Predicting frequent ED use by people with epilepsy with health information exchange data

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ABSTRACT

Objectives: To describe (1) the predictability of frequent emergency department (ED) use (a marker of inadequate disease control and/or poor access to care), and (2) the demographics, comorbidities, and use of health services of frequent ED users, among people with epilepsy.

Methods: We obtained demographics, comorbidities, and 2 years of encounter data for 8,041 people with epilepsy from a health information exchange in New York City. Using a retrospective cohort design, we explored bivariate relationships between baseline characteristics (year 1) and subsequent frequent ED use (year 2). We then built, evaluated, and compared predictive models to identify frequent ED users (≥4 visits year 2), using multiple techniques (logistic regression, lasso, elastic net, CART [classification and regression trees], Random Forests, AdaBoost, support vector machines). We selected a final model based on performance and simplicity.

Results: People with epilepsy who, in year 1, were adults (rather than children or seniors), male, Manhattan residents, frequent users of health services, users of multiple health systems, or had medical, neurologic, or psychiatric comorbidities, were more likely to frequently use the ED in year 2. Predictive techniques identified frequent ED visitors with good positive predictive value (approximately 70%) but poor sensitivity (approximately 20%). A simple strategy, selecting individuals with 11+ ED visits in year 1, performed as well as more sophisticated models.

Conclusions: People with epilepsy with 11+ ED visits in a year are at highest risk of continued frequent ED use and may benefit from targeted intervention to avoid preventable ED visits. Future work should focus on improving the sensitivity of predictions. *Neurology*® 2015;85:1031–1038

GLOSSARY

AUC = area under the receiver operating curve; **ED** = emergency department; **HIE** = health information exchange; ***ICD-9*** = *International Classification of Diseases, Ninth Revision*; **PPV** = positive predictive value.

Epilepsy is an ambulatory care sensitive condition; that is, high quality outpatient care may reduce unnecessary inpatient and emergency department (ED) care.[1–5] Thus, frequent ED use is a "health services marker," indicating inadequate disease control and/or poor access to care.[6]

Health care organizations in the United States, encouraged by recent state and federal policy changes, frequently hire care managers to coordinate care for people with ambulatory care sensitive conditions such as epilepsy.[7–9] One common strategy is to focus on patients at high risk of frequent ED use.[10] For people with epilepsy, several factors are associated with frequent ED use: low socioeconomic status, more seizures, anxiety, poor knowledge of epilepsy by self or caregivers, and greater stigma.[11–13] However, the predictability of frequent ED use is understudied.

Studying frequent ED use is challenging, in part because people often use multiple EDs for care.[14,15] Health information exchange (HIE) networks allow users to view medical information in the electronic health records of multiple unaffiliated institutions, creating a more complete record than possible from a single center's data.[14] These technologies are increasingly available,[16,17] and may provide a data source to describe and predict frequent ED use.

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Supplemental data at Neurology.org

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Here, we studied the predictability of frequent ED use in a large urban population of people with epilepsy, using data from an HIE. We (1) described the bivariate relationship between baseline characteristics and subsequent frequent ED use, (2) applied several machine learning techniques to predict frequent ED use, and (3) selected a parsimonious prediction rule and evaluated its performance.

METHODS

Study design. Via a retrospective cohort study design, we used demographic, utilization, and comorbidity data collected in 1 year to predict frequent ED visits in the following year in a group of 8,041 people with epilepsy. The Weill Cornell Medical Center institutional review board exempted analysis of this deidentified dataset from review.

Data. NYCLIX (New York Clinical Information Exchange) was an HIE network in New York from 2009 to 2012, when it merged with another HIE. NYCLIX linked patient records from 7 Manhattan hospitals, allowing us to track each individual's pattern of health service utilization over 2 years. Our data included visits to 7 of 13 Manhattan EDs, which handle approximately two-thirds of Manhattan's 800,000 yearly ED visits.[18,19]

Inclusion criteria. We included individuals who met the following 2 criteria: (1) at least one inpatient, outpatient, or ED visit from April 2009 to March 2010 at one of the 7 hospitals, and (2) one *ICD-9* code of 345.x (epilepsy) or 2 codes of 780.39 (convulsions) on separate days, satisfying the International League Against Epilepsy's recommended definition of "probable epilepsy" in administrative data.[20]

Predictor variables. Patient data included demographics (age, 3-digit zip code), visit history (ED, inpatient, and outpatient), radiology encounters, and comorbidities (*ICD-9* codes collapsed into 33 comorbidities).[21] We created several care fragmentation variables by counting the number of different hospitals ("sites") that individuals visited for different services.

