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# BMJ Open

## Statistical tools used for analyses of frequent users of emergency department: A scoping review

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Manuscripts

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4 1 Statistical tools used for analyses of frequent users  
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6 2 of emergency department: A scoping review  
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## 12 **Abstract**

13 **Objective:** Frequent users represent a small proportion of emergency department users,  
14 but they account for a disproportionately large number of visits. Their ED use is often  
15 considered suboptimal, as it would be more optimal to identify those patients earlier in  
16 their health problem trajectory, in order to treat them more efficiently. It is therefore  
17 essential to describe their characteristics and to predict their emergency department use. In  
18 order to do so, adequate statistical tools are needed. The objective of this study was to  
19 determine the statistical tools used in identifying variables associated with frequent use or  
20 predicting the risk of becoming a frequent user.

21 **Methods:** We performed a scoping review following an established 5-stage  
22 methodological framework. We searched PubMed, Scopus, and CINAHL databases in  
23 September 2017 using search strategies defined with the help of an information specialist.  
24 Out of 3 228 potential abstracts, we selected 85 articles based on defined criteria and  
25 presented in a content analysis.

26 **Results:** We identified four classes of statistical tools. Regression models were found to  
27 be the most common practice, followed by hypothesis testing. The logistic regression was  
28 found to be the most used statistical tool, followed by chi-square test and t-test of  
29 associations between variables. Other tools were marginally used.

30 **Conclusions:** This scoping review lists common statistical tools used for analyzing  
31 frequent users in emergency departments. It highlights the fact that some are well  
32 established while others are much less so. More research is needed to apply appropriate  
33 techniques to health data or to diversify statistical point of views.

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4 34 **Article summary**  
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7 35 **Strengths and limitations of this study**  
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10 36 • First overview of statistical tools used in frequent users analysis  
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12 37 • Follows a well-defined methodological framework in an extensive body of  
13  
14 38 literature  
15  
16  
17 39 • Quality assessment is not performed in a scoping review  
18  
19 40 • Studies in other languages than English or French might have been missed  
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## 1. Background

Emergency department (ED) “frequent users” are a sub-group of ED users that make repeated, multiple visits during a given amount of time. Though there is no consensual definition for frequent users, thresholds in the literature range from two to more than ten ED visits per year [1, 2], while the most common one is more than four ED visits per year [1, 2]. Frequent users represent a small proportion of ED users but account for a large number of visits [3-5]. They often display complex characteristics such as low socioeconomic status combined with physical and mental health issues [6]. As such, their ED use is considered suboptimal [7], as the best strategy would be to identify those patients at an earlier stage in their health problem trajectory, in order to treat them more efficiently [8]. Furthermore, frequent users’ visits may lead to overcrowding in EDs and decreased quality of care [2]. Identifying factors that best describe those users and predict their ED use is therefore an essential task to improve ED care as well as frequent users’ health problems. Adequate statistical tools are needed to that end. Although they are numerous, no literature review has been published yet about statistical tools used for analyzing ED frequent users. Therefore, the aim of our study was to draw up a list of statistical tools used in identifying variables associated with frequent use or predicting the risk of becoming a frequent user.

## 2. Methods

In order to list the statistical tools used in describing variables associated with and prediction of frequent ED use, we conducted a scoping review. We followed the 5-stage methodology of Arksey and O'Malley [9] adapted by Levac *et al.* [10]. The methodological

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2  
3 64 framework of a scoping review allows “mapping rapidly the key concepts underpinning a  
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5 65 research area and the main sources and types of evidence available” [11], thus allowing us  
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8 66 to identify gaps in the literature and future research opportunities.  
9

### 10 11 67 **Stage 1: Identifying the research question** 12

13  
14 68 We defined our research question as follows: What statistical tools are used in the  
15  
16 69 identification of variables associated with frequent ED users and in their prediction?  
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### 18 19 70 **Stage 2: Identifying relevant studies** 20

21  
22 71 We searched PubMed, CINAHL, and Scopus databases in September 2017, using search  
23  
24 72 strategies developed with the help of an information specialist (see the supplementary  
25  
26 73 appendix for the complete search strategy). Keywords included variants of “frequent  
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28 74 users”, “emergency departments” and “statistical tools”.  
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32 75 There were no restrictions regarding the population age or sex, health conditions, study  
33  
34 76 period or country.  
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### 36 37 77 **Stage 3: Study selection** 38

39  
40 78 Articles written in French or in English were included using the following criteria:  
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- 42  
43 79 • The study must focus on frequent users of EDs (studies focusing on re-visits or on  
44  
45 80 frequent visits other than in EDs were excluded);  
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47  
48 81 • The study must have an explicit definition of frequent users, such as four visits in  
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50 82 one year (reviews were excluded);  
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3 83 • The study must use at least one statistical tool that is classified as inferential (not  
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5 84 descriptive, as defined by The Cambridge Dictionary of Statistics [12]), such as  
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8 85 hypothesis tests, regression models, decision trees, or others;  
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10 86 • The study's objectives must include identifying variables associated with frequent  
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12 87 use or predicting the risk of becoming a frequent user.  
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15 88 We collected 3 228 potential abstracts (Fig 1). Of those, 32 were duplicates, and 3 087  
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17 89 were excluded by an investigator (YC) after reading the title and the abstract. YC and CH  
18  
19 90 independently evaluated the remaining 109 full-text articles, of which 80 matched the  
20  
21 91 above criteria. Those were included by consensus between YC and CH while FRH acted  
22  
23 92 as third reviewer in case of discrepancy. Reasons for exclusion were: duplicate (one), not  
24  
25 93 in French or English (one), no inferential statistics (three), focus not on ED (four),  
26  
27 94 systematic review (four), no explicit definition of frequent users (five), no description or  
28  
29 95 prediction of frequent users (eleven). A reference search yielded five relevant articles.  
30  
31 96 Thus, 85 articles were included in this study, of which the full texts were examined by YC,  
32  
33 97 CH, and MB.  
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39 98 **Fig 1. PRISMA flow diagram.**

#### 40 41 99 **Stage 4: Charting the data**

42  
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44 100 YC and MB independently extracted the corresponding data. Reported characteristics  
45  
46 101 were the first (two) author(s), the publication year, the study location, the population, the  
47  
48 102 frequent users' definition, the objectives, the sample size, and the statistical tools used  
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50 103 concerning the research question.  
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## 104 Stage 5: Collating, summarizing and reporting the results

105 The results are reported via a content analysis [13].

## 106 Patient and public involvement

107 Patients or public were not involved in this study.

## 108 3. Results

109 The studies main characteristics are presented in Table 1. Out of 85 studies, 47 were  
 110 conducted in the USA, 13 in Canada and 5 in Australia (Fig 2). The various statistical tools  
 111 were classified into four main categories: regression, hypothesis testing, machine learning,  
 112 and other tools.

113 Table 1. Main characteristics of the 86 included studies.

Authors, year, and country	Population	Frequent user definition	Study objectives	Sample size	Statistical tools used
Aagaard, J. et al. 2013 Denmark	Psychiatric	$\geq 5$ visits per year	To identify predictors of frequent use of a psychiatric emergency room	8 034	Logistic regression
Adams, R.J. et al. 2000 Australia	Adults with asthma	$\geq 2$ visits per year	To identify whether factors other than severity and low socioeconomic status were associated with this disproportionate use	293	Logistic regression
Alghanim, S.A. & Alomar, B.A. 2015 Saudi Arabia	All	$\geq 3$ visits per year	To determine the prevalence of frequent use of EDs in public hospitals, to determine factors associated with such use, and to identify patients' reasons for frequent use	666	Chi-square test Logistic regression
Alpern, E.R. et al. 2014 United States	All	$\geq 4$ visits per year	To describe the epidemiology of and risk factors for recurrent and high frequency use of the ED by children	695 188	Negative binomial regression Logistic regression Generalized estimating equations
Andren, K.G. & Rosenqvist, U.	All	$\geq 4$ visits per year	To follow a cohort of heavy ED users with regard to changes in	232	Decision trees Linear regression

1987 Sweden				medical and psycho-social profiles and ED use and to identify predictors for a maintained high use of ED services and the relationship between changes in access to social networks and utilization of medical care services		
Arfken, C.L. et al. 2004 United States	Psychiatric	$\geq 6$ visits per year		To identify risk factors for people who use psychiatric emergency services repeatedly and to estimate their financial charges	74	Logistic regression
Beck, A. et al. 2016 United Kingdom	Mental health	$\geq 3$ visits in 3 months		To statistically identify characteristics associated with a shorter time to re-attendance and a higher number of overall ED admissions with a Mental Health Liaison Service referral	24 010	Cox regression Negative binomial regression
Bieler, G. et al. 2012 Switzerland	All	$\geq 4$ visits per year		To identify the social and medical factors associated with frequent ED use and to determine if frequent users were more likely to have a combination of these factors in a universal health insurance system	719	Wilcoxon rank-sum test Logistic regression
Billings, J. & Raven, M.C. 2013 United States	All	$\geq 3$ visits per year $\geq 5$ visits per year $\geq 8$ visits per year $\geq 10$ visits per year		To examine whether it is possible to predict who will become a frequent ED user with predictive modeling and to compare ED expenditures to total Medicaid services expenditures	212 259	Logistic regression
Blonigen, D.M. et al. 2017 United States	Veteran psychiatric	$\geq 5$ visits per year		To identify patient-level factors associated with ED use among veteran psychiatric patients and to examine factors associated with different subgroups of ED users including “high utilizers”	226 122	Zero-truncated negative binomial regression
Boyer, L. et al. 2011 France	Psychiatric	$\geq 6$ visits per year		To examine characteristics of frequent visitors to a psychiatric emergency service in a French public teaching hospital over six years	1 285	Logistic regression
Brennan, J.J. et al. 2014	Psychiatric	$\geq 4$ visits per year		To assess the incidence of psychiatric visits among frequent ED users and	788 005	Kruskal-Wallis test Mann-Whitney U test Logistic regression

1	United States			utilization among frequent psychiatric users		
2						
3	Buhumaid, R. et al.	Psychiatric	$\geq 4$ visits per year	To evaluate demographic factors associated with increased ED use among people with psychiatric conditions	569	Logistic regression
4	2015					
5	United States					
6						
7	Cabey, W.V. et al.	All	90th percentile	To define the threshold and population factors associated with pediatric ED use above the norm during the first 36 months of life	16 664	Nonparametric distribution fit Logistic regression Bootstrap Clopper-Pearson method
8	2014					
9	United States					
10						
11	Castner, J. et al.	People with psychiatric and substance abuse diagnoses	$\geq 3$ visits per year	To stratify individuals by overall health complexity and examine the relationship of behavioral health diagnoses (psychiatric and substance abuse) as well as frequent treat-and-release ED utilization in a cohort of Medicaid recipients	56 491	Logistic regression
12	2015					
13	United States					
14						
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16	Chambers, C. et al.	Homeless	90th percentile	To identify predictors of ED use among a population-based prospective cohort of homeless adults in Toronto, Ontario	1 165	Logistic regression
17	2013					
18	Canada					
19						
20	Chang, G. et al.	Psychiatric	$\geq 4$ visits per year or $\geq 3$ visits during 2 consecutive months	To identify the patient characteristics associated with frequent ED use and develop a tool to predict risk for returning in the next month	863	Chi-square test Logistic regression
21	2014					
22	United States					
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26	Christensen, E.W. et al.	All	$\geq 4$ visits per year	To determine the patient characteristics and health care utilization patterns that predict frequent ED use ( $\geq 4$ visits per year) over time to assist health care organizations in targeting patients for care management	13 265	Zero-inflated Poisson regression Receiver operating characteristic curve
27	2017					
28	United States					
29						
30						
31	Chukmaitov, A.S. et al.	People with ambulatory care-sensitive conditions	$\geq 4$ visits per year	To study characteristics of all, occasional, and frequent ED visits due to ambulatory care-sensitive conditions	4 914 933 (number of visits)	Logistic regression
32	2012					
33	United States					
34						
35	Colligan, E.M. et al.	All	$\geq 4$ visits per year	To examine factors associated with persistent frequent ED use during a 2-year period among Medicare beneficiaries	5 400 237	Logistic regression
36	2016					
37	United States					
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					Wilcoxon rank-sum test Chi-square test LASSO logistic regression Regularized logistic regression Decision trees Random forests Support vector machines
Das, L.T. et al. 2017 United States	Children with asthma	$\geq 2$ visits per year	To explore the predictability of frequent ED use among children with asthma using data from an EHR from one medical center	2 691	
Doran, K.M. et al. 2013 United States	All	2-4 visits per year 5-10 visits per year 11-25 visits per year $\geq 25$ visits	To identify sociodemographic and clinical factors most strongly associated with frequent ED use within the Veterans Health Administration nationally	930 712	Logistic regression
Doran, K.M. et al. 2014 United States	All	$\geq 3$ visits per year	To examine patients' reasons for using the ED for low-acuity health complaints, and determine whether reasons differed for frequent ED users versus non-frequent ED users	940	Logistic regression
Doupe, M.B. et al. 2012 Canada	All	$\geq 7$ visits per year	To identify factors that define frequent and highly frequent ED users	105 687	Logistic regression Receiver operating characteristic curve
Fernandes, A.K. et al. 2003 Brazil	All	$\geq 3$ visits per year	To identify characteristics related to poor disease control and frequent visits to the ED to apply appropriate clinical management	86	Chi-square test Logistic regression
Freitag, F.G. et al. 2005 United States	People with chronic daily headache	$\geq 3$ visits per year	To examine the characteristics of chronic daily headache sufferers who use EDs and identify factors predictive of ED visits	785	Wilcoxon rank-sum test t-test Chi-square test Poisson regression Negative binomial regression Logistic regression
Friedman, B.W. et al. 2009 United States	People with severe headache	$\geq 4$ visits per year	To determine frequency of ED use and risk factors for use among patients suffering severe headache	13 451	Markov chain Monte Carlo imputation Logistic regression
Frost, D.W. et al. 2017 Canada	All	$\geq 3$ visits per year	To determine whether machine learning techniques using text from a family practice electronic medical record can be used to predict future high ED	43 111	Logistic regression

