively, refer to the proportions of true positive and true negative predictions
ML: machine learning, CART = classification and regression tree; SVM = support vector machine; RF = random forest; GBT = gradient boosted trees; LR = logistic regression.

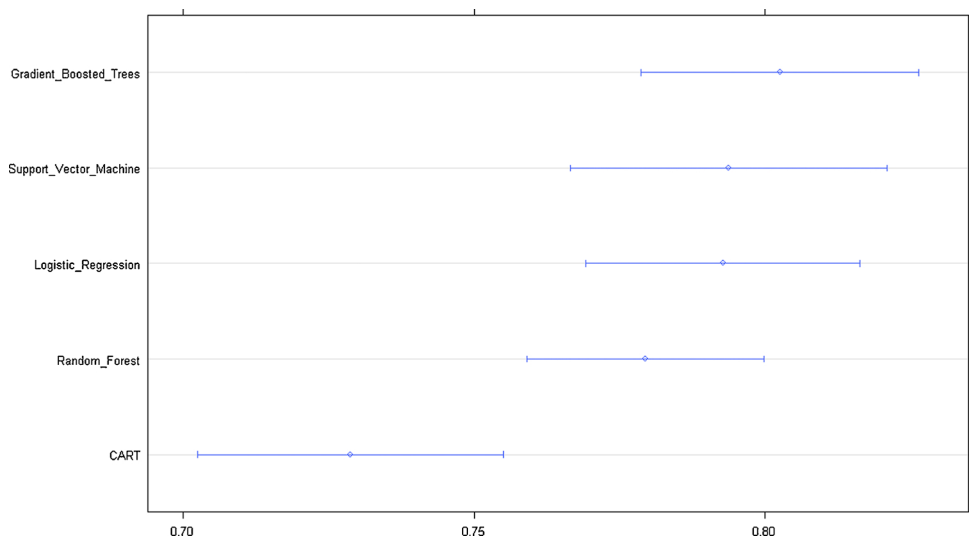

Fig. 2. Display of the 95% AUC confidence intervals for all ML models.

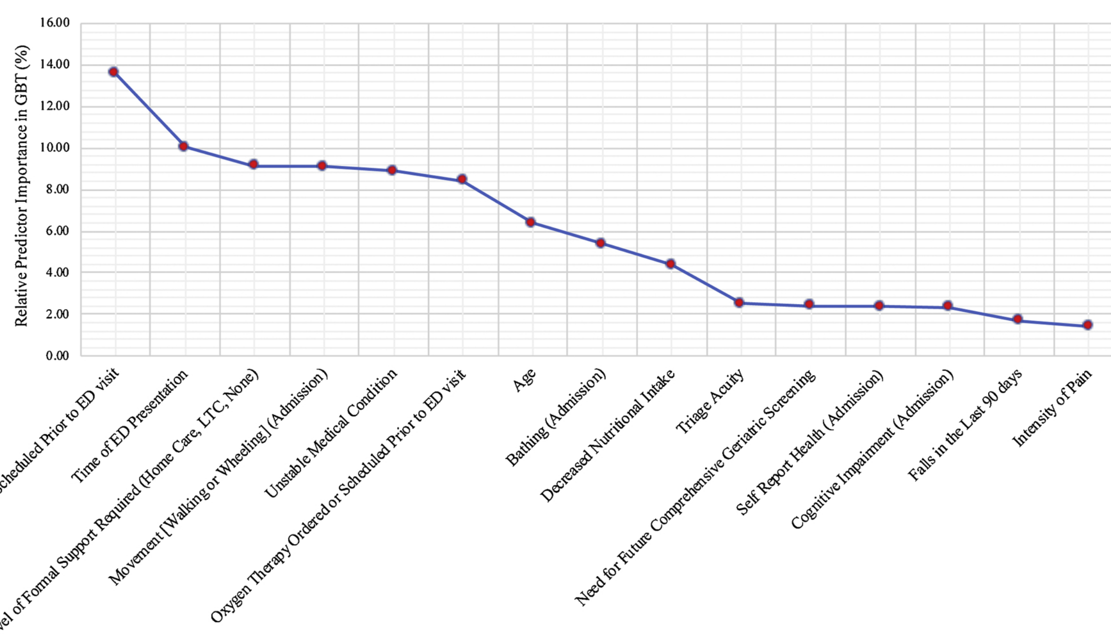

Fig. 3. Median relative importance of the Top 15 predictors across all ML algorithms.

attention immediately upon awakening are likely to be experiencing severe or worsening symptoms. This is especially true for older adults with chronic diseases like chronic obstruct pulmonary disease, considering that disease exacerbations are often experienced in the morning [54]. This finding differs from the work of Handly and colleagues, which determined that nighttime use is most predictive [37]. A likely reason for the difference in findings is that our data contained an older sample and were collected mostly during daytime hrs.