Outcome. We defined "frequent ED use" as 4 or more visits in a year—a cutoff often used in the ED literature.[6] We used a binary outcome to allow our statistical tools to produce interpretable probability estimates (i.e., the percent chance that a patient will have 4 or more ED visits in the next year). The cause of ED visit was not reliably recorded. Thus, we conceptualized an "ED visit" as any unscheduled hospital visit, and did not distinguish visits for epilepsy from visits for other reasons, or ED discharges from visits leading to inpatient admissions.

Characteristics of frequent ED users. We described the bivariate relationship between baseline characteristics in year 1 and frequent ED use in year 2. We stratified ED use in year 2 using 4 categories, based on conventions from the ED literature[6,22] and from findings described later in this report. Our choice of boundaries distinguished no visits from some visits, set 4+ visits to indicate frequent use, and let 11+ visits indicate heavy use. Thus, our 4 categories include "never" for 0 visits in year 2, "occasional" 1–3, "moderate" 4–10, and "heavy" 11 or more. We tested for significance using the χ^2 and Pearson correlation tests as indicated.

Predictability. We randomly split the dataset in half, creating a test and training set each with 4,020 individuals. We explored 7 predictive modeling techniques,[23] in order to account for irregularities often encountered in health data, such as missing data, skew distributions, large numbers of variables, and nonlinear relationships among variables. We used several regression variants, which provide relatively easy-to-interpret results. These were (1) logistic regression with the best subsets algorithm for 1, 2, and 3 variables, (2) lasso (least absolute shrinkage and selection operator) logistic regression, and (3) elastic net logistic regression. We also used decision tree algorithms and geometric algorithms, which may provide more accurate predictions, although they are more challenging to interpret. These were (4) CART (classification and regression trees), (5) Random Forests, (6) AdaBoost, and (7) support vector machines. Each technique may improve predictions in different contexts. However, it is unclear a priori which method will work best to predict ED visits among patients with epilepsy. Additional information appears in appendix e-1 on the *Neurology*® Web site at Neurology.org.

We evaluated models via 5 criteria: (1) classification error, (2) sensitivity, (3) positive predictive value (PPV), (4) calibration, and (5) area under the receiver operating curve (AUC). "Classification error" is the percentage of predictions that are incorrect. "Calibration" measures the error between predicted probability and observed proportion, as described in appendix e-1. Note that AUC often appears high when the outcome is uncommon or rare, because the specificity is high (i.e., true negatives are common).

We qualified AUC, sensitivity, and PPV with this rubric: <0.6 poor, 0.6–0.69 fair, 0.7–0.79 good, 0.8–0.89 very good, and 0.9–1 excellent. We qualified calibration with this rubric: 0%–4% excellent, 5%–9% very good, 10%–14% good, 15%–20% fair, and >20% poor.

Choice of model. We chose the model with the smallest classification error for further analysis. Two models tied—we present the simplest here (one-variable model), and describe the other in appendix e-1 (lasso model).

One-variable model. A one-variable logistic regression model based on the number of ED visits in year 1 performed as well as more sophisticated models. We thus performed 2 additional analyses to investigate the relationship between year 1 ED visits and year 2 ED visits. First, we determined the number of ED visits in year 1 that corresponded to a 50% or greater chance of frequent ED use in the follow-up year, in order to suggest a cutoff for a parsimonious prediction rule. We repeated this exercise among 5 subpopulations: children (18 years and younger), adults (19–64 years), seniors (65+ years), Manhattan residents, and people living outside of Manhattan. Second, we created a mosaic plot to graphically illustrate the relationship between ED visit frequency in year 1 and ED visit frequency in year 2.

Statistical software. Our analysis was performed with the R software environment (version 2.15.1),[24] supplemented by several additional packages (appendix e-1).

RESULTS

Characteristics of frequent ED users. There were 8,041 individuals with epilepsy identified in year 1. In year 2, 491 (6.1%) visited the ED 4 or more times, including 395 (4.9%) with moderate use (4–10 visits) and 96 (1.2%) with heavy use (11+ visits). Of the remainder, 1,543 (19.2%) had occasional ED use (1–3 visits) and 6,007 (74.7%) had none. Those who were adults (vs children or seniors), male, or who resided in the same borough as the study hospitals (Manhattan) were more likely to be frequent ED users. The number of ED visits, inpatient admissions,

Table 1 Bivariate relationship between patient characteristics in year 1, and frequency of ED use in year 2[a]