				use and total costs by patients who are not yet high ED users or high cost to the healthcare system		
				To develop a predictive model of ED utilization for patients where a diagnosis of psychosis could be identified from a claim associated with a medical service provider visit		
8	Girts, T.K. et al.	People with a diagnosis of psychosis	$\geq 2$ visits per 6 months		764	t-test Linear regression
9	2002					
10	United States					
11						
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14						Chi-square test
15						Logistic regression
16						Regularized logistic regression
17	Grinspan, Z.M. et al.	People with epilepsy	$\geq 4$ visits per year	To describe (1) the predictability of frequent 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	8 041	Elastic net logistic regression Decision trees Random forests AdaBoost Support vector machines Receiver operating characteristic curve
18						
19	2015					
20	United States					
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27	Hardie, T.L. et al.	All	$\geq 4$ visits per year	To describe frequent users of ED services in a rural community setting and the association between counts of patient's visits and discrete diagnoses	1 652	Poisson regression
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29	2015					
30	United States					
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33	Hasegawa, K. et al.	People with acute asthma	$\geq 2$ visits per year	To examine the proportion and patient characteristics of adult patients with multiple ED visits for acute asthma and the associated hospital charges	86 224	Chi-square test Kruskal-Wallis test Logistic regression
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35	2014					
36	United States					
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39	Hasegawa, K. et al.	People with acute heart failure syndrome	$\geq 2$ visits per year	To examine the proportion and characteristics of patients with frequent ED visits for acute heart failure syndrome and associated healthcare utilization	113 033	Chi-square test Kruskal-Wallis test Negative binomial regression Linear regression
40						
41	2014					
42	United States					
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46	Hasegawa, K. et al.	People with chronic obstructive pulmonary disease	$\geq 2$ visits per year	To quantify the proportion and characteristics of patients with frequent ED visits for acute exacerbation of chronic obstructive pulmonary disease and associated healthcare utilization	98 280	Chi-square test Kruskal-Wallis test Logistic regression Negative binomial regression Linear regression
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48	2014					
49	United States					
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52						
53	Huang, J.A. et al.	All	$\geq 4$ visits per year	To characterize frequent ED users and to identify the factors associated with	800	Chi-square test Logistic regression
54						
55	2003					
56	Taiwan					
57						

				frequent ED use in a hospital in Taiwan		
Hudon, C. et al.	All	$\geq 3$ visits per year	To identify prospectively personal characteristics and experience of organizational and relational dimensions of primary care that predict frequent use of ED	1 769	Mixed effect logistic regression	
Hudon, C. et al.	People with diabetes	$\geq 3$ visits for 3 consecutive years	To explore the factors associated with chronic frequent ED utilization in a population with diabetes	62 316	Logistic regression Decision trees	
Hunt, K.A. et al.	All	$\geq 4$ visits per year	To identify frequent users of the ED and determine the characteristics of these patients	49 603	Logistic regression	
Huynh, C. et al.	People with substance use disorders	$\geq 4$ visits per year	To assess the characteristics of individuals with substance use disorders according to their frequency of ED utilization, and to examine which variables were associated with an increase in ED visits using Andersen's model	4 526	Chi-square test Analysis of variance Negative binomial regression Generalized estimating equations	
Kerr, T. et al.	Injection drug users	$\geq 3$ visits during the 2 past years	To examine rates of primary care and emergency room use among injection drug users and to identify correlates of frequent emergency department use	883	Chi-square test Wilcoxon rank sign test t-test Logistic regression	
Kirby, S.E. et al.	People with chronic disease	$\geq 3$ visits per year	To explore the link between frequent readmissions in chronic disease and patient-related factors	15 806	Chi-square test Logistic regression	
Kirby, S.E. et al.	All	$\geq 4$ visits per year	To identify the factors associated with frequent re-attendances in a regional hospital thereby highlighting possible solutions to the problem	15 806	Kruskal-Wallis test Chi-square test Logistic regression	
Ko, M. et al.	All	$\geq 4$ visits per year	To describe the distribution of the frequency of ED visits among ED users in 2010 and to evaluate the association of frequent ED use with various patient characteristics	170 457	Logistic regression	
Ledoux, Y. & Minner, P.	Psychiatric	$\geq 4$ visits per year	(1) To provide a naturalistic evaluation of	2 470	Mantel-Haenszel test Analysis of variance	

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4	2006			patients repeating		Logistic regression
5	Belgium			admissions in a psychiatric		
6				emergency ward		
7				(distinguishing between		
8				occasional repeaters and		
9				frequent repeaters), (2) to		
10				identify		
11				patients' characteristics		
12				that predict repeated use of		
13				a psychiatric emergency		
14				room and (3) to propose		
15				adapted treatment models		
16				To evaluate and		
17	Legramante, J.M.			characterize hospital visits		
18	et al.			of older patients (age 65 or		t-test
19		All	$\geq 4$ visits per	hospital in Rome, in order	38 016	Logistic regression
20	2016		year	to identify clinical and		
21	Italy			social characteristics		
22				potentially associated with		
23				"elderly frequent users"		
24				To describe the		
25	Leporatti, L. et al.			characteristics of patients		Zero-truncated
26		All	90th percentile	who frequently accessed	147 864	negative binomial
27	2016		$\geq 3$ visits per	accident and emergency		regression
28	Italy		year	departments located in the		Logistic regression
29				metropolitan area of Genoa		
30				To describe the		
31	Lim. S.F. et al.			characteristics of frequent		t-test
32		People with	$\geq 4$ visits per	attenders who present	155	Chi-square test
33	2014	asthma	year	themselves multiple times		Mann-Whitney U test
34	Singapore			to the ED for asthma		Logistic regression
35				exacerbations		
36				To identify predictive		
37	Limsrivilai, J. et			factors readily available in		
38	al.	People with		a standard electronic		
39		inflammator	75th percentile	medical record to develop	1 430	Receiver operating
40	2017	y bowel	of the annual	a multivariate model to		characteristic curve
41	United States	diseases	medical charges	predict the probability of		Logistic regression
42				inflammatory bowel		
43				diseases-related		
44				hospitalization, ED visit,		
45				and high total charges in		
46				the subsequent year		
47				To examine factors		
48	Lin, W.C. et al.			associated with frequent		Chi-square test
49		Homeless	$\geq 3$ visits per	hospitalizations and ED	6 494	Analysis of variance
50	2015		year	visits among Medicaid		Negative binomial
51	United States			members who were		regression
52				homeless		
53				To determine whether		
54	Liu, S.W. et al.	People with	$\geq 4$ visits per	frequent ED users are		t-test
55		mental	year	more likely to make at	65 201	Chi-square test
56	2013	health,		least one and a majority of		Logistic regression
57	United States	alcohol or		visits for mental health,		
58						

	drug-related diagnoses			alcohol, or drug-related complaints compared to non-frequent users		
Mandelberg, J.H. et al. 2000 United States	All	$\geq 5$ visits per year		To determine how the demographic, clinical, and utilization characteristics of frequent ED users differ from those of other ED patients	43 383	Logistic regression Survival analysis
Mann, E.G. et al. 2016 Canada	People with chronic pain	90th percentile		To investigate the role of chronic pain in healthcare visits and to document the frequency of healthcare visits and to identify characteristics associated with frequent visits	1 274	Logistic regression
McMahon, C.G. et al. 2016 Ireland	All	$\geq 4$ visits per year		To examine the characteristics of the frequent ED attenders by age (under 65 and over 65 years)	19 310	Chi-square test Logistic regression
Meyer, J.P. et al. 2013 United States	Prisoners with Human Immunodeficiency Virus	$\geq 2$ visits per year		To characterize the medical, social, and psychiatric correlates of frequent ED use among released prisoners with human immunodeficiency virus	151	t-test Chi-square test Poisson regression
Milani, S.A. et al. 2016 United States	People with multimorbid chronic diseases	$\geq 4$ visits per year		To examine the association between multimorbid chronic disease and frequency ED visits in the past 6 months, by sex, in a community sample of adults from northern Florida	7 143	Breslow-Day test Logistic regression
Milbrett, P. & Halm, M. 2009 United States	All	$\geq 6$ visits per year		To describe the characteristics of patients who frequently use ED services and to determine factors most predictive of frequent ED use	201	Chi-square test Mann-Whitney U test Poisson regression
Moe, J. et al. 2013 Canada	All	95th percentile		To develop uniform definitions, quantify ED burden, and characterize adult frequent users of a suburban community ED	14 223	Chi-square test Mann-Whitney U test
Mueller, E.L. et al. 2016 United States	Children with cancer	90th percentile $\geq 4$ visits per year		To (a) evaluate patient and ED encounter characteristics of frequent ED utilizers among children with cancer and (b) quantify healthcare services for frequent ED utilizers	17 943	Chi-square test Logistic regression



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4	Nambiar, D. et al.	Injection drug users	$\geq 3$ visits per year	To describe demographic factors, patterns of substance use and previous health service use associated with frequent use of EDs in people who inject drugs	612	Negative binomial regression Logistic regression
5	2017					
6	Australia					
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11	Neufeld, E. et al.	All	$\geq 4$ visits per year	To describe factors predicting frequent ED use among rural older adults receiving home care services in Ontario, Canada	12 118	Chi-square test Logistic regression
12	2016					
13	Canada					
14						
15						
16	Neuman, M.I. et al.	All	$\geq 4$ visits per year	To compare the characteristics and ED health services of children by their ED visit frequency	1 896 547	Mantel-Haenszel test Receiver operating characteristic curve Generalized linear mixed-effects models
17	2014					
18	United States					
19						
20						
21	Ngamini-Ngui, A. et al.	Patients with schizophrenia and a co-occurring substance use disorder	$\geq 5$ visits per year	To assess factors associated over time with high use of EDs by Quebec patients who had schizophrenia and a co-occurring substance use disorder	2 921	Generalized estimating equations
22	2014					
23	Canada					
24						
25						
26						
27						
28						
29						
30	Norman, C. et al.	All	$\geq 4$ visits per year	To clearly define and describe characteristics of frequent emergency medical services users in order to provide suggestions for efficient and cost-effective interventions that address the healthcare needs of these users	539	Logistic regression
31	2016					
32	United States					
33						
34						
35						
36						
37						
38	O'Toole, T.P. et al.	Substance users	$\geq 3$ visits per year	To identify factors associated with 12-month high frequency utilization of ambulatory care, ED, and inpatient medical care in a substance-using population	326	t-test Chi-square test Logistic regression
39	2007					
40	United States					
41						
42						
43						
44	Palmer, E. et al.	All	$\geq 4$ visits per year	To determine if having a primary care provider is an important factor in frequency of ED use	59 803	Chi-square test Wilcoxon rank-sum test Logistic regression
45	2014					
46	Canada					
47						
48						
49	Panopalis, P. et al.	People with systemic lupus erythematosus	$\geq 3$ visits per year	To describe characteristics of systemic lupus erythematosus patients who are frequent users of the ED and to identify predictors of frequent ED use	807	One-way analysis of variance Logistic regression
50	2010					
51	United States					
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1 2 3 4 5 6 7 8 9	Pasic, J. et al. 2005 United States	Psychiatric	2 SD above the mean number of visits $\geq 6$ visits per year $\geq 4$ visits in a quarter	To examine the sociodemographic and clinical characteristics of high utilizers of psychiatric emergency services	17 481	Chi-square test Logistic regression
10 11 12 13 14	Paul, P. et al. 2010 Singapore	All	$\geq 5$ visits per year	To determine factors associated with frequent ED attendance at an acute general hospital in Singapore.	82 172	Chi-square test Logistic regression
15 16 17 18 19 20 21	Pereira, M. et al. 2016 United States	All	$\geq 5$ visits per year	To develop machine learning models that can predict future ED utilization of individual patients, using only information from the present and the past	4 604 252	Decision trees AdaBoost Logistic regression
22 23 24 25 26 27	Pines, J.M. & Buford, K. 2006 United States	People with asthma	90th percentile $\geq 3$ visits per year	To determine socioeconomic and demographic factors that predict frequent ED use among asthmatics in southeastern Pennsylvania	1 799	t-test Chi-square test Logistic regression
28 29 30 31 32 33 34	Quilty, S. et al. 2016 Australia	People without chronic health conditions	$\geq 6$ visits per year	To determine the clinical and environmental variables associated with frequent presentations by adult patients to a remote Australian hospital ED for reasons other than chronic health conditions	273	t-test Chi-square test Logistic regression
35 36 37 38 39 40 41 42 43	Rask, K.J. et al. 1998 United States	All	$\geq 10$ visits per 2 years	To describe primary care clinic use and emergency ED use for a cohort of public hospital patients seen in the ED, identify predictors of frequent ED use, and ascertain the clinical diagnoses of those with high rates of ED use	351	Chi-square test t-test Logistic regression
44 45 46 47 48 49	Samuels-Kalow, M.E. et al. 2017 United States	All	$\geq 4$ visits per year	To derive and test a predictive model for high frequency (4 or more visits per year), low-acuity (emergency severity index 4 or 5) utilization of the pediatric ED	60 799 (number of visits)	Likelihood ratio test Chi-square test Receiver operating characteristic curve Logistic regression
50 51 52 53 54 55 56	Schmoll, S. et al. 2015 France	Psychiatric	$\geq 9$ visits during the 6 past years	To describe demographic and clinical characteristics of frequent visitors to a psychiatric emergency ward in a French Academic hospital over 6	8 800	t-test Chi-square test Logistic regression

