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

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Complete List of Authors:	Chiu, Yohann; Université de Sherbrooke, Department of family medicine and emergency medicine Racine-Hemmings, François; Universite de Sherbrooke, Department of family medicine and emergency medicine Vanasse, Alain; University of Sherbrooke, Department of family medicine and emergency medicine Chouinard, Maud-Christine; Universite du Quebec a Chicoutimi, Département des sciences de la santé Bisson, Mathieu; Universite de Sherbrooke, Department of family medicine and emergency medicine Hudon, Catherine; Université de Sherbrooke, Department of family medicine and emergency medicine

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

Yohann M. Chiu[1*], François Racine-Hemmings[1], Alain Vanasse[1], Maud-Christine Chouinard[2], Mathieu Bisson[1], Catherine Hudon[1]

[1] Département de médecine de famille et de médecine d'urgence, Université de Sherbrooke, Sherbrooke, Québec, Canada

[2] Département des sciences de la santé, Université du Québec à Chicoutimi, Chicoutimi, Québec, Canada

[*] Correspondence: Yohann.Chiu@USherbrooke.ca

Abstract

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

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

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

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

Article summary

Strengths and limitations of this study

- First overview of statistical tools used in frequent users analysis
- Follows a well-defined methodological framework in an extensive body of literature
- Quality assessment is not performed in a scoping review
- Studies in other languages than English or French might have been missed

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 framework of a scoping review allows "mapping rapidly the key concepts underpinning a research area and the main sources and types of evidence available" [11], thus allowing us to identify gaps in the literature and future research opportunities.

Stage 1: Identifying the research question

We defined our research question as follows: What statistical tools are used in the identification of variables associated with frequent ED users and in their prediction?

Stage 2: Identifying relevant studies

We searched PubMed, CINAHL, and Scopus databases in September 2017, using search strategies developed with the help of an information specialist (see the supplementary appendix for the complete search strategy). Keywords included variants of "frequent users", "emergency departments" and "statistical tools".

There were no restrictions regarding the population age or sex, health conditions, study period or country.

Stage 3: Study selection

Articles written in French or in English were included using the following criteria:

- The study must focus on frequent users of EDs (studies focusing on re-visits or on frequent visits other than in EDs were excluded);
- The study must have an explicit definition of frequent users, such as four visits in one year (reviews were excluded);

- The study must use at least one statistical tool that is classified as inferential (not descriptive, as defined by The Cambridge Dictionary of Statistics [12]), such as hypothesis tests, regression models, decision trees, or others;
- The study's objectives must include identifying variables associated with frequent use or predicting the risk of becoming a frequent user.

We collected 3 228 potential abstracts (Fig 1). Of those, 32 were duplicates, and 3 087 were excluded by an investigator (YC) after reading the title and the abstract. YC and CH independently evaluated the remaining 109 full-text articles, of which 80 matched the above criteria. Those were included by consensus between YC and CH while FRH acted as third reviewer in case of discrepancy. Reasons for exclusion were: duplicate (one), not in French or English (one), no inferential statistics (three), focus not on ED (four), systematic review (four), no explicit definition of frequent users (five), no description or prediction of frequent users (eleven). A reference search yielded five relevant articles. Thus, 85 articles were included in this study, of which the full texts were examined by YC, CH, and MB.

Fig 1. PRISMA flow diagram.

Stage 4: Charting the data

YC and MB independently extracted the corresponding data. Reported characteristics were the first (two) author(s), the publication year, the study location, the population, the frequent users' definition, the objectives, the sample size, and the statistical tools used concerning the research question.

Stage 5: Collating, summarizing and reporting the results

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

Patient and public involvement

Patients or public were not involved in this study.