	Frequency of ED visits in year 2				
	Infrequent ED use		Frequent ED use		
	Never (0 visits) (n = 6,007)	Occasional (1-3 visits) (n = 1,543)	Moderate (4-10 visits) (n = 395)	Heavy (11+ visits) (n = 96)	*p* Value
Age					
Median (IQI)	34 (14-53)	39 (45-54)	43 (26-56)	45 (34-54)	<0.001[b]
Pediatrics (0-18 y)	1,852 (31)	394 (26)	63 (16)	3 (3)	
Adult (19-64 y)	3,391 (56)	928 (60)	287 (73)	87 (91)	
Senior (65+ y)	702 (12)	204 (13)	45 (11)	5 (5)	
Unknown	4	1	0	0	
Sex					
Male	3,146 (52)	766 (50)	219 (55)	68 (71)	<0.001[c]
Female	2,856 (48)	775 (50)	175 (44)	28 (29)	
Unknown	5	2	1	0	
Home zip code					
Manhattan	1,979 (33)	960 (62)	277 (70)	74 (77)	<0.001[c]
Other NYC boroughs	2,251 (37)	468 (30)	91 (23)	16 (17)	
Downstate NY and NJ Gateway	939 (16)	45 (3)	9 (2)	3 (3)	
Elsewhere	711 (12)	18 (1)	3 (1)	0 (0)	
Unknown	127 (2)	52 (3)	15 (4)	3 (3)	
Utilization baseline year (year 1)					
ED visits	0 (0-1)	1 (0-3)	4 (2-7)	14 (8-22)	<0.001[b]
Inpatient admissions	1 (0-1)	1 (0-2)	2 (0-3.5)	4 (2-6)	<0.001[b]
Outpatient visits	0 (0-3)	3 (0-10)	3 (0-12)	1 (0-7)	<0.001[b]
Radiology days[d]	0 (0-2)	1 (0-3)	3 (1-6)	6 (3-12)	<0.001[b]
One or more brain MRIs	880 (15)	208 (14)	54 (14)	11 (12)	0.5[c]
One or more head CTs	1,133 (19)	419 (27)	168 (42)	68 (71)	<0.001[c]
Care fragmentation					
More than 1 site for care	741 (12)	384 (25)	172 (44)	58 (60)	<0.001[c]
Brain MRI at >1 site	15 (0.2)	7 (0.5)	4 (1)	1 (1)	0.03[c]
Head CT at >1 site	48 (0.8)	23 (1.5)	24 (6.1)	18 (19)	<0.001[c]
Comorbidity burden					
Jetté score ≥1	1,641 (27)	547 (36)	165 (42)	44 (46)	<0.001[c]
Jetté score ≥2	1,097 (18)	321 (21)	98 (25)	26 (27)	<0.001[c]
Psychiatric comorbidities[e]					
Depression	525 (8.7)	236 (15)	121 (31)	40 (42)	<0.001[c]
Psychosis	194 (3.2)	93 (6)	46 (12)	27 (28)	<0.001[c]
Alcohol abuse	400 (6.7)	147 (9.5)	103 (26)	63 (66)	<0.001[c]
Drug abuse	342 (5.7)	138 (8.9)	98 (25)	43 (45)	<0.001[c]
Neurologic comorbidities[e]					
Traumatic brain injury	103 (1.7)	42 (2.7)	26 (6.6)	17 (18)	<0.001[c]
Cerebrovascular disease	500 (8.3)	177 (12)	43 (11)	12 (12)	<0.001[c]

Continued

Table 1 Continued

	Frequency of ED visits in year 2				
	Infrequent ED use		Frequent ED use		
	Never (0 visits) (n = 6,007)	Occasional (1–3 visits) (n = 1,543)	Moderate (4–10 visits) (n = 395)	Heavy (11+ visits) (n = 96)	*p* Value
Medical comorbidities[e]					
Arrhythmia	388 (6.5)	117 (7.6)	37 (9.4)	13 (14)	0.004[c]
Fracture	113 (1.9)	60 (3.9)	29 (7.3)	10 (10)	<0.001[c]
Hypertension	1,047 (17)	400 (26)	127 (32)	36 (38)	<0.001[c]
Chronic pulmonary disease	559 (9.3)	246 (16)	117 (30)	36 (38)	<0.001[c]
Diabetes, uncomplicated	358 (6)	116 (7.5)	42 (11)	12 (12)	<0.001[c]
Mild liver disease	123 (2)	60 (3.9)	39 (9.9)	13 (14)	<0.001[c]

Abbreviations: ED = emergency department; NYC = New York City.
[a] All values are either median (interquartile interval) or no. (% of patients within the category of ED use in year 2).
[b] Pearson correlation. ED visits in year 2 treated as a continuous variable.
[c] The χ^2 test. ED visits in year 2 treated as a 4-valued categorical variable.
[d] The number of days in which at least one study was performed.
[e] The following comorbidities were also available to the predictive models, but were less than 10% prevalent in all 4 groups of ED use: paraplegia and hemiplegia, hypoxic ischemic encephalopathy, brain tumor, CNS infection, cerebral palsy, encephalopathy, metastatic cancer, multiple sclerosis, peptic ulcer disease, autoimmune disease, tumor without metastasis, valvular disease, aspiration pneumonia, congestive heart failure, dementia, moderate to severe liver disease, myocardial infarction, peripheral vascular disease, renal disease, diabetes complicated, pulmonary circulation disorders.