				years in comparison to non-frequent visitors		
Soler, J.J. et al.	People with chronic obstructive pulmonary disease	$\geq 3$ visits per year	To identify factors associated with frequent use of hospital services (emergency care and admissions) in patients with chronic obstructive pulmonary disease	64	t-test Chi-square test Kolmogorov-Smirnov test Mann-Whitney U test Logistic regression	
Sun, B.C. et al.	All	$\geq 4$ visits per year	To identify predictors and outcomes associated with frequent ED users	2 333	Likelihood ratio test Chi-square test Hosmer-Lemeshow test Logistic regression Bootstrap	
Tangherlini, N. et al.	All	$\geq 4$ visits per year	To identify the factors that lead to increased use of emergency medical services (EMS) by patients $\geq 65$ years of age in an urban EMS system	10 918	Kruskal-Wallis test Chi-square test Logistic regression	
Thakarar, K. et al.	Homeless	$\geq 2$ visits per year	To identify risk factors for frequent emergency room (ER) visits and to examine the effects of housing status and HIV serostatus on ER utilization	412	Chi-square test Logistic regression	
Vandyk, A.D. et al.	Mental health	$\geq 5$ visits per year	To explore the population profile and associated socio demographic, clinical, and service use factors of individuals who make frequent visits (5+annually) to hospital EDs for mental health complaints	536	Hosmer-Lemeshow test Logistic regression	
Vinton, V.T. et al.	Chronic diseases and mental health	$\geq 4$ visits per year	To compare the characteristics of US adults by frequency of ED utilization, specifically the prevalence of chronic diseases and outpatient primary care and mental health utilization	157 818	Logistic regression	
Vu, F. et al.	Mental health and substance users	$\geq 4$ visits per year	To determine the proportions of psychiatric and substance use disorders suffered by EDs' frequent users compared to the mainstream ED population, to evaluate how effectively these disorders were diagnosed in both groups of patients by ED physicians, and to determine if these	389	Fisher exact test Chi-square test Logistic regression	

				disorders were predictive of a frequent use of ED services		
Wajnberg, A. et al.	All	$\geq 4$ visits over 6 months	To determine factors associated with frequent ED utilization by older adults	5 718	Chi-square test t-test	
2012 United States						
Watase, H. et al.	Adults with asthma	$\geq 2$ visits per year	To characterise the adult patients who frequently presented to the ED for asthma exacerbation in Japan	1 002	One-way analysis of variance Chi-square test Kruskal-Wallis test Logistic regression Negative binomial regression	
2015 Japan						
Woo, J.H. et al.	All	$\geq 4$ visits per year	To understand whether the findings about frequent ED users in prior studies in the US healthcare system would be replicated in the Korean population, and whether these findings are independent of insurance status or ethnicity	156 246	t-test Chi-square test Linear regression Logistic regression	
2016 Korea						
Wu, J. et al.	All	$\geq 16$ visits during the 2 past years	To assess the feasibility of using routinely gathered registration data to predict patients who will visit EDs with high frequency	1 272 367	Logistic regression Receiver operating characteristic curve	
2016 United States						

114

115 **Fig 2. Number of studies by country.**116 **Regression**

117 Regression tools consist of a set of processes aimed at quantifying the relationships  
 118 between a dependent variable and other explanatory variables [14]. They are useful for  
 119 description and prediction. Some regression models may be *regularized*, which in this case  
 120 means avoiding overfitting with too many explanatory variables, or *zero-truncated*, which  
 121 means that the model is not allowed to take null values.

122 Out of the four categories (regression, hypothesis testing, machine learning, and other  
 123 tools), the most reported tool was the logistic regression (70 studies [3-5, 15-81], two of  
 124 which are regularized by LASSO or elastic net techniques), followed by the binomial

1  
2  
3 125 regression (11 studies [18, 46, 55, 73, 76, 77, 82-86], 2 of which are zero-truncated). To a  
4  
5 126 lesser extent, the linear regression (five studies [74, 76, 83, 87, 88]), the analysis of variance  
6  
7 127 (five studies [44, 59, 73, 84, 85]), the Poisson regression (five studies [77, 89-92], one of  
8  
9 128 which is zero-truncated), and the Cox regression (one study [86]) were also used. In those  
10  
11 129 studies, the results are often associated with odds-ratio. The mixed-effects models were  
12  
13 130 mentioned twice [39, 93]. Regression parameters were estimated by generalized estimating  
14  
15 131 equations in three studies [18, 84, 94] while parameter confidence intervals were estimated  
16  
17 132 by the bootstrap procedure (two studies [25, 67]) and the Clopper-Pearson method (one  
18  
19 133 study [25]). The receiver operating characteristic curve (ROC), or equivalently the  
20  
21 134 sensitivity, specificity, or area under the curve (“c-statistic”), was computed in  
22  
23 135 seven studies [4, 36, 48, 63, 75, 89, 93]. Finally, one study performed Markov chain Monte  
24  
25 136 Carlo imputation to account for missing data [78].  
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### 31 **Hypothesis testing**

32  
33  
34 138 Statistical tests aim at testing a specific hypothesis about data and rely on probability  
35  
36 139 distributions [95]. In the selected studies, the tests aimed mainly at comparing two samples  
37  
38 140 (frequent users and non-frequent users).  
39  
40  
41

42 141 The most common statistical tests were the chi-square test (40 studies [17, 28, 31, 34, 36-  
43  
44 142 38, 40-42, 47, 49, 52, 54, 56, 58, 60, 62-69, 72-74, 76, 77, 79-81, 83-85, 91, 92, 96, 97])  
45  
46 143 and the t-test (15 studies [40, 45, 47, 49, 62, 63, 65, 66, 74, 77, 79, 81, 88, 91, 97]), which  
47  
48 144 measured associations between variables and goodness-of-fit. As an alternative to the  
49  
50 145 chi-square test for association, one study used the Fisher exact test [72]. Sample mean  
51  
52 146 differences were assessed by 17 studies with the Mann-Whitney U test (also called the  
53  
54 147 Wilcoxon rank-sum test [20, 23, 31, 47, 58, 66, 77, 92, 96]), its variant for dependent  
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3 148 samples the Wilcoxon signed rank test [40], or the Kruskal-Wallis test [23, 37, 42, 68, 73,  
4  
5 149 76, 83]. The Mantel-Haenszel test (test for differences in contingency tables, two studies  
6  
7 150 [44, 93]), the likelihood ratio test (significance test for nested models, two studies [64, 67]),  
8  
9 151 the Hosmer-Lemeshow test (goodness-of-fit for logistic regression, two studies [67, 70]),  
10  
11 152 and the Breslow-Day test (test for homogeneity in contingency tables odds ratio [53]) were  
12  
13 153 also used to a lesser degree. Finally, one study checked the assumption of normality with  
14  
15 154 the Kolmogorov-Smirnov test [66].  
16  
17  
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## 20 155 **Machine learning**

21  
22  
23 156 Machine learning tools are a set of algorithms that can learn and adapt to data in order to  
24  
25 157 classify or predict, for instance [98]. In the selected studies, the machine learning tools  
26  
27 158 aimed mainly at classifying users (frequent versus non-frequent).  
28  
29

30  
31 159 Two studies used random forests [31, 36] along with support vector machines. Decision  
32  
33 160 trees, which include classification and regression trees, were implemented by five studies  
34  
35 161 [5, 31, 36, 61, 87]. Adaptive boosting, or AdaBoost, is a meta-algorithm that combines  
36  
37 162 with other algorithms and helps for better performances. It was computed in two studies  
38  
39 163 [36, 61].  
40  
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## 43 164 **Other tools**

44  
45  
46 165 One study fitted a nonparametric distribution to their data [25], while another one used  
47  
48 166 survival analysis [50].  
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## 167 **4. Discussion**

168 The most exploited statistical tools arguably came from regression analysis. This may be  
169 because regression is well established in medical statistics or also because it is the most  
170 natural tool when trying to find significant variables to explain a dependent variable (in  
171 this case, to be a frequent user). Moreover, it allows predicting easily the risk of a new user  
172 becoming a frequent user, depending on its covariates. Other tools from hypothesis testing  
173 or machine learning also proved to be popular, albeit to a much lesser extent. Combining  
174 these statistical techniques may help in discovering significant patterns compared to using  
175 tools from one class only. In our scoping review, only two studies mixed statistical tools  
176 from regression, hypothesis testing, and machine learning [31, 36].

177 The analysis of frequent ED users could benefit from using more machine learning  
178 techniques. Those were found to be not as common as regression or hypothesis testing,  
179 although they are especially appropriate when dealing with classification, prediction, or  
180 big data. Tools such as support vector machines (which were used by two studies in this  
181 scoping review [31, 36]), artificial neural networks, or Bayesian networks are common  
182 classifiers and predictors in the artificial intelligence community [99]. They are popular for  
183 instance in cancer diagnostic and prognosis, which strongly rely on classification and  
184 prediction [100-102]. In particular, support vector machines, decision trees or  
185 self-organizing maps can deal with binary outcomes, which is usually the case for frequent  
186 use outcomes. They require large datasets, but this is becoming less and less of an issue in  
187 the medical field [103]. Nevertheless, machine learning tools often use a black box  
188 approach. This means that intermediary steps leading to the final solution can be difficult

189 to interpret, although in the end they display good performances in classifying and  
190 predicting. Those methods would thus turn out to be less useful in data exploration [104].

191 Other tools exist that may also be suitable for describing the associated variables or the  
192 prediction of frequent ED users but were not reported in the literature. Among those,  
193 principal component analysis (PCA) is a dimensional reduction and visualization  
194 technique, sometimes used with cluster or discriminant analysis [105]. Based on all the  
195 original explanatory variables, PCA constructs new ones by summing and weighing them  
196 differently. More weight is given to relevant variables so that those latter become dominant  
197 in the new constructions while still including all variables. For instance,  
198 Burgel *et al.* (2010) built chronic obstructive pulmonary disease clinical phenotypes by  
199 constructing new relevant variables with PCA and by grouping similar subjects in this new  
200 space with cluster analysis [106]. Moreover, PCA has already been used for the  
201 construction of questionnaires and diagnosis tools in a medical context [107, 108], both of  
202 which can prove useful in the identification of frequent users.

203 As mentioned, regression techniques were common in the selected studies. Yet, quantile  
204 regression (QR, [109]) was not mentioned. QR is a generalization of mean regression in  
205 the sense that its focus is not only the mean of the dependent variable distribution (such as  
206 in classical linear regression) but any quantile of it. QR thus represents an alternative to  
207 define frequent users by the high quantiles of ED visit distribution (e.g. the 90th quantile).  
208 Eight studies [25, 27, 46, 48, 51, 54, 62, 96] defined frequent users with quantiles, but they  
209 did not use QR. QR would allow for finer investigations in the different quantiles of ED  
210 users in relationship to the explanatory variables. For instance, the association between age  
211 and the number of ED visits may be significantly different across the 10th (low users) and



1  
2  
3 212 90th (frequent users) quantiles. Such a heterogeneous association would be uncovered by  
4  
5 213 QR, while usually unseen with a classical mean regression. Ding *et al.* (2010) used QR to  
6  
7 214 characterize waiting room and treatment times in EDs [110]. They explored the lowest,  
8  
9 215 median and highest of those times and highlighted predictors that were significant only in  
10  
11 216 particular quantiles. Usually, QR requires a continuous dependent variable as opposed to a  
12  
13 217 logistic regression, though it is possible to combine these two regressions [111].  
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15 218 Furthermore, defining frequent users by quantiles would allow for better comparison  
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17 219 between studies.  
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## 22 **Strengths and limitations**

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25 221 To the best of our knowledge, this scoping review is the first to list statistical tools that are  
26  
27 222 used in the identification of variables associated with frequent ED use and the prediction  
28  
29 223 of frequent users. Besides, it was conducted following a well-defined methodological  
30  
31 224 framework. The search strategies were designed with an information specialist in three  
32  
33 225 different databases. Two independent evaluators selected the articles and extracted the data  
34  
35 226 while a third independent evaluator settled disagreements, ensuring that all included studies  
36  
37 227 were relevant. One limitation of our study is that quality assessment is not performed in a  
38  
39 228 scoping review. However, this should not alter the results, since the aim was to list which  
40  
41 229 statistical tools have been applied in the literature. Moreover, the majority of articles were  
42  
43 230 in English, which may introduce a selection bias (for instance, one excluded article was in  
44  
45 231 Spanish). More than half of the reviewed studies were indeed conducted in the USA,  
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47 232 making the results difficult to compare to other countries.  
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## 233 **5. Conclusions**

234 Frequent ED users represent a complex issue, and their analysis require adequate statistical  
235 tools. In this context, this scoping review shows that some tools are well established, such  
236 as logistic regression and chi-square test, while others such as support vector machines are  
237 less so, though they would deserve to get more attention. It also outlines some research  
238 opportunities with other tools not yet explored.

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## 242 **Authors contributions**

243 YC and CH designed the study with FRH and AV. YC, CH, and MB collected and analysed  
244 the data. In case of disagreement, FRH acted as third reviewer. YC and CH wrote the first  
245 draft of the manuscript. FRH, AV, MCC, and MB contributed to the writing of the  
246 manuscript. All authors read and approved the final manuscript.