3. Results

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

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	≥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	≥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	≥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	≥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	≥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	≥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	≥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	≥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	≥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
Blonigen, D.M. et al. 2017 United States	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	Zero-truncated negative binomial regression
Boyer, L. et al. 2011 France	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
Brennan, J.J. et al. 2014	Psychiatric	≥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

United States			utilization among frequent psychiatric users		
Buhumaid, R. et al. 2015 United States	Psychiatric	≥4 visits per year	To evaluate demographic factors associated with increased ED use among people with psychiatric conditions	569	Logistic regression
Cabey, W.V. et al. 2014 United States	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
Castner, J. et al. 2015 United States	People with psychiatric and substance abuse diagnoses	≥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
Chambers, C. et al. 2013 Canada	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
Chang, G. et al. 2014 United States	Psychiatric	≥4 visits per year or ≥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
Christensen, E.W. et al. 2017 United States	All	≥4 visits per year	To determine the patient characteristics and health care utilization patterns that predict frequent ED use (≥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
Chukmaitov, A.S. et al. 2012 United States	People with ambulatory care-sensitive conditions	≥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
Colligan, E.M. et al. 2016 United States	All	≥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

Das, L.T. et al. 2017 United States	Children with asthma	≥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	Wilcoxon rank-sum test Chi-square test LASSO logistic regression Regularized logistic regression Decision trees Random forests Support vector machines
Doran, K.M. et al. 2013 United States	All	2-4 visits per year 5-10 visits per year 11-25 visits per year ≥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	≥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	≥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	≥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	≥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	≥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	≥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		
Girts, T.K. et al. 2002 United States	People with a diagnosis of psychosis	≥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
Grinspan, Z.M. et al. 2015 United States	People with epilepsy	≥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
Hardie, T.L. et al. 2015 United States	All	≥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
Hasegawa, K. et al. 2014 United States	People with acute asthma	≥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
Hasegawa, K. et al. 2014 United States	People with acute heart failure syndrome	≥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
Hasegawa, K. et al. 2014 United States	People with chronic obstructive pulmonary disease	≥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
Huang, J.A. et al. 2003 Taiwan	All	≥4 visits per year	To characterize frequent ED users and to identify the factors associated with	800	Chi-square test Logistic regression

			frequent ED use in a hospital in Taiwan		
Hudon, C. et al. 2016 Canada	All	≥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. 2017 Canada	People with diabetes	≥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. 2006 United States	All	≥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. 2016 Canada	People with substance use disorders	≥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. 2004 Canada	Injection drug users	≥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. 2010 Australia	People with chronic disease	≥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. 2011 Australia	All	≥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. 2015 Taiwan	All	≥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	≥4 visits per year	(1) To provide a naturalistic evaluation of	2 470	Mantel-Haenszel test Analysis of variance

2006 Belgium			patients repeating admissions in a psychiatric emergency ward (distinguishing between 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		Logistic regression
Legramante, J.M. et al. 2016 Italy	All	≥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. et al. 2016 Italy	All	90th percentile ≥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. et al. 2014 Singapore	People with asthma	≥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. et al. 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. et al. 2015 United States	Homeless	≥3 visits per year	To examined 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. et al. 2013 United States	People with mental health, alcohol or	≥4 visits per year	To determine whether frequent ED users are more likely to make at least one and a majority of visits for mental health,	65 201	t-test Chi-square test Logistic regression

	drug-related diagnoses		alcohol, or drug-related complaints compared to non-frequent users		
Mandelberg, J.H. et al. 2000 United States	All	≥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	≥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	≥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	≥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	≥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 ≥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

Nambiar, D. et al. 2017 Australia	Injection drug users	≥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
Neufeld, E. et al. 2016 Canada	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
Neuman, M.I. et al. 2014 United States	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
Ngamini-Ngui, A. et al. 2014 Canada	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
Norman, C. et al. 2016 United States	All	≥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
O'Toole, T.P. et al. 2007 United States	Substance users	≥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
Palmer, E. et al. 2014 Canada	All	≥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
Panopalis, P. et al. 2010 United States	People with systemic lupus erythematosus	≥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

Pasic, J. et al. 2005 United States	Psychiatric	2 SD above the mean number of visits ≥6 visits per year ≥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
Paul, P. et al. 2010 Singapore	All	≥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
Pereira, M. et al. 2016 United States	All	≥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
Pines, J.M. & Buford, K. 2006 United States	People with asthma	90th percentile ≥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
Quilty, S. et al. 2016 Australia	People without chronic health conditions	≥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
Rask, K.J. et al. 1998 United States	All	≥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
Samuels-Kalow, M.E. et al. 2017 United States	All	≥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
Schmoll, S. et al. 2015 France	Psychiatric	≥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. 2004 Spain	People with chronic obstructive pulmonary disease	≥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. 2003 United States	All	≥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. 2010 United States	All	≥4 visits per year	To identify the factors that lead to increased use of emergency medical services (EMS) by patients ≥65 years of age in an urban EMS system	10 918	Kruskal-Wallis test Chi-square test Logistic regression
Thakarar, K. et al. 2015 United States	Homeless	≥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. 2014 Canada	Mental health	≥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. 2014 United States	Chronic diseases and mental health	≥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. 2015 Switzerland	Mental health and substance users	≥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. 2012 United States	All	≥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. et al. 2015 Japan	Adults with asthma	≥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
Woo, J.H. et al. 2016 Korea	All	≥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
Wu, J. et al. 2016 United States	All	≥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