outpatient visits, radiology days, and head CTs in year 1 were each correlated with increased ED use in year 2. Brain MRIs were not correlated. Use of multiple health systems in year 1 was also associated with frequent ED use in year 2: 17% (230 of 1,355) of individuals who used multiple systems in year 1 were frequent ED users compared with 4% (261 of 6,686) of individuals who used only a single system. In addition, individuals with a high comorbidity burden (i.e., high Jetté index) in year 1 were more likely to be frequent ED users in year 2. The presence of each of 4 psychiatric, 3 neurologic, and 12 medical comorbidities in year 1 was associated with frequent ED use in year 2 (tables 1 and e-1; all cited comparisons statistically significant).

Predictability of frequent ED use. All 9 algorithms demonstrated qualitatively similar performance. AUCs ranged from 0.78 to 0.88, indicating very good predictability. PPVs were fair to good (60%–81%) although the sensitivity was uniformly poor (12%–30%). Calibration was good to very good (5%–15%). Classification error ranged from 5.17% to 5.67% (table 2).

Model selection. Two models tied for best performance, with a classification error of 5.17%: the lasso model, with 9 variables, and a one-variable logistic regression model, based solely on number of ED visits in year 1. The lasso model demonstrated a higher AUC compared with the one-variable logistic regression model (0.88 for the lasso vs 0.86 for one-variable logistic regression; table e-2).

One-variable model. The one-variable model depended only on the number of ED visits in the first year. Similar to other models, it had good AUC (0.86), good PPV (70%), very good calibration (7%), but poor sensitivity (25%). According to this model, any individual with 11 or more ED visits in year 1 had a 50% or higher probability of frequent ED use in year 2 (figure 1A). The threshold (11 or more) was the same in a subanalysis of adults only, Manhattan residents only, and non-Manhattan residents only; it was lower (9 or more) for children and seniors (figure 1, B–F). Of note, the model often underestimated the probability of frequent ED use in year 2 by moderate ED users in year 1 (figure 1A). Receiver operating characteristic curves are presented in figure e-1.

The mosaic plot illustrates the trajectory of individuals with different numbers of ED visits in year 1. Among those with no ED visits in year 1, only 1% (47 of 4,641) were frequent ED users (4+ visits) in year 2. Among those with 1 to 3 ED visits in year 1, 5.7% (149 of 2,614) became frequent ED users in year 2. Even among the moderate ED users (4–10 visits in year 1), only 29% (185 of 633) continued to be frequent ED users. However, among the heaviest ED users (11+ in year 1), 72% (110 of 153) continued to be frequent ED users (figure 2).

Table 2 Evaluation of predictive modeling techniques on a test set of 4,020 patients with epilepsy

Technique	No. of variables	Classification error, %	AUC	Sensitivity, %	PPV, %	Calibration, %
Logistic regression, best subsets	1	5.17	0.86	25	70	7
	2	5.20	0.86	23	73	8
	3	5.22	0.87	26	68	9
Lasso	9	5.17	0.88	20	79	10
Elastic net	7	5.50	0.87	12	81	15
Random Forests	All (51)	5.67	0.88	19	60	7
AdaBoost	All (51)	5.32	0.88	30	63	5
CART	4	5.20	0.78	22	75	14
Support vector machines	All (51)	5.47	0.82	16	73	10

Abbreviations: AUC = area under the receiver operating curve; CART = classification and regression trees; PPV = positive predictive value.

DISCUSSION First, we found several potential predictors for frequent ED use among people with epilepsy. Individuals who, in year 1, were adults (rather than children or seniors), male, Manhattan residents, frequent users of health services, users of multiple health systems, or had specific medical, neurologic, or psychiatric comorbidities were more likely to frequent the ED in year 2. Second, we demonstrated that visit history, basic demographics, and comorbidity information stored in an HIE network provides sufficient information to predict future frequent ED visitation among people with epilepsy with very good accuracy (AUC >0.85, PPV >70%) but with poor sensitivity (approximately 20%). The predicted probabilities were well calibrated, within 5 to 10 percentage points of observed probabilities. Third, we found that a single-variable model, which only used prior ED use, performed as well as more complex models. Heavy ED users (11+ visits in a year) have more than 50% chance of frequent ED use in the following year. The threshold of "heavy use" is lower (9) for children and seniors.

The performance of this prediction rule is similar to published predictive algorithms for frequent ED use, which tend to have good PPV but low sensitivity.[25] This indicates that a small group of repeat frequent ED users are easily identified; however, the majority of frequent ED use is challenging to predict. For example, a recent predictive model based on Medicaid data identified frequent ED users with a PPV of 66% and sensitivity of 23%.[25] Of note, that model included more than 40 variables, whereas our one-variable model performed just as well.