Next, our study determined that the level of formal support required for healthy aging was the third most informative predictor of hospital admission. More specifically, those living in a long-term care home were least likely to require a hospital admission when compared to those receiving publicly-funded home care services and well-being of older adults. This finding corroborates the prior work of Wilson and Truman, the only other study to examine health service use among these three cohorts of patients [55]. Approximately 25% of all ED transfers from long-term care in Ontario are deemed to be preventable or unnecessary [56]. Furthermore, residents in long-term care receive 24 h monitoring by medical professionals, and this knowledge may increase clinician comfort when discharging potentially complex patients.

Additionally, our study found that the level of independence in walking or wheeling between locations was the fourth most informative predictor of hospital admission. This finding is consistent with prior literature reporting that impairment in ADL and daily functioning are associated with admission for in-patient care in community-dwelling older adults [57,58]. Finally, the presence of a medical condition or disease that makes cognitive, ADL, mood, or behavior patterns unstable was deemed an informative predictor of hospitalization. This is to be expected; however, we are unable to comment on whether the association is stronger in older adults compared to other emergency patients, or whether the effect is similar across patient demographics.

In the general ED population, findings varied with regard to predictor importance. Two studies determined that triage acuity was the most informative predictor [27,39], and one study further validated the importance of triage acuity by reporting triage acuity as one of the top five most informative predictors [34]. Triage acuity was ranked as our tenth most informative predictor in the GBT model. Prior work has demonstrated that the triage process for older adults is often more cumbersome and challenging for ED clinicians, partly because older adults may not mount the same physiological response to illness when compared to their younger counterparts [13]. Interestingly, Hong et al. determined that the regular use of cardiac medication was the most predictive factor of hospital admission [34]. Finally, it is worth noting that the majority of studies examining general ED use determined that age was an informative predictor [27,34,37–39]. Our study did not rank this variable with the same level of importance. Prior work has demonstrated that in the later stages of life, geriatric complexity and multimorbidity are the driving factors of health services use, rather than age [42,59].

4.2. Clinical and policy implications

The ability to predict hospital admission using a series of geriatric syndromes, functional assessments, and baseline care needs demonstrates the clinical and predictive utility of these patient characteristics. Furthermore, these findings further demonstrated the predictive validity of the interRAI ED Contact Assessment. Our findings add to prior work by Costa and colleagues who used similar data to predict extended hospital length of stays and repeat hospital use in older ED patients [42]. Given that geriatric syndromes and functional needs are highly associated with health services use for older ED patients, ED clinicians and policymakers should aim to implement the evaluation of these characteristics as a standard of care within emergency management pathways.

Early knowledge of hospital admission risk in the ED could be used to predict hospital bed capacity needs and reduce the typically long ED stays. This is important in light of recent evidence showing that long ED stays are harmful to older adults, with increased risk of delirium, and higher mortality associated with ED overcrowding [60,61]. Furthermore, given the high risk of functional decline for older adults admitted for in-patient care, this information can be used to identify older ED patients who may benefit from geriatric tailored services and consultations prior to admission (i.e., physiotherapy and occupational therapy, dietary consults, etc.) Advanced knowledge of admission status also allows hospitals to expedite in-patient care plans, referrals, and consultations. This is particularly important when hospitals are operating abovetheir bed capacity. Such ML processes could become integrated into clinical decision support tools within the electronic medical record for operationalization purposes. Additionally, families and home support teams would also benefit from knowing the admission status in advance, as it would allow for them to arrange accommodations prior to hospital discharge.