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## 252 **Competing interests**

253 The authors declare that they have no competing interests.

## 254 **Data sharing statement**

255 No additional data are available.

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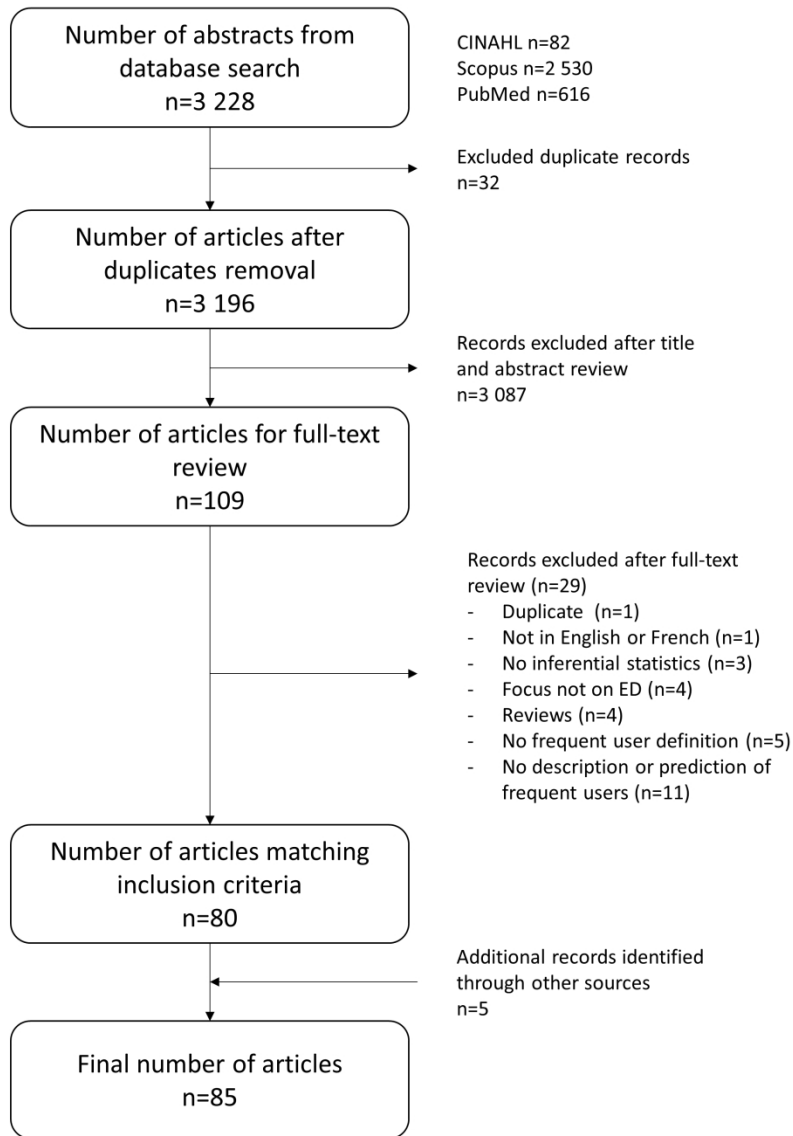


Fig 1. PRISMA flow diagram.

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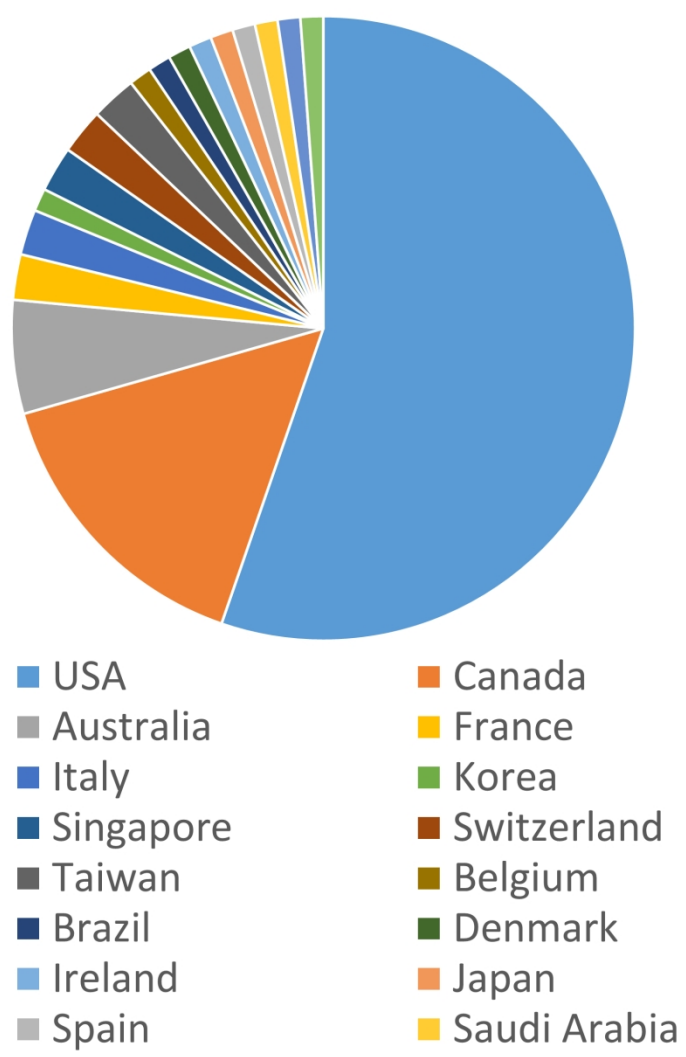


Fig 2. Number of studies by country.  
189x209mm (300 x 300 DPI)

Research strategies used in:

- **CINAHL:** ( "revolving door" OR (frequen\* OR high OR heavy OR repeat) N3 (hospital\* OR utili?ation OR attend\* OR consult\* OR visit\* OR flyer\* OR use\* OR patient\*)) AND "emergency department" AND ((statistic\* OR predict\* OR \*variate OR model\* OR "regression")
- **Scopus:** TITLE-ABS-KEY ( "revolving door" OR ( frequen\* OR high OR heavy OR repeat ) W/3 ( hospital\* OR utili?ation OR attend\* OR consult\* OR visit\* OR flyer\* OR use\* OR patient\* ) ) AND TITLE-ABS-KEY ( "emergency department" ) AND ( TITLE-ABS-KEY ( predict\* OR "univariate" OR "multivariate" OR model\* OR "regression" ) OR KEY ( {statistics and numerical data} ) ) AND ( EXCLUDE ( EXACTKEYWORD , "Controlled Study " ) OR EXCLUDE ( EXACTKEYWORD , " Comparative Study " ) OR EXCLUDE ( EXACTKEYWORD , "Clinical Trial" ) OR EXCLUDE ( EXACTKEYWORD , " Controlled Clinical Trial " ) )
- **PUBMED:** (((("Emergency Medical Services"[Mesh] OR emergency OR emergencies)) AND ("repeat use" OR "heavy user" OR "heavy users" OR "high attender" OR "high attenders" OR "high attendance" OR "high use" OR "high uses" OR "high user" OR "high users" OR "high utilisation" OR "high utilization" OR "frequent consultation" OR "frequent consultations" OR "frequent consultant" OR "frequent consultants" OR "frequent consult" OR "frequent consults" OR "frequent attender" OR "frequent attenders" OR "frequent attendance" OR "frequent visit" OR "frequent visits" OR "frequent visitor" OR "frequent visitors" OR "frequent flyer" OR "frequent flyers" OR "frequent use" OR "frequent uses" OR "frequent

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13 "repeat hospitalization" OR "repeat hospitalizations" OR "revolving door")) AND  
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15 ("Statistics"[Mesh] OR "predictive" OR "univariate" OR "multivariate" OR  
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19 "modelling" OR "modelisation" OR "regression")  
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# BMJ Open

## Statistical tools used for analyses of frequent users of emergency department: A scoping review

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## 12 **Abstract**

13 **Objective:** Frequent users represent a small proportion of emergency department users,  
14 but they account for a disproportionately large number of visits. Their use of emergency  
15 departments is often considered suboptimal. It would be more efficient to identify and treat  
16 those patients earlier in their health problem trajectory. It is therefore essential to describe  
17 their characteristics and to predict their emergency department use. In order to do so,  
18 adequate statistical tools are needed. The objective of this study was to determine the  
19 statistical tools used in identifying variables associated with frequent use or predicting the  
20 risk of becoming a frequent user.

21 **Methods:** We performed a scoping review following an established 5-stage  
22 methodological framework. We searched PubMed, Scopus, and CINAHL databases in  
23 February 2019 using search strategies defined with the help of an information specialist.  
24 Out of 4,534 potential abstracts, we selected 114 articles based on defined criteria and  
25 presented in a content analysis.

26 **Results:** We identified four classes of statistical tools. Regression models were found to  
27 be the most common practice, followed by hypothesis testing. The logistic regression was  
28 found to be the most used statistical tool, followed by chi-square test and t-test of  
29 associations between variables. Other tools were marginally used.

30 **Conclusions:** This scoping review lists common statistical tools used for analyzing  
31 frequent users in emergency departments. It highlights the fact that some are well  
32 established while others are much less so. More research is needed to apply appropriate  
33 techniques to health data or to diversify statistical point of views.

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4 34 **Article summary**  
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7 35 **Strengths and limitations of this study**  
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10 36 • First overview of statistical tools used in frequent users analysis  
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12 37 • Follows a well-defined methodological framework in an extensive body of  
13  
14 38 literature  
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16 39 • Quality assessment is not performed in a scoping review  
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19 40 • Studies in other languages than English or French might have been missed  
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## 1. Background

Emergency department (ED) “frequent users” are a sub-group of ED users that make repeated, multiple visits during a given amount of time. Though there is no consensus about definition for frequent users, thresholds in the literature range from two to more than ten ED visits per year [1, 2], while the most common one is more than four ED visits per year [1, 2]. Frequent users represent a small proportion of ED users but account for a large number of visits [3-5]. They often display complex characteristics such as low socioeconomic status combined with physical and mental health issues [6]. As such, their ED use is considered suboptimal [7], as the best strategy would be to identify those patients at an earlier stage in their health problem trajectory, in order to treat them more efficiently [8]. Furthermore, frequent users’ visits may lead to overcrowding in EDs and decreased quality of care [2]. Identifying factors that best describe those users and predict their ED use is therefore an essential task to improve ED care as well as frequent users’ health problems. Adequate statistical tools are needed to that end. Although they are numerous, no literature review has been published yet about statistical tools used for analyzing ED frequent users. Therefore, the aim of our study was to draw up a list of statistical tools used in identifying variables associated with frequent use or predicting the risk of becoming a frequent user.

## 2. Methods

In order to list the statistical tools used in describing variables associated with and prediction of frequent ED use, we conducted a scoping review. We followed the 5-stage methodology of Arksey and O'Malley [9] adapted by Levac *et al.* [10]. The methodological

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3 64 framework of a scoping review allows “mapping rapidly the key concepts underpinning a  
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5 65 research area and the main sources and types of evidence available” [11], thus allowing us  
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8 66 to identify gaps in the literature and future research opportunities.  
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### 10 11 67 **Stage 1: Identifying the research question** 12

13  
14 68 We defined our research question as follows: What statistical tools are used in the  
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16 69 identification of variables associated with frequent ED users and in their prediction?  
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### 18 19 70 **Stage 2: Identifying relevant studies** 20

21  
22 71 We searched PubMed, CINAHL, and Scopus databases in February 2019, using search  
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24 72 strategies developed with the help of an information specialist (see the supplementary  
25  
26 73 appendix for the complete search strategy). Keywords included variants of “frequent  
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29 74 users”, “emergency departments” and “statistical tools”.  
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32 75 There were no restriction regarding the population age or sex, health conditions, study  
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34 76 period or country.  
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### 36 37 77 **Stage 3: Study selection** 38

39  
40 78 Articles written in French or in English were included using the following criteria:  
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43 79 • The study must focus on frequent users of EDs (studies focusing on re-visits or on  
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45 80 frequent visits other than in EDs were excluded);  
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48 81 • The study must have an explicit definition of frequent users, such as four visits in  
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50 82 one year (reviews were excluded);  
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- 83 • The study must use at least one statistical tool that is classified as inferential (not  
84 descriptive, as defined by The Cambridge Dictionary of Statistics [12]), such as  
85 hypothesis tests, regression models, decision trees, or others;
- 86 • The study's objectives must include identifying variables associated with frequent  
87 use or predicting the risk of becoming a frequent user.

88 We collected 4,534 potential abstracts (Fig 1). Of those, 32 were duplicates, and 4,344  
89 were excluded by an investigator (YC) after reading the title and the abstract. At this stage,  
90 studies were discarded if it was explicit from the title and the abstract that they were unfit  
91 for the scoping review (for instance studies about frequent use of inpatient services,  
92 systematic reviews, etc.). In case of uncertainty, studies were kept for complete reading.  
93 Then, YC and FRH or ID independently evaluated the remaining 158 full text articles, of  
94 which 109 matched the above criteria. A third evaluator was consulted in case of  
95 discrepancy. Reasons for exclusion were: not in French or English (one), duplicate (three),  
96 systematic review (four), no inferential statistics (five), no explicit definition of frequent  
97 users (five), focus not on ED (fourteen), no description or prediction of frequent users  
98 (seventeen). A reference search among the references of the 109 included articles yielded  
99 five relevant articles. Thus, 114 articles were included in this study, of which YC, ID, and  
100 MB examined the full texts.

101 **Fig 1. PRISMA flow diagram.**

## 102 **Stage 4: Charting the data**

103 YC, MB and ID independently extracted the corresponding data. Reported characteristics  
104 were the first (two) author(s), the publication year, the study location, the population, the

105 frequent users' definition, the objectives, the sample size, and the statistical tools used  
 106 concerning the research question.

## 107 **Stage 5: Collating, summarizing and reporting the results**

108 The results are reported via a content analysis [13].

## 109 **Patient and public involvement**

110 Patients or public were not involved in this study.

## 111 **3. Results**

112 The studies main characteristics are presented in Table 1. Out of 114 studies, 65 were  
 113 conducted in the United States, 17 in Canada and 8 in Australia (Fig 2). The various  
 114 statistical tools were classified into four main categories: regression, hypothesis testing,  
 115 machine learning, and other tools.