Our findings are relevant to care delivery. We identified an easily defined population with epilepsy to potentially enroll in interventions to improve outpatient care. The fact that prior ED visits were so strongly predictive of subsequent ED visits indicates that high-risk patients are already known to the health care system. These individuals could potentially be enrolled in care management programs at the time of an ED visit, a strategy shown to improve outpatient follow-up and reduce ED visits.[10] Alternatively, outpatient programs focused on patient education and care management can also be effective.[26] For people with epilepsy, emerging evidence suggests these strategies can improve seizure control,[27] lower ED visits,[27,28] and reduce health care costs.[29]

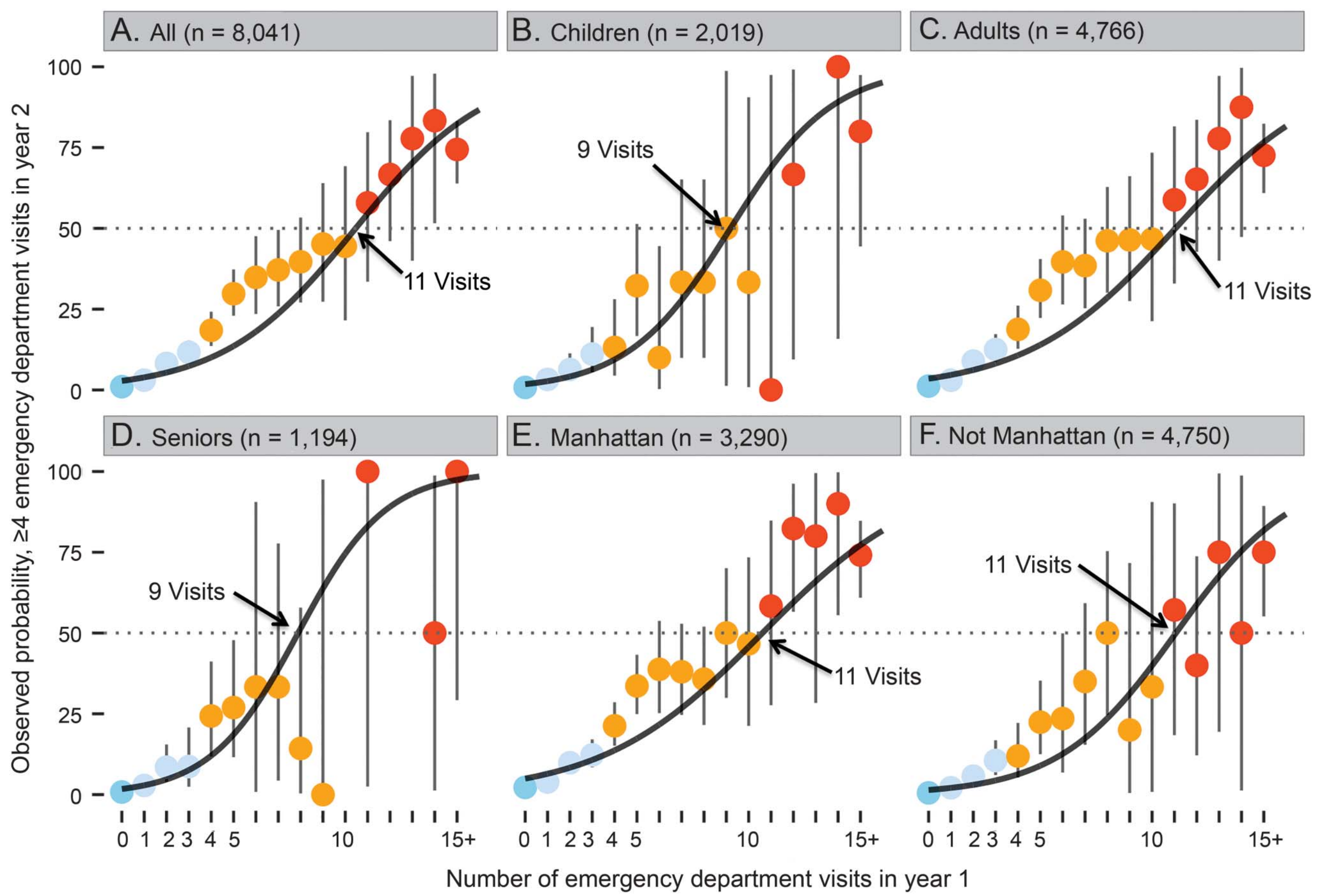
Although other variables in our study did not add predictive value, they are helpful to provide a clinical description of frequent ED users with epilepsy. These individuals are predominantly working age adults who live near the study hospitals (same borough, in our data). They often use multiple health systems for their care, and they frequently have psychiatric and medical comorbidities (e.g., depression, psychosis, or substance abuse; hypertension or pulmonary disease). Thus, successful programs might prioritize care coordination, work with local health care providers, incorporate access to psychiatric and general medical services, and seek funding from payers catering to working age adults (i.e., Medicaid, commercial insurance, or Accountable Care Organizations).