4.3. Strengths, limitations, and future research

Our study used data with a comprehensive set of geriatric syndromes, such as cognitive, functional, and nutritional status, to name a few. These features are not typically available in an emergency setting. Data on presenting complaint and diagnoses would have provided informative features which may have increased predictive accuracy and provided a better contextual understanding of the data. Data pertaining to time spent in a clinical treatment area would have also strengthened our models. Unfortunately, our data were not structured in a way to allow us to delineate the patient location after ED registration or the time spent in the waiting room. While we did not have access to these important predictors, it is worth noting that we were able to outperform a prior study of older ED patients that had access to these clinical features [41].

We were also limited by the relatively small sample size ($n = 2274$). Given that ML methods are better able to learn with large data sets, a larger ED cohort would likely have increased predictive accuracy [31]. Despite these barriers, we were able to demonstrate a strong and robust predictive validity of ML using the data available. Finally, the majority of data were collected during daytime hrs between 07:00 and 19:00 hrs, limiting the generalizability of findings to nighttime visitors. Cognizant of their limited funding, the authors of the original study elected to prioritize daytime data collection to best capture current geriatric models of care [43], given that older adults most often present for care during daytime hrs [44,45]. Future research should aim to build on these limitations and focus on improving ML methods to predict other health service outcomes, such as repeat hospital use, hospital length of stay, and mortality, which are important to clinicians, policymakers, and key stakeholders.

5. Conclusion

To our knowledge, this was the first study to predict hospital admission in older ED patients using a series of geriatric syndromes, functional assessments, and baseline care needs. We employed a series of ML methods and were able to obtain an AUC of 0.8 and an accuracy of 0.76 using GBT. Furthermore, our study highlighted a number of patient features that are predictive of hospital admission in older adults. This information can be used to inform decision-making about ED disposition and may expedite admission processes and proactive discharge planning.

Authors' contributions

Fabrice Mowbray drafted the initial document and conducted all statistical and predictive analytics. Dr. Manaf Zargoush contributed to the design of the machine learning algorithms, oversaw all analyses, and contributed substantial edits through all drafts of this paper. Aaron Jones, Dr. Kerstin de Wit, and Dr. Andrew Costa contributed to the edits of this paper and provided key insights into the clinical and policy implications of our findings.

Summary Points

What was already known on the topic?

1. Older adults are at greater risk for hospital admission and emergency department use.
2. Little is known about the performance and utility of ML methods in predicting hospital admission among older ED patients.
3. Geriatric syndromes are predictive of health service use in older ED patients.
4. The decision to admit or discharge older adults can be challenging for ED clinicians.

What this study added to our knowledge?

1. This study was the first to use a series of geriatric syndromes and assessments to predict hospital admission.
2. ML can accurately predict hospital admission among older ED patients.
3. Geriatric syndromes and assessments are predictive of hospital admission in older ED patients.
4. This study identified several patient and clinical features that are predictive of hospital admission in older ED patients.

Declaration of Competing Interest

The authors declare no conflict of interest in this study.

Acknowledgment

We are grateful to MacData Institutefor funding our research. We are also grateful to the colleagues who provided feedback on this study.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.ijmedinf.2020.104163.