Fig 2. Number of studies by country.

Regression

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

Out of the four categories (regression, hypothesis testing, machine learning, and other tools), the most reported tool was the logistic regression (70 studies [3-5, 15-81], two of which are regularized by LASSO or elastic net techniques), followed by the binomial regression (11 studies [18, 46, 55, 73, 76, 77, 82-86], 2 of which are zero-truncated). To a lesser extent, the linear regression (five studies [74, 76, 83, 87, 88]), the analysis of variance (five studies [44, 59, 73, 84, 85]), the Poisson regression (five studies [77, 89-92], one of which is zero-truncated), and the Cox regression (one study [86]) were also used. In those studies, the results are often associated with odds-ratio. The mixed-effects models were mentioned twice [39, 93]. Regression parameters were estimated by generalized estimating equations in three studies [18, 84, 94] while parameter confidence intervals were estimated by the bootstrap procedure (two studies [25, 67]) and the Clopper-Pearson method (one study [25]). The receiver operating characteristic curve (ROC), or equivalently the sensitivity, specificity, or area under the curve ("c-statistic"), was computed in seven studies [4, 36, 48, 63, 75, 89, 93]. Finally, one study performed Markov chain Monte Carlo imputation to account for missing data [78].

Hypothesis testing

Statistical tests aim at testing a specific hypothesis about data and rely on probability distributions [95]. In the selected studies, the tests aimed mainly at comparing two samples (frequent users and non-frequent users).

The most common statistical tests were the chi-square test (40 studies [17, 28, 31, 34, 36-38, 40-42, 47, 49, 52, 54, 56, 58, 60, 62-69, 72-74, 76, 77, 79-81, 83-85, 91, 92, 96, 97]) and the t-test (15 studies [40, 45, 47, 49, 62, 63, 65, 66, 74, 77, 79, 81, 88, 91, 97]), which measured associations between variables and goodness-of-fit. As an alternative to the chi-square test for association, one study used the Fisher exact test [72]. Sample mean differences were assessed by 17 studies with the Mann-Whitney U test (also called the Wilcoxon rank-sum test [20, 23, 31, 47, 58, 66, 77, 92, 96]), its variant for dependent samples the Wilcoxon signed rank test [40], or the Kruskal-Wallis test [23, 37, 42, 68, 73, 76, 83]. The Mantel-Haenszel test (test for differences in contingency tables, two studies [44, 93]), the likelihood ratio test (significance test for nested models, two studies [64, 67]), the Hosmer-Lemeshow test (goodness-of-fit for logistic regression, two studies [67, 70]), and the Breslow-Day test (test for homogeneity in contingency tables odds ratio [53]) were also used to a lesser degree. Finally, one study checked the assumption of normality with the Kolmogorov-Smirnov test [66].

Machine learning

Machine learning tools are a set of algorithms that can learn and adapt to data in order to classify or predict, for instance [98]. In the selected studies, the machine learning tools aimed mainly at classifying users (frequent versus non-frequent).

Two studies used random forests [31, 36] along with support vector machines. Decision trees, which include classification and regression trees, were implemented by five studies [5, 31, 36, 61, 87]. Adaptive boosting, or AdaBoost, is a meta-algorithm that combines with other algorithms and helps for better performances. It was computed in two studies [36, 61].

Other tools

One study fitted a nonparametric distribution to their data [25], while another one used survival analysis [50].