116 **Table 1. Main characteristics of the 86 included studies.**

Authors, year, and country	Population	Frequent user definition	Study main objectives	Study cohort size	Statistical tools used
Aagaard, J. <i>et al.</i> 2013 Denmark	Psychiatric	≥5 visits per year	To identify predictors of frequent use of a psychiatric emergency room	8,034	Logistic regression
Adams, R.J. <i>et al.</i> 2000 Australia	Adults with asthma	≥2 visits per year	To identify whether factors other than severity and low socioeconomic status were associated with this disproportionate use	293	Logistic regression
Ahn, E. <i>et al.</i> 2018 Australia	General population aged ≤70 years	≥4 visits per year	To examine the characteristics of frequent visitors to EDs and develop a predictive model to identify those with high risk of a future representations to ED among younger and general population	170,134	Maximum likelihood monotone coarse classifier algorithm Logistic regression Mixed-effects model

Alghanim, S.A. & Alomar, B.A.	All	$\geq 3$ visits per year	To determine the prevalence of frequent use of EDs in public hospitals, to determine factors associated with such use, and to identify patients' reasons for frequent use	666	Chi-square test Logistic regression
2015 Saudi Arabia					
Alpern, E.R. <i>et al.</i>	All	$\geq 4$ visits per year	To describe the epidemiology of and risk factors for recurrent and high frequency use of the ED by children	695,188	Negative binomial regression Logistic regression Generalized estimating equations
2014 United States					
Andren, K.G. & Rosenqvist, U.	All	$\geq 4$ visits per year	To follow a cohort of heavy ED users with regard to changes in medical and psycho-social profiles and ED use and to identify predictors for a maintained high use of ED services and the relationship between changes in access to social networks and utilization of medical care services	232	Decision trees Linear regression
1987 Sweden					
Andrews, C.M. <i>et al.</i>	Medicaid enrollees with addiction	$\geq 2$ visits during a 2 year-period	To examine whether the number of outpatient addiction programs accepting Medicaid in South Carolina counties is linked to repeat use of the emergency department for addiction-related conditions	2,401	Logistic regression
2018 United States					
Arfken, C.L. <i>et al.</i>	Psychiatric	$\geq 6$ visits per year	To identify risk factors for people who use psychiatric emergency services repeatedly and to estimate their financial charges	74	Logistic regression
2004 United States					
Batra, P. <i>et al.</i>	Women	$\geq 3$ visits per 3 months	To use population data to identify patient characteristics associated with a postpartum maternal emergency department visit within 90 days of discharge after birth	1,071,232	Logistic regression Receiver operating characteristic curve
2017 United States					
Beck, A. <i>et al.</i>	Mental health	$\geq 3$ visits in 3 months	To statistically identify characteristics associated with a shorter time to re-attendance and a higher number of overall ED admissions with a Mental Health Liaison Service referral	24,010	Cox regression Negative binomial regression
2016 United Kingdom					
Bieler, G. <i>et al.</i>	All	$\geq 4$ visits per year	To identify the social and medical factors associated	719	Wilcoxon rank-sum test



2012	Switzerland			with frequent ED use and to determine if frequent users were more likely to have a combination of these factors in a universal health insurance system		Logistic regression
Billings, J. & Raven, M.C.	All	≥3 visits per year ≥5 visits per year ≥8 visits per year ≥10 visits per year		To examine whether it is possible to predict who will become a frequent ED user with predictive modeling and to compare ED expenditures to total Medicaid services expenditures	212,259	Logistic regression
2013	United States					
Birmingham, L.E. <i>et al.</i>	All	≥4 visits per year		To characterize frequent ED users, including their reason for presenting to the ED and to identify perceived barriers to care from the users' perspective	1,523	t-test Chi-square test Wilcoxon rank-sum test
2017	United States					
Blair, M. <i>et al.</i>	Children	≥4 visits per year		To describe the sociodemographic and clinical characteristics of preschoolers who attend ED a large District General Hospital	10,169	Chi-square test Poisson regression Mann-Whitney U test
2017	United-Kingdom					
Blonigen, D.M. <i>et al.</i>	Veteran psychiatric	≥5 visits per year		To identify patient-level factors associated with ED use among veteran psychiatric patients and to examine factors associated with different subgroups of ED users including "high utilizers"	226,122	Chi-square test Zero-truncated negative binomial regression Logit regression
2011	France					
Boyer, L. <i>et al.</i>	Psychiatric	≥6 visits per year		To examine characteristics of frequent visitors to a psychiatric emergency service in a French public teaching hospital over six years	1,285	Logistic regression
2014	United States					
Brennan, J.J. <i>et al.</i>	Psychiatric	≥4 visits per year		To assess the incidence of psychiatric visits among frequent ED users and utilization among frequent psychiatric users	788,005	Kruskal-Wallis test Mann-Whitney U test Logistic regression
2015	United States					
Buhumaid, R. <i>et al.</i>	Psychiatric	≥4 visits per year		To evaluate demographic factors associated with increased ED use among people with psychiatric conditions	569	Logistic regression
2018	United States					
Burner, E. <i>et al.</i>	People with diabetes	≥3 visits per 6 months		To describe characteristics of patients with poorly controlled diabetes who have high ED utilization, and compare them with	108	Logistic regression

				patients with lower ED utilization		
6	Cabey, W.V. <i>et al.</i>	All	90th percentile	To define the threshold and population factors associated with pediatric ED use above the norm during the first 36 months of life	16,664	Nonparametric distribution fit Logistic regression Bootstrap Clopper-Pearson method
8	2014 United States					
13	Castner, J. <i>et al.</i>	People with psychiatric and substance abuse diagnoses	$\geq 3$ visits per year	To stratify individuals by overall health complexity and examine the relationship of behavioral health diagnoses (psychiatric and substance abuse) as well as frequent treat-and-release ED utilization in a cohort of Medicaid recipients	56,491	Logistic regression
15	2015 United States					
21	Chambers, C. <i>et al.</i>	Homeless	90th percentile	To identify predictors of ED use among a population-based prospective cohort of homeless adults in Toronto, Ontario	1,165	Logistic regression
23	2013 Canada					
27	Chang, G. <i>et al.</i>	Psychiatric	$\geq 4$ visits per year or $\geq 3$ visits during 2 consecutive months	To identify the patient characteristics associated with frequent ED use and develop a tool to predict risk for returning in the next month	863	Chi-square test Logistic regression
29	2014 United States					
34	Christensen, E.W. <i>et al.</i>	All	$\geq 4$ visits per year	To determine the patient characteristics and health care utilization patterns that predict frequent ED use ( $\geq 4$ visits per year) over time to assist health care organizations in targeting patients for care management	13,265	Zero-inflated Poisson regression Receiver operating characteristic curve
36	2017 United States					
41	Chukmaitov, A.S. <i>et al.</i>	People with ambulatory care-sensitive conditions	$\geq 4$ visits per year	To study characteristics of all, occasional, and frequent ED visits due to ambulatory care-sensitive conditions	4,914,933 (number of visits)	Logistic regression
43	2012 United States					
46	Colligan, E.M. <i>et al.</i>	Medicare beneficiaries	$\geq 4$ visits per year	To examine factors associated with persistent frequent ED use during a 2-year period among Medicare beneficiaries	5,400,237	Logistic regression Wald test
48	2016 United States					
51	Colligan, E.M. <i>et al.</i>	Medicare beneficiaries	$\geq 4$ visits per year	To examine factors related to frequent ED use in a large, nationally representative sample of Medicare beneficiaries	5,778,038	Chi-square test Analysis of variance Logistic regression Wald test
53	2017 United States					

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5	Cunningham, A.			To compare frequent and		
6	<i>et al.</i>			infrequent ED visitors'		
7		All	95th percentile	primary care utilization	1,113	t-test
8	2017		$\geq 10$ visits per	and perceptions of primary		Chi-square test
9	United States		year	care access, continuity, and		Logistic regression
10				connectedness and to		
11				examine primary care		
12				utilization and perceptions		
13				as predictors of ED use		
14						Wilcoxon rank-sum
15	Das, L.T. <i>et al.</i>			To explore the		test
16		Children	$\geq 2$ visits per	predictability of frequent	2,691	Chi-square test
17	2017	with asthma	year	ED use among children		LASSO logistic
18	United States			with asthma using data		regression
19				from an EHR from one		Regularized logistic
20				medical center		regression
21						Decision trees
22						Random forests
23			2-4 visits per	To identify		Support vector
24	Doran, K.M. <i>et al.</i>		year	sociodemographic and		machines
25		All	5-10 visits per	clinical factors most	930,712	
26	2013		year	strongly associated with		Logistic regression
27	United States		11-25 visits per	frequent ED use within the		
28			year	Veterans Health		
29			$\geq 25$ visits	Administration nationally		
30						
31	Doran, K.M. <i>et al.</i>			To examine patients'		
32		All	$\geq 3$ visits per	reasons for using the ED	940	Logistic regression
33	2014		year	for low-acuity health		
34	United States			complaints, and determine		
35				whether reasons differed		
36				for frequent ED users		
37				versus non-frequent ED		
38				users		
39	Doupe, M.B.			To identify factors that	105,687	Logistic regression
40	<i>et al.</i>	All	$\geq 7$ visits per	define frequent and highly		Receiver operating
41	2012		year	frequent ED users		characteristic curve
42	Canada					
43	Fernandes, A.K.			To identify characteristics		
44	<i>et al.</i>	All	$\geq 3$ visits per	related to poor disease	86	Chi-square test
45	2003		year	control and frequent visits		Logistic regression
46	Brazil			to the ED to apply		
47				appropriate clinical		
48				management		
49	Flood, C. <i>et al.</i>	Children	$\geq 4$ visits per	To identify factors	2,631	Chi-square test
50			year	associated with high ED		t-test
51	2017			utilization among children		Logistic regression
52	United States			in vulnerable families		
53						Wilcoxon rank-sum
54	Freitag, F.G. <i>et al.</i>	People with	$\geq 3$ visits per	To examine the	785	test
55		chronic daily	year	characteristics of chronic		t-test
56	2005	headache		daily headache sufferers		Chi-square test
57	United States			who use EDs and identify		Poisson regression
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			factors predictive of ED visits		Negative binomial regression Logistic regression
Friedman, B.W. <i>et al.</i>	People with severe headache	$\geq 4$ visits per year	To determine frequency of ED use and risk factors for use among patients suffering severe headache	13,451	Markov chain Monte Carlo imputation Logistic regression
2009 United States					
Frost, D.W. <i>et al.</i>	All	$\geq 3$ visits per year	To determine whether machine learning techniques using text from a family practice electronic medical record can be used to predict future high ED use and total costs by patients who are not yet high ED users or high cost to the healthcare system	43,111	Logistic regression
2017 Canada					
Girts, T.K. <i>et al.</i>	People with a diagnosis of psychosis	$\geq 2$ visits per 6 months	To develop a predictive model of ED utilization for patients where a diagnosis of psychosis could be identified from a claim associated with a medical service provider visit	764	t-test Linear regression
2002 United States					
Grinspan, Z.M. <i>et al.</i>	People with epilepsy	$\geq 4$ visits per year	To describe (1) the predictability of frequent 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	8,041	Chi-square test Logistic regression Regularized logistic regression Elastic net logistic regression Decision trees Random forests AdaBoost Support vector machines Receiver operating characteristic curve
2015 United States					
Gruneir, A. <i>et al.</i>	Nursing home residents	$\geq 3$ visits per year	To describe repeat ED visits over one year, identify risk factors for repeat use, and characterize "frequent" ED visitors	25,653	Logistic regression Andersen-Gill model
2018 Canada					
Hardie, T.L. <i>et al.</i>	All	$\geq 4$ visits per year	To describe frequent users of ED services in a rural community setting and the association between counts of patient's visits and discrete diagnoses	1,652	Poisson regression
2015 United States					
Hasegawa, K. <i>et al.</i>	People with acute asthma	$\geq 2$ visits per year	To examine the proportion and patient characteristics of adult patients with multiple ED visits for	86,224	Chi-square test Kruskal-Wallis test Logistic regression
2014 United States					

				acute asthma and the associated hospital charges		
Hasegawa, K. <i>et al.</i>	People with acute heart failure syndrome	$\geq 2$ visits per year	To examine the proportion and characteristics of patients with frequent ED visits for acute heart failure syndrome and associated healthcare utilization	113,033	Chi-square test Kruskal-Wallis test Negative binomial regression Linear regression	
2014 United States						
Hasegawa, K. <i>et al.</i>	People with chronic obstructive pulmonary disease	$\geq 2$ visits per year	To quantify the proportion and characteristics of patients with frequent ED visits for acute exacerbation of chronic obstructive pulmonary disease and associated healthcare utilization	98,280	Chi-square test Kruskal-Wallis test Logistic regression Negative binomial regression Linear regression	
2014 United States						
Huang, J.A. <i>et al.</i>	All	$\geq 4$ visits per year	To characterize frequent ED users and to identify the factors associated with frequent ED use in a hospital in Taiwan	800	Chi-square test Logistic regression	
2003 Taiwan						
Hudon, C. <i>et al.</i>	All	$\geq 3$ visits per year	To identify prospectively personal characteristics and experience of organizational and relational dimensions of primary care that predict frequent use of ED	1,769	Mixed-effects logistic regression	
2016 Canada						
Hudon, C. <i>et al.</i>	People with diabetes	$\geq 3$ visits for 3 consecutive years	To explore the factors associated with chronic frequent ED utilization in a population with diabetes	62,316	Logistic regression Decision trees	
2017 Canada						
Hunt, K.A. <i>et al.</i>	All	$\geq 4$ visits per year	To identify frequent users of the ED and determine the characteristics of these patients	49,603	Logistic regression	
2006 United States						
Huynh, C. <i>et al.</i>	People with substance use disorders	$\geq 4$ visits per year	To assess the characteristics of individuals with substance use disorders according to their frequency of ED utilization, and to examine which variables were associated with an increase in ED visits using Andersen's model	4,526	Chi-square test Analysis of variance Negative binomial regression Generalized estimating equations	
2016 Canada						
Kanzaria, H.K. <i>et al.</i>	Adults aged 18-55 years	$\geq 4$ visits per year	To examine the persistence of frequent ED use over an eleven-year period, describe characteristics of persistent versus non-persistent frequent ED users, and identify	173,273	Logistic regression	
2017 United States						