References

[1] H. Wan, D. Goodkind, P. Kowal, An Aging World: 2015 (US Census Bureau, International Population Reports, P95/16-1), US Government Publishing Office, Washington, DC, 2016.
[2] O.T. Rutschmann, T. Chevalley, C. Zumwald, C. Luthy, B. Vermeulen, F. Sarasin, Pitfalls in the emergency department triage of frail elderly patients without specific complaints, Swiss Med. Wkly. 135 (2005) 145–150.
[3] D.C. Roberts, M.P. McKay, A. Shaffer, Increasing rates of emergency department visits for elderly patients in the United States, 1993 to 2003, Ann. Emerg. Med. 51 (2008) 769–774.
[4] J.H. Kahn, B. Magauran, Trends in geriatric emergency medicine, Emerg. Med. Clin. 24 (2006) 243–260.
[5] L.P. Latham, S. Ackroyd-Stolarz, Emergency department utilization by older adults: a descriptive study, Can. Geriatr. J. 17 (2014) 118.
[6] J.M. Pines, P.M. Mullins, J.K. Cooper, L.B. Feng, K.E. Roth, National trends in emergency department use, care patterns, and quality of care of older adults in the United States, J. Am. Geriatr. Soc. 61 (2013) 12–17.
[7] Canadian Institute for Health Information, Health Care in Canada, 2011: A Focus on Seniors and Aging, Author Ottawa, ON, 2011.
[8] A.C. of E. Physicians, American Geriatrics Society, Emergency Nurses Association, Society for Academic Emergency Medicine, Geriatric Emergency Department Guidelines Task Force, Geriatric emergency department guidelines, Ann. Emerg. Med. 63 (2014) e7–25.
[9] J.J. McCabe, S.P. Kennelly, Acute care of older patients in the emergency department: strategies to improve patient outcomes, Open Access Emerg. Med. OAEM 7 (2015) 45.
[10] A. Perry, J.M. Tejada, D. Melady, An approach to the older patient in the emergency department, Clin. Geriatr. Med. 34 (2018) 299–311.
[11] R.M. McNamara, E. Rousseau, A.B. Sanders, Geriatric emergency medicine: a survey of practicing emergency physicians, Ann. Emerg. Med. 21 (1992) 796–801.
[12] T. Snider, D. Melady, A.P. Costa, A national survey of Canadian emergency medicine residents' comfort with geriatric emergency medicine, Can. J. Emerg. Med. 19 (2017) 9–17.
[13] M.J. Bullard, D. Melady, M. Emond, E. Musgrave, B. Unger, E. van der Linde, R. Grierson, T. Skeldon, D. Warren, J. Swain, Guidance when applying the canadian triage and acuity scale (CTAS) to the geriatric patient: executive summary, Can. J. Emerg. Med. 19 (2017) S28–S37.
[14] P. Nugus, A. Holdgate, M. Fry, R. Forero, S. McCarthy, J. Braithwaite, Work pressure and patient flow management in the emergency department: findings from an ethnographic study, Acad. Emerg. Med. 18 (2011) 1045–1052.
[15] C.R. Carpenter, R.T. Griffey, S. Stark, C.M. Coopersmith, B.F. Gage, Physician and nurse acceptance of technicians to screen for geriatric syndromes in the emergency department, West. J. Emerg. Med. 12 (2011) 489.
[16] A. Rodríguez-Molinero, M. López-Diéguez, A.I. Tabuenca, J.J. de la Cruz, J.R. Banegas, Functional assessment of older patients in the emergency department: comparison between standard instruments, medical records and physicians' perceptions, BMC Geriatr. 6 (2006) 13.
[17] F. Aminzadeh, W.B. Dalziel, Older adults in the emergency department: a systematic review of patterns of use, adverse outcomes, and effectiveness of interventions, Ann. Emerg. Med. 39 (2002) 238–247.
[18] M.C. Odden, D. Melzer, Machine Learning in Aging Research, Oxford University Press US, 2019.
[19] A. Jones, A.P. Costa, A. Pesevski, P.D. McNicholas, Predicting hospital and emergency department utilization among community-dwelling older adults: statistical and machine learning approaches, PLoS One 13 (2018).
[20] L.C. Gray, N.M. Peel, A.P. Costa, E. Burkett, A.B. Dey, P.V. Jonsson, P. Lakhan, G. Ljunggren, F. Sjostrand, W. Swoboda, Profiles of older patients in the emergency department: findings from the interRAI Multinational Emergency Department Study, Ann. Emerg. Med. 62 (2013) 467–474.
[21] L.A. Calder, T. Arnason, C. Vaillancourt, J.J. Perry, I.G. Stiell, A.J. Forster, How do emergency physicians make discharge decisions? Emerg. Med. J. 32 (2015) 9–14.