Our findings highlight the potential value of HIE networks to support health care utilization predictions for people with epilepsy, in alignment with the Institute of Medicine's suggestions to improve health information technology for people with epilepsy.[30] State and federal programs have increasingly looked to HIE networks to improve communication between unaffiliated providers.[17] This is important for frequent ED users with epilepsy because data collected from a single medical center may notably underestimate ED use,[14] and people with epilepsy often visit multiple centers.[15] Our work demonstrates that data collected by HIE networks can support accurate predictions. Future development of HIE networks might include delivery of prediction results to providers at the point of care, to identify individuals for interventions designed to reduce ED use.

We were surprised that utilization, demographics, and comorbidity information provided little additional predictive value, above the number of previous ED visits. One interpretation is that the other variables are statistically collinear with ED use, or in the causal pathway between current and future ED use. Alternatively, the comorbidity and demographics data may be insufficiently granular or of insufficient quality to contribute meaningfully to predictions of future ED use.

These findings suggest several areas for future research. First, our data did not include potentially

Figure 1 Calibration of one-variable model in the sample and subsets



(A) We grouped individuals from the entire sample (n = 8,041) by the number of emergency department (ED) visits in year 1 (x-axis), and plotted the observed proportion who visited the ED 4 or more times in year 2 (y-axis). Dots are colored to indicate categories of ED use in year 1: no use (0 visits, slate gray), occasional use (1–3 visits, sky blue), moderate use (4–10, orange), and heavy use (11+, red). Error bars display the 95% confidence interval of the observed probability (exact binomial test). The horizontal dotted gray line illustrates which individuals had a 50% predicted chance or higher of frequent ED visits in year 2. The black sinusoidal line represents the predicted probability, based on logistic regression. The threshold of "11 visits" is highlighted by an arrow and annotation. Of note, the model tends to underestimate the probability of frequent ED use in year 2 by moderate ED users in year 1. (B–F) Same visual representation for subanalysis of (B) children, (C) adults, (D) seniors, (E) Manhattan residents, and (F) non-Manhattan residents.

prognostic variables, such as laboratory and imaging results, medications, insurance status, physician notes, physician characteristics, outpatient care quality, or the structure of the care team. Future work should explore these data types, particularly to improve the sensitivity of predictions.

Second, although our findings suggest ideas for interventions, such interventions need to be designed, implemented, and evaluated.

Third, although we selected individuals with 50% or greater likelihood of frequent ED use, this threshold could be modified based on financial considerations. A financial analysis would consider the "business case" for an intervention, incorporating the cost of the program, the number of individuals enrolled, and the expected effect on use of health services.[31]

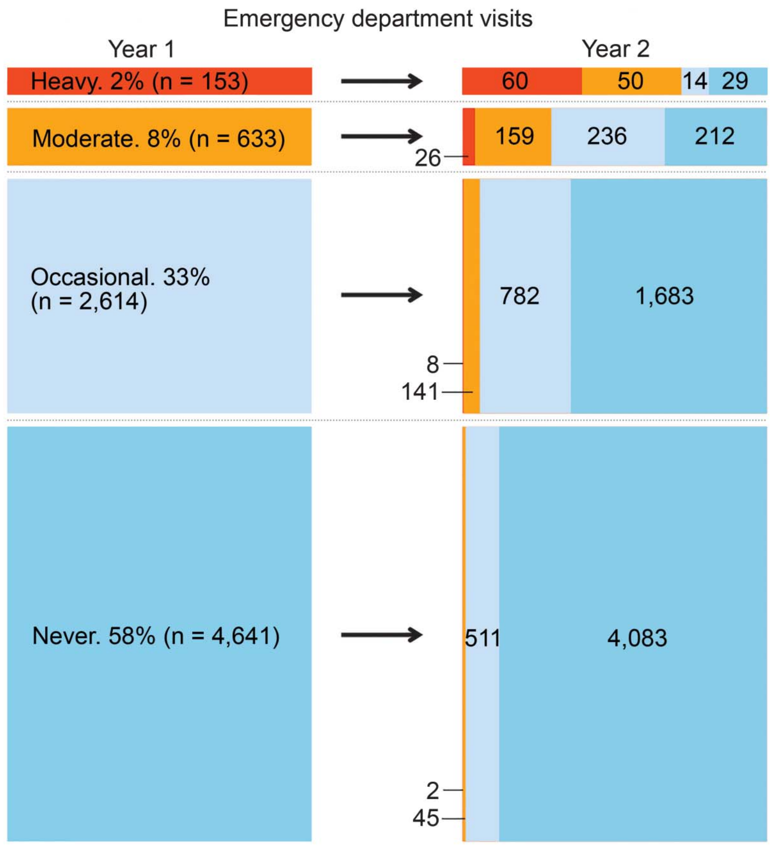
Fourth, it is unclear whether epilepsy is similar to other ambulatory care sensitive conditions. Like asthma, epilepsy is paroxysmal; like diabetes, epilepsy may require polypharmacy; but unlike congestive heart failure, epilepsy is not typically progressive. Further research could compare the predictability of frequent ED use among individuals with different diseases.