4. Discussion

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

The analysis of frequent ED users could benefit from using more machine learning techniques. Those were found to be not as common as regression or hypothesis testing, although they are especially appropriate when dealing with classification, prediction, or big data. Tools such as support vector machines (which were used by two studies in this scoping review [31, 36]), artificial neural networks, or Bayesian networks are common classifiers and predictors in the artificial intelligence community [99]. They are popular for instance in cancer diagnostic and prognosis, which strongly rely on classification and prediction [100-102]. In particular, support vector machines, decision trees or self-organizing maps can deal with binary outcomes, which is usually the case for frequent use outcomes. They require large datasets, but this is becoming less and less of an issue in the medical field [103]. Nevertheless, machine learning tools often use a black box approach. This means that intermediary steps leading to the final solution can be difficult to interpret, although in the end they display good performances in classifying and predicting. Those methods would thus turn out to be less useful in data exploration [104].

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

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

90th (frequent users) quantiles. Such a heterogeneous association would be uncovered by QR, while usually unseen with a classical mean regression. Ding *et al*. (2010) used QR to characterize waiting room and treatment times in EDs [110]. They explored the lowest, median and highest of those times and highlighted predictors that were significant only in particular quantiles. Usually, QR requires a continuous dependent variable as opposed to a logistic regression, though it is possible to combine these two regressions [111]. Furthermore, defining frequent users by quantiles would allow for better comparison between studies.

Strengths and limitations

To the best of our knowledge, this scoping review is the first to list statistical tools that are used in the identification of variables associated with frequent ED use and the prediction of frequent users. Besides, it was conducted following a well-defined methodological framework. The search strategies were designed with an information specialist in three different databases. Two independent evaluators selected the articles and extracted the data while a third independent evaluator settled disagreements, ensuring that all included studies were relevant. One limitation of our study is that quality assessment is not performed in a scoping review. However, this should not alter the results, since the aim was to list which statistical tools have been applied in the literature. Moreover, the majority of articles were in English, which may introduce a selection bias (for instance, one excluded article was in Spanish). More than half of the reviewed studies were indeed conducted in the USA, making the results difficult to compare to other countries.

5. Conclusions

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

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Authors contributions

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

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Competing interests

The authors declare that they have no competing interests.

Data sharing statement

No additional data are available.

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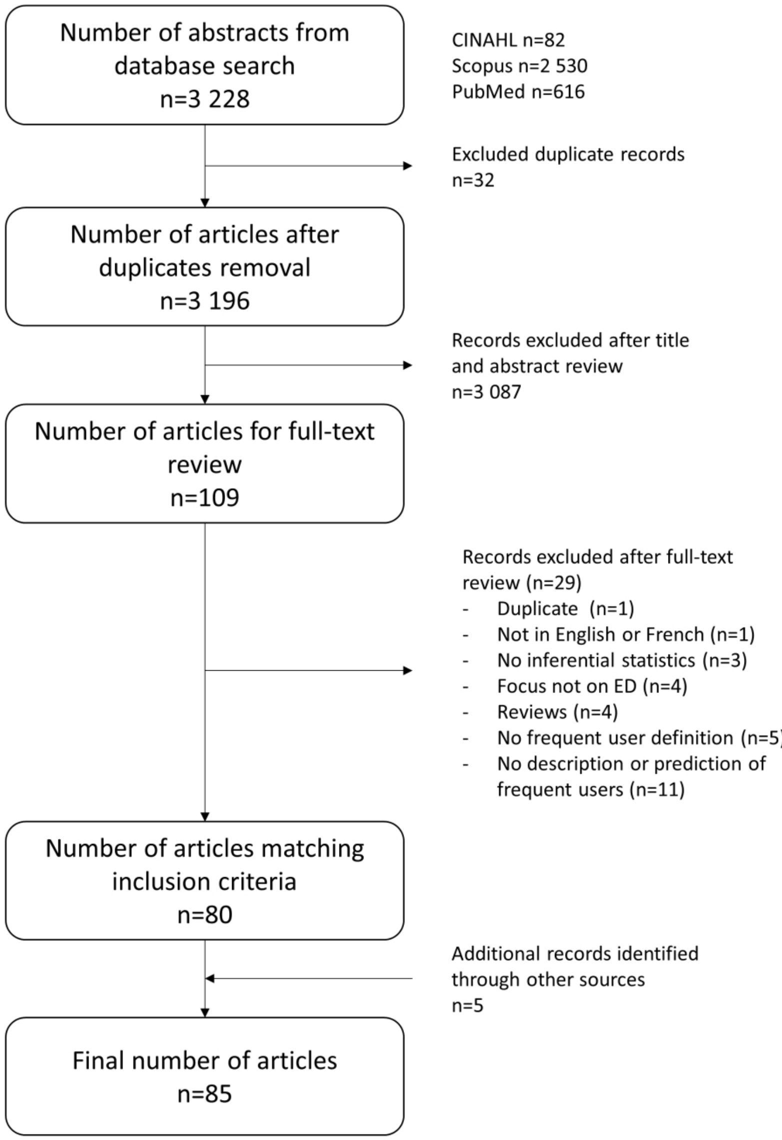