[22] M.C. Creditor, Hazards of hospitalization of the elderly, Ann. Intern. Med. 118 (1993) 219–223.
[23] N. Samaras, T. Chevalley, D. Samaras, G. Gold, Older patients in the emergency department: a review, Ann. Emerg. Med. 56 (2010) 261–269.
[24] S. Purdey, A. Huntley, Predicting and preventing avoidable hospital admissions: a review., J. R, Coll. Physicians Edinb. 43 (2013) 340–344.
[25] H. Patel, S. Morduchowicz, M. Mourad, Using a systematic framework of interventions to improve early discharges, Jt. Comm. J. Qual. Patient Saf. 43 (2017) 189–196.
[26] D. Golmohammadi, Predicting hospital admissions to reduce emergency department boarding, Int. J. Prod. Econ. 182 (2016) 535–544, https://doi.org/10.1016/j.ijpe.2016.09.020.
[27] Y. Sun, B.H. Heng, S.Y. Tay, E. Seow, Predicting hospital admissions at emergency department triage using routine administrative data, Acad. Emerg. Med. 18 (2011) 844–850.
[28] N. Shafaf, H. Malek, Applications of machine learning approaches in emergency medicine; a review article, Arch. Acad. Emerg. Med. 7 (2019).
[29] P. Bennett, N.R. Hardiker, The use of computerized clinical decision support systems in emergency care: a substantive review of the literature, J. Am. Med. Inform. Assoc. 24 (2017) 655–668.
[30] T. Hastie, R. Tibshirani, J. Friedman, The elements of statistical learning: data mining, inference, and prediction, second edition, 2nd ed. 2009, Corr. 9th Printing 2017 Edition, Springer, New York, NY, 2017.
[31] M. Kuhn, K. Johnson, Applied Predictive Modeling, Springer, 2013.
[32] F.R. Lucini, F.S. Fogliatto, G.J. da Silveira, J.L. Neyeloff, M.J. Anzanello, R. de S. Kuchenbecker, B.D. Schaan, Text mining approach to predict hospital admissions using early medical records from the emergency department, Int. J. Med. Inf. 100 (2017) 1–8.
[33] N.W. Sterling, R.E. Patzer, M. Di, J.D. Schrager, Prediction of emergency department patient disposition based on natural language processing of triage notes, Int. J. Med. Inf. 129 (2019) 184–188.
[34] W.S. Hong, A.D. Haimovich, R.A. Taylor, Predicting hospital admission at emergency department triage using machine learning, PLoS One 13 (2018).
[35] J.W. Dexheimer, J. Leegon, D. Aronsky, Predicting hospital admission at triage in an emergency department, AMIA, Annu. Symp. Proc., 2007 pp. 937–937.
[36] Z.F. Meisel, C.V. Pollack, C.C. Mechem, J.M. Pines, Derivation and internal validation of a rule to predict hospital admission in prehospital patients, Prehosp. Emerg. Care 12 (2008) 314–319.
[37] N. Handly, D.A. Thompson, J. Li, D.M. Chuirazzi, A. Venkat, Evaluation of a hospital admission prediction model adding coded chief complaint data using neural network methodology, Eur. J. Emerg. Med. 22 (2015) 87–91.
[38] J.S. Peck, J.C. Benneyan, D.J. Nightingale, S.A. Gaehde, Predicting emergency department inpatient admissions to improve same-day patient flow, Acad. Emerg. Med. 19 (2012) E1045–E1054.
[39] C.A. Parker, N. Liu, S.X. Wu, Y. Shen, S.S.W. Lam, M.E.H. Ong, Predicting hospital admission at the emergency department triage: a novel prediction model, Am. J. Emerg. Med. 37 (2019) 1498–1504.
[40] J. Leegon, I. Jones, K. Lanaghan, D. Aronsky, Predicting hospital admission in a pediatric emergency department using an artificial neural network, AMIA Annu. Symp. Proc., American Medical Informatics Association, 2006 pp. 1004–1004.
[41] M.A. LaMantia, T.F. Platts-Mills, K. Biese, C. Khandelwal, C. Forbach, C.B. Cairns, J. Busby-Whitehead, J.S. Kizer, Predicting hospital admission and returns to the emergency department for elderly patients, Acad. Emerg. Med. 17 (2010) 252–259.
[42] A.P. Costa, J.P. Hirdes, G.A. Heckman, A.B. Dey, P.V. Jonsson, P. Lakhan, G. Ljunggren, K. Singler, F. Sjostrand, W. Swoboda, Geriatric syndromes predict postdischarge outcomes among older emergency department patients: findings from the interRAI Multinational Emergency Department Study, Acad. Emerg. Med. 21