Fifth, it may be enlightening to understand the history of year 1 frequent ED users who did not continue to be frequent users (aside from those who moved away or died). Review of their cases may highlight successful existing interventions.

Several important limitations merit discussion. First, we must separate inference from prediction. A predictive model identifies individuals at risk of a poor outcome, but cannot provide conclusions about why those individuals are at risk. It remains uncertain why these individuals are using the ED. They may have poorly controlled epilepsy or more pressing unmet medical, psychiatric, or social needs causing this pattern of care-seeking.

Second, using *ICD-9* codes to identify diseases is commonly known to be imprecise. The *ICD-9*–based

Figure 2 **Distribution of the number of ED visits by 8,041 people with epilepsy in 2 sequential years, stratified by number of visits in year 1 (baseline year)**



Left boxes represent the distribution of emergency department (ED) visits in year 1. Individuals with heavy use (2%; n = 153) visited the ED 11 or more times (red), moderate use (8%; n = 633) 4 to 10 times (orange), occasional use (33%; n = 2,614) 1 to 3 times (lighter blue), and no use (58%; n = 4,641) 0 times (darker blue). The right boxes represent the number of ED visits in the follow-up year, stratified by the frequency of visits in year 1. For example, among the 153 people with heavy use in year 1, 60 were again heavy users, 50 moderate, 14 occasional, and 29 no use. Orange and red together represent "frequent ED users" (≥4 visits in a year).

definition of "probable epilepsy" endorsed by the International League Against Epilepsy has good sensitivity and PPV.[20] However, we likely included some people without epilepsy, such as people with migraine (346) miscoded as epilepsy (345), or people with multiple episodes of acute symptomatic seizures (780.39).

Third, the generalizability of our predictions is unclear. New York City is the most densely populated geographic region in the country; our model may not work in other locations.

Fourth, frequent ED use is only one of several indicators suggesting an individual with epilepsy needs additional services. Vulnerable individuals might be identified via other important markers of inadequate disease control (multiple medications, multiple inpatient admissions) or of poor access to care (distance to nearest hospital, availability of neurologists).

In conclusion, people with epilepsy who are currently heavy ED users (11+ visits in a year) are at highest risk of continued frequent ED use in the following year, and therefore may benefit from health services interventions.

AUTHOR CONTRIBUTIONS

Dr. Grinspan: study concept and design, statistical analysis, writing of the manuscript, clinical expertise in epilepsy evaluation and treatment, research expertise in analysis of health information exchange data and biostatistics. Dr. Shapiro: critical revision of the manuscript for important intellectual content, acquisition of the data, expertise in health information exchange implementation and evaluation. Dr. Abramson: critical revision of the manuscript for important intellectual content, expertise in evaluation of health information technology. Dr. Hooker: critical revision of the manuscript for important intellectual content, expertise in predictive modeling. Dr. Kaushal: critical revision of the manuscript for important intellectual content, international leader in the study of health information technology effects on health and health care. Dr. Kern: critical revision of the manuscript for important intellectual content, expertise in health services research and analysis of health information exchange data.

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REFERENCES

1. Bardsley M, Blunt I, Davies S, Dixon J. Is secondary preventive care improving? Observational study of 10-year trends in emergency admissions for conditions amenable to ambulatory care. BMJ Open 2013;3: e002007.
2. Weissman JS, Gatsonis C, Epstein AM. Rates of avoidable hospitalization by insurance status in Massachusetts and Maryland. JAMA 1992;268:2388–2394.
3. Oster A, Bindman AB. Emergency department visits for ambulatory care sensitive conditions: insights into preventable hospitalizations. Med Care 2003; 41:198–207.
4. Billings J, Zeitel L, Lukomnik J, Carey TS, Blank AE, Newman L. Impact of socioeconomic status on hospital use in New York City. Health Aff 1993;12:162–173.
5. Flores G, Abreu M, Chaisson CE, Sun D. Keeping children out of hospitals: parents' and physicians' perspectives on how pediatric hospitalizations for ambulatory care-sensitive conditions can be avoided. Pediatrics 2003;112: 1021–1030.
6. LaCalle E, Rabin E. Frequent users of emergency departments: the myths, the data, and the policy implications. Ann Emerg Med 2010;56:42–48.