Fig 1. PRISMA flow diagram.

190x275mm (300 x 300 DPI)

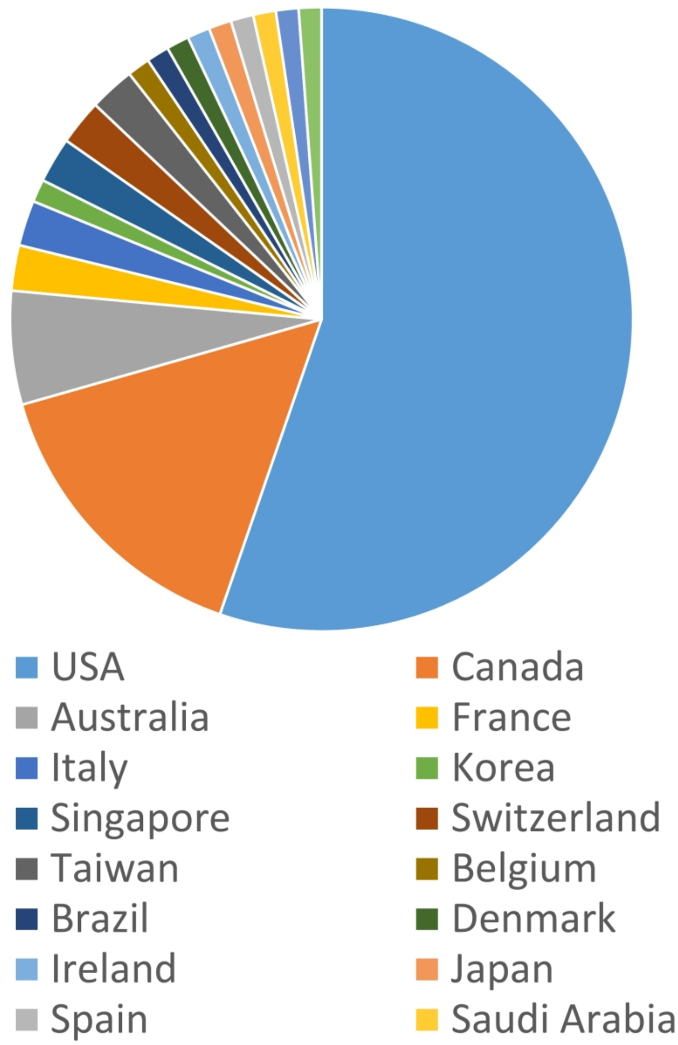

Fig 2. Number of studies by country.

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

user" OR "frequent users" OR "frequent utilisation" OR "frequent utilization" OR "high consultation" OR "high consultations" OR "high consultant" OR "high consultants" OR "high consult" OR "high consults" OR "frequent hospitalisation" OR "frequent hospitalisations" OR "frequent hospitalization" OR "frequent hospitalizations" OR "repeat hospitalisation" OR "repeat hospitalisations" OR "repeat hospitalization" OR "repeat hospitalizations" OR "revolving door")) AND ("Statistics"[Mesh] OR "predictive" OR "univariate" OR "multivariate" OR "prediction" OR "model" OR "models" OR "modeling" OR "modelization" OR "modelling" OR "modelisation" OR "regression")

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Complete List of Authors:	Chiu, Yohann; Université de Sherbrooke, Department of family medicine and emergency medicine Racine-Hemmings, François; Université de Sherbrooke, Department of family medicine and emergency medicine Dufour, Isabelle; Universite de Sherbrooke, Department of family medicine and emergency medicine Vanasse, Alain; Université de Sherbrooke, Department of family medicine and emergency medicine Chouinard, Maud-Christine; Université du Québec à Chicoutimi, Department of Health Sciences Bisson, Mathieu; Université de Sherbrooke, Department of family medicine and emergency medicine Hudon, Catherine; Université de Sherbrooke, Department of family medicine and emergency medicine