(2014) 422–433.
[43] A.P. Costa, Older Adults Seeking Emergency Care: An Examination of Unplanned Emergency Department Use, Patient Profiles, and Adverse Patient Outcomes Post Discharge, (2013).
[44] E.W. Nawar, R.W. Niska, J. Xu, National Hospital Ambulatory Medical Care Survey: 2005 Emergency Department Summary, (2007).
[45] G. Li, J.T. Lau, M.L. McCarthy, M.J. Schull, M. Vermeulen, G.D. Kelen, Emergency department utilization in the United States and Ontario, Canada, Acad. Emerg. Med. 14 (2007) 582–584.
[46] A. Downing, R. Wilson, Older people's use of accident and emergency services, Age Ageing 34 (2004) 24–30.
[47] A. Costa, J. Hirdes, S. Ariño-Blasco, K. Berg, V. Boscart, C. Carpenter, N. Curtin-Telegdi, M. Emond, L. Gray, G. Heckman, interRAI Emergency Department (ED) Assessment System Manual, for Use With the interRAI ED Screener (EDS) and ED Contact Assessment (ED-CA), interRAI, Washington DC, 2017.
[48] N.I. Wellens, M. Deschodt, S. Boonen, J. Flamaing, L. Gray, P. Moons, K. Milisen, Validity of the interRAI Acute Care based on test content: a multi-center study, Aging Clin. Exp. Res. 23 (2011) 476–486.
[49] J.P. Hirdes, G. Ljunggren, J.N. Morris, D.H. Frijters, H.F. Soveri, L. Gray, M. Björkgren, R. Gilgen, Reliability of the interRAI suite of assessment instruments: a 12-country study of an integrated health information system, BMC Health Serv. Res. 8 (2008) 277.
[50] N.I. Wellens, A. Van Lancker, J. Flamaing, L. Gray, P. Moons, G. Verbeke, S. Boonen, K. Milisen, Interrater reliability of the interRAI Acute Care (interRAI AC), Arch. Gerontol. Geriatr. 55 (2012) 165–172.
[51] A.-A. Brousseau, E. Dent, R. Hubbard, D. Melady, M. Émond, É. Mercier, A.P. Costa, M.E.D.S.G.L.C.H.J.P.D.A.B.J.P.V.L.P.L.G.S.K.S.F.S.W.W.N. I.H, Identification of older adults with frailty in the emergency department using a frailty index: results from a multinational study, Age Ageing 47 (2018) 242–248.
[52] M. Kuhn, K. Johnson, Feature Engineering and Selection: A Practical Approach for Predictive Models, CRC Press, 2019.
[53] M. Kuhn, Classification and Regression Training (CARET), R Program. Lang. Package, (2015).
[54] M.R. Partridge, N. Karlsson, I.R. Small, Patient insight into the impact of chronic obstructive pulmonary disease in the morning: an internet survey, Curr. Med. Res. Opin. 25 (2009) 2043–2048, https://doi.org/10.1185/03007990903103006.
[55] D. Wilson, C. Truman, Comparing the health services utilization of long-term-care residents, home-care recipients, and the well elderly, Can. J. Nurs. Res. Arch. 37 (2005).
[56] A. Gruneir, C.M. Bell, S.E. Bronskill, M. Schull, G.M. Anderson, P.A. Rochon, Frequency and pattern of emergency department visits by long-term care residents—a population-based study, J. Am. Geriatr. Soc. 58 (2010) 510–517.
[57] T.M. Damush, D.M. Smith, A.J. Perkins, P.R. Dexter, F. Smith, Risk factors for nonelective hospitalization in frail and older adult, inner-city outpatients, The Gerontologist 44 (2004) 68–75.
[58] G. Mazzaglia, L. Roti, G. Corsini, A. Colombini, G. Maciocco, N. Marchionni, E. Buiatti, L. Ferrucci, M.D. Bari, Screening of older community-dwelling people at risk for death and hospitalization: the Assistenza Socio-Sanitaria in Italia project, J. Am. Geriatr. Soc. 55 (2007) 1955–1960.
[59] F. Mowbray, A.-A. Brousseau, E. Mercier, D. Melady, M. Émond, A.P. Costa, Examining the relationship between triage acuity and frailty to inform the care of older emergency department patients: findings from a large Canadian multisite cohort study, Can. J. Emerg. Med. 22 (2020) 74–81, https://doi.org/10.1017/cem.2019.432.
[60] M. Émond, D. Grenier, J. Morin, D. Eagles, V. Boucher, N. Le Sage, É. Mercier, P. Voyer, J.S. Lee, Emergency department stay associated delirium in older patients, Can. Geriatr. J. 20 (2017) 10.
[61] D.B. Richardson, Increase in patient mortality at 10 days associated with emergency department overcrowding, Med. J. Aust. 184 (2006) 213–216.