				predictors of persistent frequent ED use		
Kerr, T. <i>et al.</i>	Injection drug users	$\geq 3$ visits during the 2 past years		To examine rates of primary care and emergency room use among injection drug users and to identify correlates of frequent emergency department use	883	Chi-square test Wilcoxon signed-rank test t-test Logistic regression
Kidane, B. <i>et al.</i>	Patients who received oesophagectomy	$\geq 3$ visits per year		To evaluate healthcare resource utilization, specifically ED visits within 1 year of oesophagectomy, and to identify risk factors for ED visits and frequent ED use	3,344	t-test Wilcoxon rank-sum test Fisher exact tests Logistic regression
Kim, J.J. <i>et al.</i>	All	99th percentile		To describe patient and visit characteristics for Canadian ED highly frequent users and patient subgroups with mental illness, substance misuse, or $\geq 30$ yearly ED visits.	261	t-test Wilcoxon rank-sum test
Kirby, S.E. <i>et al.</i>	People with chronic disease	$\geq 3$ visits per year		To explore the link between frequent readmissions in chronic disease and patient-related factors	15,806	Chi-square test Logistic regression
Kirby, S.E. <i>et al.</i>	All	$\geq 4$ visits per year		To identify the factors associated with frequent re-attendances in a regional hospital thereby highlighting possible solutions to the problem	15,806	Kruskal-Wallis test Chi-square test Logistic regression
Klein, LR. <i>et al.</i>	Adults who present to the ED repeatedly for acute alcohol intoxication	$\geq 20$ visits per year		To describe frequent ED users who present to the ED repeatedly for acute alcohol intoxication and their ED encounters	325	Difference in proportions test
Ko, M. <i>et al.</i>	All	$\geq 4$ visits per year		To describe the distribution of the frequency of ED visits among ED users in 2010 and to evaluate the association of frequent ED use with various patient characteristics	170,457	Logistic regression
Ledoux, Y. & Minner, P.	Psychiatric	$\geq 4$ visits per year		(1) To provide a naturalistic evaluation of patients repeating admissions in a psychiatric emergency ward (distinguishing between	2,470	Mantel-Haenszel test Analysis of variance Logistic regression

				occasional repeaters and frequent repeaters), (2) to identify patients' characteristics that predict repeated use of a psychiatric emergency room and (3) to propose adapted treatment models	
Lee, J. <i>et al.</i> 2018 United States	Persons with systemic lupus erythematosus	$\geq 3$ visits per year	To identify lupus erythematosus patients who persistently frequented the ED over four years	129	t-test Chi-square test Fisher exact test Logistic regression
Legramante, J.M. <i>et al.</i> 2016 Italy	All	$\geq 4$ visits per year	To evaluate and characterize hospital visits of older patients (age 65 or greater) to the ED of a university teaching hospital in Rome, in order to identify clinical and social characteristics potentially associated with "elderly frequent users"	38,016	t-test Logistic regression
Leporatti, L. <i>et al.</i> 2016 Italy	All	90th percentile $\geq 3$ visits per year	To describe the characteristics of patients who frequently accessed accident and emergency departments located in the metropolitan area of Genoa	147,864	Zero-truncated negative binomial regression Logistic regression
Lim, S.F. <i>et al.</i> 2014 Singapore	People with asthma	$\geq 4$ visits per year	To describe the characteristics of frequent attenders who present themselves multiple times to the ED for asthma exacerbations	155	t-test Chi-square test Mann-Whitney U test Logistic regression
Limsrivilai, J. <i>et al.</i> 2017 United States	People with inflammatory bowel diseases	75th percentile of the annual medical charges	To identify predictive factors readily available in a standard electronic medical record to develop a multivariate model to predict the probability of inflammatory bowel diseases-related hospitalization, ED visit, and high total charges in the subsequent year	1,430	Receiver operating characteristic curve Logistic regression
Lin, W.C. <i>et al.</i> 2015 United States	Homeless people	$\geq 3$ visits per year	To examine factors associated with frequent hospitalizations and ED visits among Medicaid members who were homeless	6,494	Chi-square test Analysis of variance Negative binomial regression
Liu, S.W. <i>et al.</i> 2013	People with mental health,	$\geq 4$ visits per year	To determine whether frequent ED users are more likely to make at	65,201	t-test Chi-square test Logistic regression

United States	alcohol or drug-related diagnoses			least one and a majority of visits for mental health, alcohol, or drug-related complaints compared to non-frequent users		
Mandelberg, J.H. <i>et al.</i> 2000 United States	All	$\geq 5$ visits per year		To determine how the demographic, clinical, and utilization characteristics of frequent ED users differ from those of other ED patients	43,383	Logistic regression Survival analysis
Mann, E.G. <i>et al.</i> 2016 Canada	People with chronic pain	90th percentile		To investigate the role of chronic pain in healthcare visits and to document the frequency of healthcare visits and to identify characteristics associated with frequent visits	1,274	Logistic regression
Mann, E.G. <i>et al.</i> 2017 Canada	People with chronic pain	90th percentile		To describe factors associated with high clinic and emergency room use among individuals with chronic pain	702	t-test Logistic regression
McMahon, C.G. <i>et al.</i> 2016 Ireland	All	$\geq 4$ visits per year		To examine the characteristics of the frequent ED attenders by age (under 65 and over 65 years)	19,310	Chi-square test Logistic regression
Meyer, J.P. <i>et al.</i> 2013 United States	Prisoners with Human Immunodeficiency Virus	$\geq 2$ visits per year		To characterize the medical, social, and psychiatric correlates of frequent ED use among released prisoners with human immunodeficiency virus	151	t-test Chi-square test Poisson regression
Milani, S.A. <i>et al.</i> 2016 United States	People with multimorbid chronic diseases	$\geq 4$ visits per year		To examine the association between multimorbid chronic disease and frequency ED visits in the past 6 months, by sex, in a community sample of adults from northern Florida	7,143	Breslow-Day test Logistic regression
Milbrett, P. & Halm, M. 2009 United States	All	$\geq 6$ visits per year		To describe the characteristics of patients who frequently use ED services and to determine factors most predictive of frequent ED use	201	Chi-square test Mann-Whitney U test Poisson regression
Moe, J. <i>et al.</i> 2013 Canada	All	95th percentile		To develop uniform definitions, quantify ED burden, and characterize adult frequent users of a suburban community ED	14,223	Chi-square test Mann-Whitney U test



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5	Mueller, E.L. <i>et al.</i>	Children with cancer	90th percentile ≥4 visits per year	To (a) evaluate patient and ED encounter characteristics of frequent ED utilizers among children with cancer and (b) quantify healthcare services for frequent ED utilizers	17,943	Chi-square test Logistic regression
6	2016					
7	United States					
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12	Nambiar, D. <i>et al.</i>	Adults who inject drugs	≥3 visits per year	To describe demographic factors, patterns of substance use and previous health service use associated with frequent use of EDs in people who inject drugs	612	Negative binomial regression Logistic regression
13	2017					
14	Australia					
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20	Nambiar, D. <i>et al.</i>	Adults who inject drugs	≥3 visits per year	To describe characteristics of state-wide ED presentations in a cohort of people who inject drugs, compare presentation rates to the general population, and to examine characteristics associated with frequent ED use	678	Negative-binomial regression Generalized estimating equations
21	2018					
22	Australia					
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28	Naseer, M. <i>et al.</i>	Older adults	≥4 visits during a 4 year-period	To assess the association of health related quality of life with time to first ED visit and/or frequent ED use in older adults during four-year period and if this association differs in 66-80 and 80+ age groups	673	Cox proportional hazard model Logistic regression
29	2018					
30	Sweden					
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35	Neufeld, E. <i>et al.</i>	All	≥4 visits per year	To describe factors predicting frequent ED use among rural older adults receiving home care services in Ontario, Canada	12,118	Chi-square test Logistic regression
36	2016					
37	Canada					
38						
39						
40	Neuman, M.I. <i>et al.</i>	All	≥4 visits per year	To compare the characteristics and ED health services of children by their ED visit frequency	1,896,547	Mantel-Haenszel test Receiver operating characteristic curve Generalized linear mixed-effects models
41	2014					
42	United States					
43						
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45	Ngamini-Ngui, A. <i>et al.</i>	Patients with schizophrenia and a co-occurring substance use disorder	≥5 visits per year	To assess factors associated over time with high use of EDs by Quebec patients who had schizophrenia and a co-occurring substance use disorder	2,921	Generalized estimating equations
46	2014					
47	Canada					
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52	Norman, C. <i>et al.</i>	All	≥4 visits per year	To clearly define and describe characteristics of frequent emergency medical services users in order to provide	539	Logistic regression
53	2016					
54	United States					
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				suggestions for efficient and cost-effective interventions that address the healthcare needs of these users		
O'Toole, T.P. <i>et al.</i>	Substance users	$\geq 3$ visits per year		To identify factors associated with 12-month high frequency utilization of ambulatory care, ED, and inpatient medical care in a substance-using population	326	t-test Chi-square test Logistic regression
2007 United States						
Palmer, E. <i>et al.</i>	All	$\geq 4$ visits per year		To determine if having a primary care provider is an important factor in frequency of ED use	59,803	Chi-square test Wilcoxon rank-sum test Logistic regression
2014 Canada						
Panopolis, P. <i>et al.</i>	People with systemic lupus erythematosus	$\geq 3$ visits per year		To describe characteristics of systemic lupus erythematosus patients who are frequent users of the ED and to identify predictors of frequent ED use	807	One-way analysis of variance Logistic regression
2010 United States						
Pasic, J. <i>et al.</i>	Psychiatric	2 SD above the mean number of visits $\geq 6$ visits per year $\geq 4$ visits in a quarter		To examine the sociodemographic and clinical characteristics of high utilizers of psychiatric emergency services	17,481	Chi-square test Logistic regression
2005 United States						
Paul, P. <i>et al.</i>	All	$\geq 5$ visits per year		To determine factors associated with frequent ED attendance at an acute general hospital in Singapore.	82,172	Chi-square test Logistic regression
2010 Singapore						
Peltz, A. <i>et al.</i>	Medicaid-insured children	$\geq 4$ visits per year		To describe the characteristics of children who sustain high-frequency ED use over the following 2 years	470,449	Chi-square test Wilcoxon signed-rank test Logistic regression
2017 United States						
Pereira, M. <i>et al.</i>	All	$\geq 5$ visits per year		To develop machine learning models that can predict future ED utilization of individual patients, using only information from the present and the past	4,604,252	Decision trees AdaBoost Logistic regression
2016 United States						
Pines, J.M. & Buford, K.	People with asthma	90th percentile $\geq 3$ visits per year		To determine socioeconomic and demographic factors that predict frequent ED use among asthmatics in southeastern Pennsylvania	1,799	t-test Chi-square test Logistic regression
2006 United States						
Quilty, S. <i>et al.</i>	People without	$\geq 6$ visits per year		To determine the clinical and environmental	273	t-test Chi-square test

2016 Australia	chronic health conditions			variables associated with frequent presentations by adult patients to a remote Australian hospital ED for reasons other than chronic health conditions		Fisher exact tests Logistic regression
Rask, K.J. <i>et al.</i> 1998 United States	All	$\geq 10$ visits per 2 years		To describe primary care clinic use and emergency ED use for a cohort of public hospital patients seen in the ED, identify predictors of frequent ED use, and ascertain the clinical diagnoses of those with high rates of ED use	351	Chi-square test t-test Logistic regression
Rauch, J. <i>et al.</i> 2017 Germany	All	$\geq 3$ visits per year		To examine (1) what ambulatory care sensitive conditions are linked to frequent use, (2) how frequent users can be clustered into subgroups with respect to their diagnoses, acuity and admittance, and (3) whether frequent use is related to higher acuity or admission rate	23,364	Chi-square test t-test Linear regression Non-negative matrix factorization
Sacamo, P. <i>et al.</i> 2018 United States	Persons with substance use	$\geq 2$ visits per 6 months		To examine associations of individuals and their social networks with high frequency ED use among persons reporting substance use	653	Poisson regression
Samuels-Kalow, M.E. <i>et al.</i> 2017 United States	All	$\geq 4$ visits per year		To derive and test a predictive model for high frequency (4 or more visits per year), low-acuity (emergency severity index 4 or 5) utilization of the pediatric ED	60,799 (number of visits)	Likelihood ratio test Chi-square test Receiver operating characteristic curve Logistic regression
Samuels-Kalow, M.E. <i>et al.</i> 2018 United States	Patients with asthma exacerbation	$\geq 4$ visits per year		To create a predictive model to prospectively identify patients at risk of high-frequency ED utilization for asthma and to examine how that model differed using state wide versus single-center data	254,132	Chi-square test Fisher exact tests Wilcoxon rank-sum test Hosmer-Lemeshow test Receiver operating characteristic curve Logistic regression
Samuels-Kalow, M.E. <i>et al.</i> 2018 United States	Children	$\geq 3$ visits per year		To develop a population-based model for predicting Medicaid-insured children at risk for high frequency of low-resource-intensity ED visits	743,016	Chi-square test Receiver operating characteristic curve Logistic regression