7. US Government Publishing Office. Affordable Care Act. Public Law 111-148; 2010.
8. American College of Physicians. The Advanced Medical Home: A Patient-Centered, Physician-Guided Model of Health Care. Philadephia: American College of Physicians; 2005.
9. Carlson J. Behind the scenes. Although patients may not know it, ACOs are increasingly on their team, aiming to provide better care at lower costs. Mod Healthc 2013;43: 30–32, 35.
10. Katz EB, Carrier ER, Umscheid CA, Pines JM. Comparative effectiveness of care coordination interventions in the emergency department: a systematic review. Ann Emerg Med 2012;60:12–23.e11.
11. Ridsdale L, Virdi C, Noble A, Morgan M. Explanations given by people with epilepsy for using emergency medical services: a qualitative study. Epilepsy Behav 2012;25: 529–533.
12. Noble AJ, Goldstein LH, Seed P, Glucksman E, Ridsdale L. Characteristics of people with epilepsy who attend emergency departments: prospective study of metropolitan hospital attendees. Epilepsia 2012;53:1820–1828.
13. Begley C, Basu R, Lairson D, et al. Socioeconomic status, health care use, and outcomes: persistence of disparities over time. Epilepsia 2011;52:957–964.
14. Shapiro JS, Johnson SA, Angiollilo J, Fleischman W, Onyile A, Kuperman G. Health information exchange improves identification of frequent emergency department users. Health Aff 2013;32:2193–2198.
15. Grinspan ZM, Abramson EL, Banerjee S, Kern LM, Kaushal R, Shapiro JS. People with epilepsy who use multiple hospitals; prevalence and associated factors assessed via a health information exchange. Epilepsia 2014;55:734–745.
16. Hsiao C, Hing E, Socey T, Cai W. Electronic health record systems and intent to apply for meaningful use incentives among office-based physician practices: United States, 2001–2011. NCHS Data Brief 2011:1–8.
17. Williams C, Mostashari F, Mertz K, Hogin E, Atwal P. From the office of the national coordinator: the strategy for advancing the exchange of health information. Health Aff 2012;31:527–536.
18. NYS Health Profiles. Available at: http://profiles.health.ny.gov/hospital/service/Emergency+Department. Accessed August 12, 2015.
19. Emergency Departments of New York State. Available at: http://www.health.ny.gov/statistics/sparcs/ed/2006/. Accessed August 12, 2015.
20. Thurman DJ, Beghi E, Begley CE, et al. Standards for epidemiologic studies and surveillance of epilepsy. Epilepsia 2011;52(suppl 7):2–26.
21. St Germaine-Smith C, Liu M, Quan H, Wiebe S, Jette N. Development of an epilepsy-specific risk adjustment comorbidity index. Epilepsia 2011;52:2161–2167.
22. Murphy SM, Neven D. Cost-effective: emergency department care coordination with a regional hospital information system. J Emerg Med 2014;47:223–231.
23. Hastie T, Tibshirani R, Friedman JH. The Elements of Statistical Learning: Data Mining, Inference, and Prediction, 2nd ed. New York: Springer; 2009.
24. R: A Language and Environment for Statistical Computing [computer program]. Vienna, Austria: R Foundation for Statistical Computing; 2011.
25. Billings J, Raven MC. Dispelling an urban legend: frequent emergency department users have substantial burden of disease. Health Aff 2013;32:2099–2108.
26. Morgan SR, Chang AM, Alqatari M, Pines JM. Non-emergency department interventions to reduce ED utilization: a systematic review. Acad Emerg Med 2013;20: 969–985.
27. Tatum WO IV, Al-Saadi S, Orth TL. Outpatient case management in low-income epilepsy patients. Epilepsy Res 2008;82:156–161.
28. Patel AD. A case series using a care management checklist to decrease emergency department visits and hospitalizations in children with epilepsy. J Child Neurol 2014;29:243–246.
29. Noble AJ, Morgan M, Virdi C, Ridsdale L. A nurse-led self-management intervention for people who attend emergency departments with epilepsy: the patients' view. J Neurol 2013;260:1022–1030.
30. Institute of Medicine (US) Committee on the Public Health Dimensions of the Epilepsies; England MJ, Liverman CT, Schultz AM, Strawbridge LM, editors. Epilepsy Across the Spectrum: Promoting Health and Understanding. Washington, DC: National Academies Press; 2012.
31. Billings J, Blunt I, Steventon A, Georghiou T, Lewis G, Bardsley M. Development of a predictive model to identify inpatients at risk of re-admission within 30 days of discharge (PARR-30). BMJ Open 2012;2:e001667.