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5	Schlichting, L.E.	Children	$\geq 2$ visits per year	To examine the utilization of the ED by children with different forms of insurance and describe factors associated with repeat ED use and high reliance on the ED in a nationally representative sample of children in the United States	47,926	Logistic regression
6	<i>et al.</i>					
7	2018					
8	United States					
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13	Schmoll, S. <i>et al.</i>	Psychiatric	$\geq 9$ visits during the 6 past years	To describe demographic and clinical characteristics of frequent visitors to a psychiatric emergency ward in a French Academic hospital over 6 years in comparison to non-frequent visitors	8,800	t-test Chi-square test Logistic regression
14	2015					
15	France					
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21	Soler, J.J. <i>et al.</i>	People with chronic obstructive pulmonary disease	$\geq 3$ visits per year	To identify factors associated with frequent use of hospital services (emergency care and admissions) in patients with chronic obstructive pulmonary disease	64	t-test Chi-square test Kolmogorov-Smirnov test Mann-Whitney U test Logistic regression
22	2004					
23	Spain					
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28	Street, M. <i>et al.</i>	Adults aged $\geq 65$ years	$\geq 4$ visits per year	To characterise older people who frequently use ED and compare patient outcomes with older non-frequent ED attenders	21,073	Chi-square test Wilcoxon rank-sum test Ordinal regression
29	2018					
30	Australia					
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33	Sun, B.C. <i>et al.</i>	All	$\geq 4$ visits per year	To identify predictors and outcomes associated with frequent ED users	2,333	Likelihood ratio test Chi-square test Hosmer-Lemeshow test Logistic regression Bootstrap
34	2003					
35	United States					
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37						
38	Supat, B. <i>et al.</i>	Children	$\geq 6$ visits per year	To assess pediatric ED utilization in California and to describe those identified as frequent ED users	690,130	Logistic regression
39	2018					
40	United States					
41						
42	Tangherlini, N. <i>et al.</i>	All	$\geq 4$ visits per year	To identify the factors that lead to increased use of emergency medical services (EMS) by patients $\geq 65$ years of age in an urban EMS system	10,918	Kruskal-Wallis test Chi-square test Logistic regression
43	2010					
44	United States					
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48	Thakarar, K. <i>et al.</i>	Homeless	$\geq 2$ visits per year	To identify risk factors for frequent emergency room (ER) visits and to examine the effects of housing status and HIV serostatus on ER utilization	412	Chi-square test Logistic regression
49	2015					
50	United States					
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53	Vandyk, A.D. <i>et al.</i>	Mental health	$\geq 5$ visits per year	To explore the population profile and associated socio demographic,	536	Hosmer-Lemeshow test Logistic regression
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2014 Canada				clinical, and service use factors of individuals who make frequent visits (5+annually) to hospital EDs for mental health complaints		
Vinton, V.T. <i>et al.</i> 2014 United States	Chronic diseases and mental health	$\geq 4$ visits per year		To compare the characteristics of US adults by frequency of ED utilization, specifically the prevalence of chronic diseases and outpatient primary care and mental health utilization	157,818	Logistic regression
Vu, F. <i>et al.</i> 2015 Switzerland	Mental health and substance users	$\geq 4$ visits per year		To determine the proportions of psychiatric and substance use disorders suffered by EDs' frequent users compared to the mainstream ED population, to evaluate how effectively these disorders were diagnosed in both groups of patients by ED physicians, and to determine if these disorders were predictive of a frequent use of ED services	389	Fisher exact tests Chi-square test Logistic regression
Wajnberg, A. <i>et al.</i> 2012 United States	All	$\geq 4$ visits over 6 months		To determine factors associated with frequent ED utilization by older adults	5,718	Chi-square test t-test
Watase, H. <i>et al.</i> 2015 Japan	Adults with asthma	$\geq 2$ visits per year		To characterise the adult patients who frequently presented to the ED for asthma exacerbation in Japan	1,002	One-way analysis of variance Chi-square test Kruskal-Wallis test Logistic regression Negative binomial regression
Weidner, T.K. <i>et al.</i> 2018 United States	Patients with colorectal cancer	$\geq 3$ visits per year		To assess ED utilization in patients with colorectal cancer to identify factors associated with ED visits and subsequent admission, as well as identify a high-risk subset of patients that could be targeted to reduce ED visits	13,446	Chi-square test t-test Logistic regression Negative binomial regression
Wong, T.H. <i>et al.</i> 2018 Singapore	Patients with cancer	$\geq 4$ visits per year		To identify factors associated with patients becoming ED frequent attenders after a cancer-related hospitalization	47,235	Cox regression Survival analysis

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45	46	47	48	49	50	51	52	53	54	55
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118 **Fig 2. Number of studies by country.**119 **Regression**

120 Regression tools consist of a set of processes aimed at quantifying the relationships  
 121 between a dependent variable and other explanatory variables [14]. They are useful for  
 122 description and prediction. Some regression models may be *regularized*, which in this case  
 123 means avoiding overfitting with too many explanatory variables, or *zero-truncated*, which  
 124 means that the model is not allowed to take null values.

125 Out of the four categories (regression, hypothesis testing, machine learning, and other  
 126 tools), the most reported tool was the logistic regression (90 studies [3-5, 15-101], two of  
 127 which are regularized by LASSO or elastic net techniques), followed by the binomial  
 128 regression (13 studies [18, 46, 55, 73, 76, 77, 82, 89, 102-106], 2 of which are  
 129 zero-truncated). To a lesser extent, the Poisson regression (seven studies [77, 107-112],  
 130 one of which is zero-truncated), the linear regression (six studies [74, 76, 102, 113-115]),

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3 131 the analysis of variance (six studies [44, 59, 73, 96, 103, 104]), the Cox regression (four  
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5 132 studies [87, 93, 105, 116]), and hierarchical models (one study [90]) were also used. In  
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8 133 those studies, the results are often associated with odds-ratios. The mixed-effects models  
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10 134 were mentioned three times [39, 91, 117]. Regression parameters were estimated by  
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12 135 generalized estimating equations in four studies [18, 103, 106, 118] while parameter  
13  
14 136 confidence intervals were estimated by the bootstrap procedure (two studies [25, 67]) and  
15  
16 137 the Clopper-Pearson method (one study [25]). The receiver operating characteristic curve  
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18 138 (ROC), or equivalently the sensitivity, specificity, or area under the curve (“c-statistic”),  
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20 139 was computed in ten studies [4, 36, 48, 64, 75, 83, 88, 107, 117, 119]. Finally, two studies  
21  
22 140 performed imputation to account for missing data (Markov chain Monte Carlo and multiple  
23  
24 141 imputations [78, 90]).

## 142 **Hypothesis testing**

143 Statistical tests aim at testing a specific hypothesis about data and rely on probability  
144 distributions [120]. In the selected studies, the tests aimed mainly at comparing two  
145 samples (frequent users and non-frequent users).

146 The most common statistical tests were the chi-square test (53 studies [17, 28, 31, 34, 36-  
147 38, 40-42, 47, 49, 52, 54, 56, 58, 60, 62-69, 72-74, 76, 77, 79-82, 85, 88, 89, 94, 96, 97,  
148 101-104, 109, 110, 112, 115, 119, 121-124]) and the t-test (24 studies [40, 45, 47, 49, 62,  
149 63, 65, 66, 74, 77, 79, 81, 85, 89, 94, 95, 97, 98, 109, 114, 115, 122, 124, 125]), which  
150 measured associations between variables and goodness-of-fit. As an alternative to the  
151 chi-square test for association, five studies used the Fisher exact test [63, 72, 94, 98, 119].  
152 Sample mean differences were assessed by 23 studies with the Mann-Whitney U test (also  
153 called the Wilcoxon rank-sum test [20, 23, 31, 47, 58, 66, 77, 98, 110, 119, 121, 123-125]),

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3 154 its variant for dependent samples the Wilcoxon signed rank test [40, 101], or the  
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5 155 Kruskal-Wallis test [23, 37, 42, 68, 73, 76, 102]. The difference in proportions test [126],  
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7 156 Mantel-Haenszel test (test for differences in contingency tables, two studies [44, 117]), the  
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9 157 likelihood ratio test (significance test for nested models, two studies [64, 67]), the  
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11 158 Hosmer-Lemeshow test (goodness-of-fit for logistic regression, two studies [67, 70]), the  
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13 159 Wald test (significance test for regression coefficients, two studies [30, 96]), and the  
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15 160 Breslow-Day test (test for homogeneity in contingency tables odds ratio [53]) were also  
16  
17 161 used to a lesser degree. Finally, one study checked the assumption of normality with the  
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19 162 Kolmogorov-Smirnov test [66].  
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## 24 163 **Machine learning**

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27 164 Machine learning tools are a set of algorithms that can learn and adapt to data in order to  
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29 165 classify or predict, for instance [127]. In the selected studies, the machine learning tools  
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31 166 aimed mainly at classifying users (frequent versus non-frequent).  
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35 167 Two studies used random forests [31, 36] along with support vector machines. Decision  
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37 168 trees, which include classification and regression trees, were implemented by five studies  
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39 169 [5, 31, 36, 61, 113]. Adaptive boosting, or AdaBoost, is a meta-algorithm that combines  
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41 170 with other algorithms and helps for better performances. It was computed in two studies  
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43 171 [36, 61].  
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## 47 172 **Other tools**

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50 173 Two studies used survival analysis [50, 116], while another one fitted a nonparametric  
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52 174 distribution to their data [25]. Finally, maximum likelihood monotone coarse classifier  
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3 175 algorithm was used as a binning method [91] and non-negative matrix factorization as a  
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5 176 clustering technique [115].  
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## 9 177 **4. Discussion**

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12 178 The most exploited statistical tools arguably came from regression analysis. This may be  
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14 179 because regression is well established in medical statistics or also because it is the most  
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17 180 natural tool when trying to find significant variables to explain a dependent variable (in  
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19 181 this case, to be a frequent user). Moreover, it allows predicting easily the risk of a new user  
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21 182 becoming a frequent user, depending on its covariates. Other tools from hypothesis testing  
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23  
24 183 or machine learning also proved to be popular, albeit to a much lesser extent. Combining  
25  
26 184 these statistical techniques may help in discovering significant and complementary  
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28 185 patterns, compared to using tools from one class only. In our scoping review, two studies  
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30 186 mixed statistical tools from regression, hypothesis testing, and machine learning [31, 36].  
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33 187 In those studies, the author evaluated various performance criteria. While logistic  
34  
35 188 regression performed well, other techniques such as random forests or LASSO regression  
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37 189 were also competitive. Besides the fact that logistic regression can display modest  
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39 190 performances [128], random forests and LASSO regression can complete logistic  
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42 191 regression. The first technique can be used to assess the importance of each independent  
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44 192 variable in the model, while the second technique can be useful for automatic selection of  
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46 193 features. Likewise, using a variety of statistical tools can help complete or confirm results  
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48 194 obtained with established methodologies. Different tools from one class can also be mixed  
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50 195 in order to achieve different stages of the analysis (for instance, different types of  
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52 196 regression [82]).  
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3 197 The analysis of frequent ED users could benefit from using more machine learning  
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5 198 techniques. Those were found to be not as common as regression or hypothesis testing,  
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8 199 although they are especially appropriate when dealing with classification, prediction, or  
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10 200 big data. Tools such as support vector machines (which were used by two studies in this  
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12 201 scoping review [31, 36]), artificial neural networks, or Bayesian networks are common  
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14 202 classifiers and predictors in the artificial intelligence community [129]. They are popular  
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16 203 for instance in cancer diagnostic and prognosis, which strongly rely on classification and  
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18 204 prediction [130-132]. In particular, support vector machines, decision trees or  
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20 205 self-organizing maps can deal with binary outcomes, which is usually the case for frequent  
21  
22 206 use outcomes. They usually require large datasets in order to overcome overfitting, but this  
23  
24 207 is becoming less and less of an issue in health sciences [133]. Nevertheless, machine  
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26 208 learning tools often use a black box approach as there are many intermediary steps leading  
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28 209 to the final solution. While each step usually consists of simple arithmetic operations, their  
29  
30 210 multiple interactions can be more difficult to interpret. In spite of this opacity, they still  
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32 211 display good performances in classifying and predicting. In some cases, they may be more  
33  
34 212 accurate than the widely used logistic regression [134]. Those methods would thus turn out  
35  
36 213 to be less useful in data exploration [135]. Machine learning tools are getting popular in  
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38 214 other fields in health sciences, such as critical care [136], cardiology [137] or emergency  
39  
40 215 medicine [138]. The authors state that their fields would benefit from this growing  
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42 216 popularity, though results need to be analyzed and interpreted in collaboration with  
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44 217 clinicians.

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52 218 Other tools exist that may also be suitable for describing the associated variables or the  
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54 219 prediction of frequent ED users but were not reported in the literature. Among those,  
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3 220 principal component analysis (PCA) is a dimensional reduction and visualization  
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5 221 technique, sometimes used with cluster or discriminant analysis [139]. Based on all the  
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7 222 original explanatory variables, PCA constructs new ones by summing and weighing them  
8  
9 223 differently. More weight is given to relevant variables so that those latter become dominant  
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11 224 in the new constructions while still including all variables. For instance,  
12  
13 225 Burgel *et al.* (2010) built chronic obstructive pulmonary disease clinical phenotypes by  
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15 226 constructing new relevant variables with PCA and by grouping similar subjects in this new  
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17 227 space with cluster analysis [140]. Moreover, PCA has already been used for the  
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19 228 construction of questionnaires and diagnosis tools in a medical context [141, 142], both of  
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21 229 which can prove useful in the identification of frequent users.  
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27 230 As mentioned, regression techniques were common in the selected studies. Yet, quantile  
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29 231 regression (QR, [143]) was not mentioned. QR is a generalization of mean regression in  
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31 232 the sense that its focus is not only the mean of the dependent variable distribution (such as  
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33 233 in classical linear regression) but any quantile of it. QR thus represents an alternative to  
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35 234 define frequent users by the high quantiles of ED visit distribution (e.g. the 90th quantile).  
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37 235 Eight studies [25, 27, 46, 48, 51, 54, 62, 121] defined frequent users with quantiles, but  
38  
39 236 they did not use QR. QR would allow for finer investigations in the different quantiles of  
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41 237 ED users in relationship to the explanatory variables. For instance, the association between  
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43 238 age and the number of ED visits may be significantly different across the 10th (low users)  
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45 239 and 90th (frequent users) quantiles. Such a heterogeneous association would be uncovered  
46  
47 240 by QR, while usually unseen with a classical mean regression. Ding *et al.* (2010) used QR  
48  
49 241 to characterize waiting room and treatment times in EDs [144]. They explored the lowest,  
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51 242 median and highest of those times and highlighted predictors that were significant only in  
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3 243 particular quantiles. Usually, QR requires a continuous dependent variable as opposed to a  
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5 244 logistic regression, though it is possible to combine these two regressions [145].  
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8 245 Furthermore, defining frequent users by quantiles would allow for better comparison  
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10 246 between studies as there is no common definition for frequent users.  
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## 13 247 **Strengths and limitations**

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16 248 To the best of our knowledge, this scoping review is the first to list statistical tools that are  
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18 249 used in the identification of variables associated with frequent ED use and the prediction  
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20 250 of frequent users. Besides, it was conducted following a well-defined methodological  
21  
22 251 framework. The search strategies were designed with an information specialist in three  
23  
24 252 different databases. Two independent evaluators selected the articles and extracted the data  
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26 253 while a third independent evaluator settled disagreements, ensuring that all included studies  
27  
28 254 were relevant. One limitation of our study is that quality assessment is not performed in a  
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30 255 scoping review. However, this should not alter the results, since the aim was to list which  
31  
32 256 statistical tools have been applied in the literature. Moreover, the majority of articles were  
33  
34 257 in English, which may introduce a selection bias (for instance, one excluded article was in  
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36 258 Spanish). More than half of the reviewed studies were indeed conducted in the USA,  
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38 259 making the results difficult to compare to other countries.  
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## 45 260 **5. Conclusions**

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48 261 Frequent ED users represent a complex issue, and their analysis require adequate statistical  
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50 262 tools. In this context, this scoping review shows that some tools are well established, such  
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52 263 as logistic regression and chi-square test, while others such as support vector machines are  
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3 264 less so, though they would deserve to get more attention. It also outlines some research  
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5 265 opportunities with other tools not yet explored.  
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11  
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13  
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## 18 269 **Authors contributions**

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20  
21 270 YC and CH designed the study with FRH, ID, and AV. YC, ID, CH, and MB collected and  
22  
23 271 analysed the data. YC and CH wrote the first draft of the manuscript. FRH, ID, AV, MCC,  
24  
25 272 and MB contributed to the writing of the manuscript. All authors read and approved the  
26  
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28 273 final manuscript.  
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## 45 279 **Competing interests**

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48 280 The authors declare that they have no competing interests.  
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## 51 281 **Data sharing statement**

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55 282 No additional data are available.  
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For peer review only

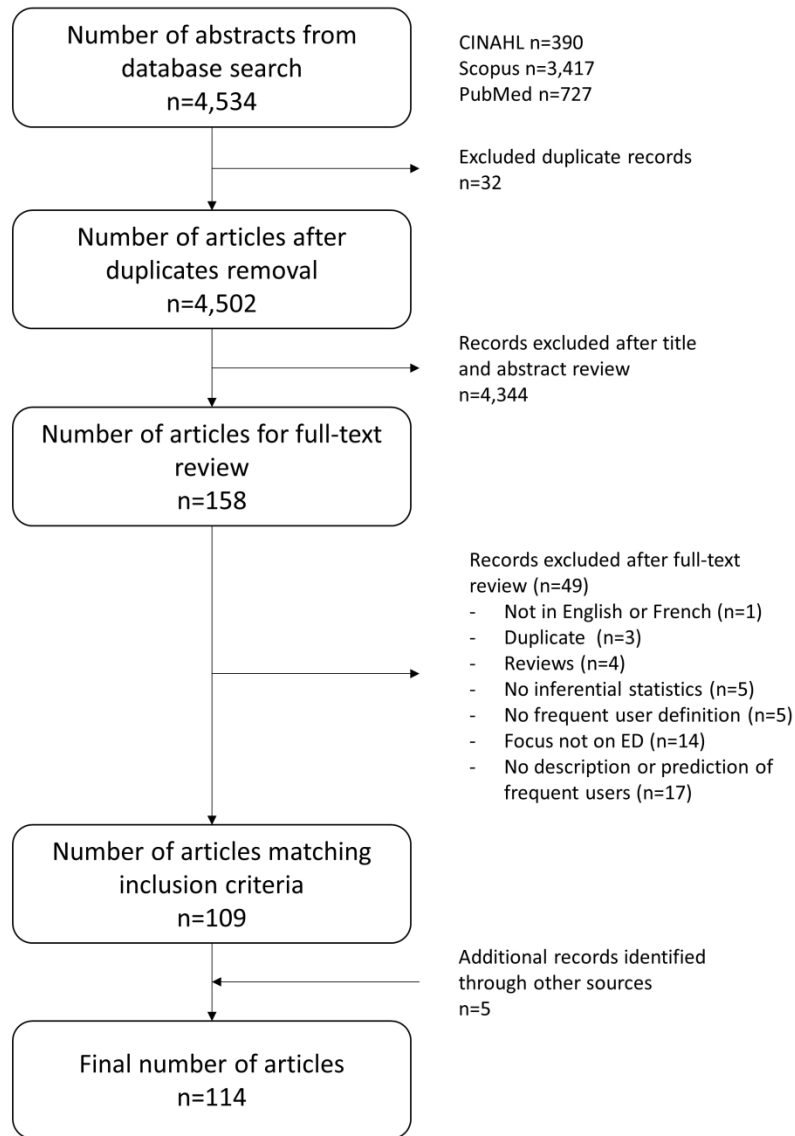


Fig 1. PRISMA flow diagram.

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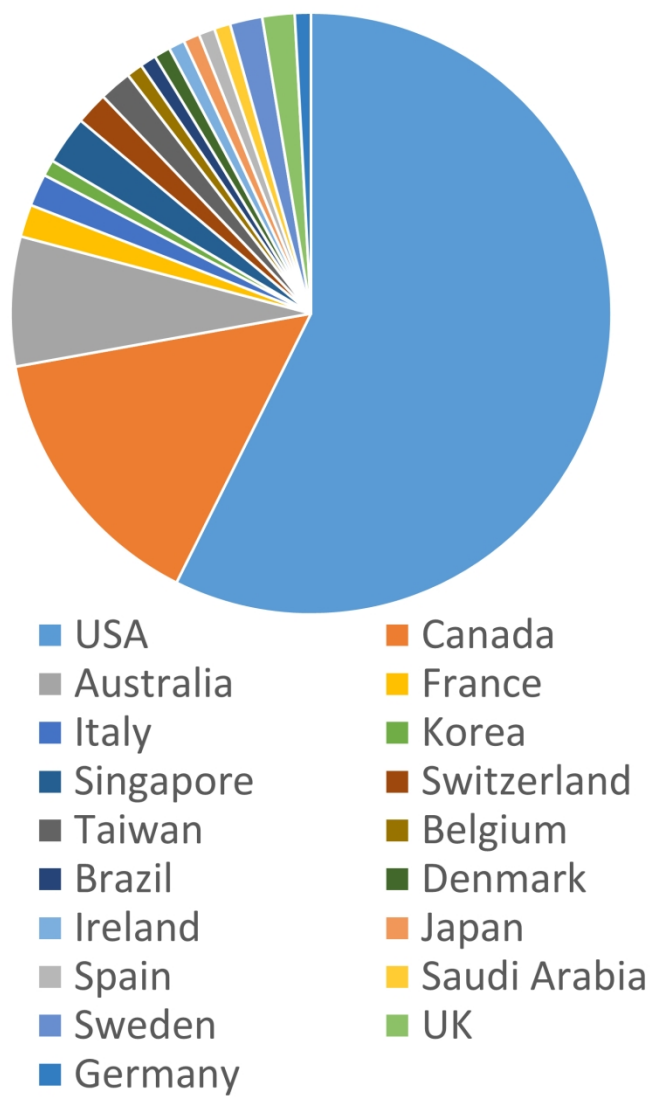


Fig 2. Number of studies by country.  
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Research strategies used in:

- **CINAHL:** ( "revolving door" OR (frequen\* OR high OR heavy OR repeat) N3 (hospital\* OR utili?ation OR attend\* OR consult\* OR visit\* OR flyer\* OR use\* OR patient\*)) AND "emergency department" AND ((statistic\* OR predict\* OR \*variate OR model\* OR "regression")
- **Scopus:** TITLE-ABS-KEY ( "revolving door" OR ( frequen\* OR high OR heavy OR repeat ) W/3 ( hospital\* OR utili?ation OR attend\* OR consult\* OR visit\* OR flyer\* OR use\* OR patient\* ) ) AND TITLE-ABS-KEY ( "emergency department" ) AND ( TITLE-ABS-KEY ( predict\* OR "univariate" OR "multivariate" OR model\* OR "regression" ) OR KEY ( {statistics and numerical data} ) ) AND ( EXCLUDE ( EXACTKEYWORD , "Controlled Study " ) OR EXCLUDE ( EXACTKEYWORD , " Comparative Study " ) OR EXCLUDE ( EXACTKEYWORD , "Clinical Trial" ) OR EXCLUDE ( EXACTKEYWORD , " Controlled Clinical Trial " ) )
- **PUBMED:** (((("Emergency Medical Services"[Mesh] OR emergency OR emergencies)) AND ("repeat use" OR "heavy user" OR "heavy users" OR "high attender" OR "high attenders" OR "high attendance" OR "high use" OR "high uses" OR "high user" OR "high users" OR "high utilisation" OR "high utilization" OR "frequent consultation" OR "frequent consultations" OR "frequent consultant" OR "frequent consultants" OR "frequent consult" OR "frequent consults" OR "frequent attender" OR "frequent attenders" OR "frequent attendance" OR "frequent visit" OR "frequent visits" OR "frequent visitor" OR "frequent visitors" OR "frequent flyer" OR "frequent flyers" OR "frequent use" OR "frequent uses" OR "frequent

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3 user" OR "frequent users" OR "frequent utilisation" OR "frequent utilization" OR  
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5 "high consultation" OR "high consultations" OR "high consultant" OR "high  
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7 consultants" OR "high consult" OR "high consults" OR "frequent hospitalisation"  
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9 OR "frequent hospitalisations" OR "frequent hospitalization" OR "frequent  
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11 hospitalizations" OR "repeat hospitalisation" OR "repeat hospitalisations" OR  
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13 "repeat hospitalization" OR "repeat hospitalizations" OR "revolving door")) AND  
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15 ("Statistics"[Mesh] OR "predictive" OR "univariate" OR "multivariate" OR  
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17 "prediction" OR "model" OR "models" OR "modeling" OR "modelization" OR  
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19 "modelling" OR "modelisation" OR "regression")  
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## Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) Checklist

SECTION	ITEM	PRISMA-ScR CHECKLIST ITEM	REPORTED ON PAGE #
<b>TITLE</b>			
Title	1	Identify the report as a scoping review.	1
<b>ABSTRACT</b>			
Structured summary	2	Provide a structured summary that includes (as applicable): background, objectives, eligibility criteria, sources of evidence, charting methods, results, and conclusions that relate to the review questions and objectives.	2
<b>INTRODUCTION</b>			
Rationale	3	Describe the rationale for the review in the context of what is already known. Explain why the review questions/objectives lend themselves to a scoping review approach.	4
Objectives	4	Provide an explicit statement of the questions and objectives being addressed with reference to their key elements (e.g., population or participants, concepts, and context) or other relevant key elements used to conceptualize the review questions and/or objectives.	4
<b>METHODS</b>			
Protocol and registration	5	Indicate whether a review protocol exists; state if and where it can be accessed (e.g., a Web address); and if available, provide registration information, including the registration number.	-
Eligibility criteria	6	Specify characteristics of the sources of evidence used as eligibility criteria (e.g., years considered, language, and publication status), and provide a rationale.	5-6
Information sources*	7	Describe all information sources in the search (e.g., databases with dates of coverage and contact with authors to identify additional sources), as well as the date the most recent search was executed.	5-6
Search	8	Present the full electronic search strategy for at least 1 database, including any limits used, such that it could be repeated.	Supplementary material
Selection of sources of evidence†	9	State the process for selecting sources of evidence (i.e., screening and eligibility) included in the scoping review.	5-6
Data charting process‡	10	Describe the methods of charting data from the included sources of evidence (e.g., calibrated forms or forms that have been tested by the team before their use, and whether data charting was done independently or in duplicate) and any processes for obtaining and confirming data from investigators.	6
Data items	11	List and define all variables for which data were sought and any assumptions and simplifications made.	6
Critical appraisal of individual sources of evidence§	12	If done, provide a rationale for conducting a critical appraisal of included sources of evidence; describe the methods used and how this information was used in any data synthesis (if appropriate).	-
Synthesis of results	13	Describe the methods of handling and summarizing the data that were charted.	6-7

SECTION	ITEM	PRISMA-ScR CHECKLIST ITEM	REPORTED ON PAGE #
<b>RESULTS</b>			
Selection of sources of evidence	14	Give numbers of sources of evidence screened, assessed for eligibility, and included in the review, with reasons for exclusions at each stage, ideally using a flow diagram.	6-7
Characteristics of sources of evidence	15	For each source of evidence, present characteristics for which data were charted and provide the citations.	7-22
Critical appraisal within sources of evidence	16	If done, present data on critical appraisal of included sources of evidence (see item 12).	-
Results of individual sources of evidence	17	For each included source of evidence, present the relevant data that were charted that relate to the review questions and objectives.	7-22
Synthesis of results	18	Summarize and/or present the charting results as they relate to the review questions and objectives.	22-25
<b>DISCUSSION</b>			
Summary of evidence	19	Summarize the main results (including an overview of concepts, themes, and types of evidence available), link to the review questions and objectives, and consider the relevance to key groups.	25-28
Limitations	20	Discuss the limitations of the scoping review process.	28
Conclusions	21	Provide a general interpretation of the results with respect to the review questions and objectives, as well as potential implications and/or next steps.	29
<b>FUNDING</b>			
Funding	22	Describe sources of funding for the included sources of evidence, as well as sources of funding for the scoping review. Describe the role of the funders of the scoping review.	29

JBI = Joanna Briggs Institute; PRISMA-ScR = Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews.

\* Where *sources of evidence* (see second footnote) are compiled from, such as bibliographic databases, social media platforms, and Web sites.

† A more inclusive/heterogeneous term used to account for the different types of evidence or data sources (e.g., quantitative and/or qualitative research, expert opinion, and policy documents) that may be eligible in a scoping review as opposed to only studies. This is not to be confused with *information sources* (see first footnote).

‡ The frameworks by Arksey and O'Malley (6) and Levac and colleagues (7) and the JBI guidance (4, 5) refer to the process of data extraction in a scoping review as data charting.

§ The process of systematically examining research evidence to assess its validity, results, and relevance before using it to inform a decision. This term is used for items 12 and 19 instead of "risk of bias" (which is more applicable to systematic reviews of interventions) to include and acknowledge the various sources of evidence that may be used in a scoping review (e.g., quantitative and/or qualitative research, expert opinion, and policy document).

From: Tricco AC, Lillie E, Zarin W, O'Brien KK, Colquhoun H, Levac D, et al. PRISMA Extension for Scoping Reviews (PRISMA-ScR): Checklist and Explanation. *Ann Intern Med.* ;169:467–473. doi: 10.7326/M18-0850