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

Yohann M. Chiu[1*], François Racine-Hemmings[1], Isabelle Dufour[1], Alain Vanasse[1], Maud-Christine Chouinard[2], Mathieu Bisson[1], Catherine Hudon[1]

[1] Département de médecine de famille et de médecine d'urgence, Université de Sherbrooke, Sherbrooke, Québec, Canada

[2] Département des sciences de la santé, Université du Québec à Chicoutimi, Chicoutimi, Québec, Canada

[*] Correspondence: yohann.chiu@usherbrooke.ca

Abstract

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

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

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

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

Article summary

Strengths and limitations of this study

- First overview of statistical tools used in frequent users analysis
- Follows a well-defined methodological framework in an extensive body of literature
- Quality assessment is not performed in a scoping review
- Studies in other languages than English or French might have been missed

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 framework of a scoping review allows "mapping rapidly the key concepts underpinning a research area and the main sources and types of evidence available" [11], thus allowing us to identify gaps in the literature and future research opportunities.

Stage 1: Identifying the research question

We defined our research question as follows: What statistical tools are used in the identification of variables associated with frequent ED users and in their prediction?

Stage 2: Identifying relevant studies

We searched PubMed, CINAHL, and Scopus databases in February 2019, using search strategies developed with the help of an information specialist (see the supplementary appendix for the complete search strategy). Keywords included variants of "frequent users", "emergency departments" and "statistical tools".

There were no restriction regarding the population age or sex, health conditions, study period or country.

Stage 3: Study selection

Articles written in French or in English were included using the following criteria:

- The study must focus on frequent users of EDs (studies focusing on re-visits or on frequent visits other than in EDs were excluded);
- The study must have an explicit definition of frequent users, such as four visits in one year (reviews were excluded);

- The study must use at least one statistical tool that is classified as inferential (not descriptive, as defined by The Cambridge Dictionary of Statistics [12]), such as hypothesis tests, regression models, decision trees, or others;
- The study's objectives must include identifying variables associated with frequent use or predicting the risk of becoming a frequent user.

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

Fig 1. PRISMA flow diagram.

Stage 4: Charting the data

YC, MB and ID independently extracted the corresponding data. Reported characteristics were the first (two) author(s), the publication year, the study location, the population, the frequent users' definition, the objectives, the sample size, and the statistical tools used concerning the research question.

Stage 5: Collating, summarizing and reporting the results

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

Patient and public involvement

Patients or public were not involved in this study.

3. Results

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

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. *et al.* 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. *et al.* 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. *et al.* 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. 2015 Saudi Arabia	All	≥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	≥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. 1987 Sweden	All	≥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
Andrews, C.M. *et al*. 2018 United States	Medicaid enrollees with addiction	≥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
Arfken, C.L. *et al*. 2004 United States	Psychiatric	≥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
Batra, P. *et al*. 2017 United States	Women	≥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
Beck, A. *et al*. 2016 United Kingdom	Mental health	≥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*.	All	≥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. 2013 United States	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
Birmingham, L.E. *et al.* 2017 United States	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
Blair, M. *et al.* 2017 United-Kingdom	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
Blonigen, D.M. *et al.* 2017 United States	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
Boyer, L. *et al.* 2011 France	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
Brennan, J.J. *et al.* 2014 United States	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
Buhumaid, R. *et al.* 2015 United States	Psychiatric	≥4 visits per year	To evaluate demographic factors associated with increased ED use among people with psychiatric conditions	569	Logistic regression
Burner, E. *et al.* 2018 United States	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		
Cabey, W.V. *et al.* 2014 United States	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
Castner, J. *et al.* 2015 United States	People with psychiatric and substance abuse diagnoses	≥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
Chambers, C. *et al.* 2013 Canada	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
Chang, G. *et al.* 2014 United States	Psychiatric	≥4 visits per year or ≥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
Christensen, E.W. *et al.* 2017 United States	All	≥4 visits per year	To determine the patient characteristics and health care utilization patterns that predict frequent ED use (≥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
Chukmaitov, A.S. *et al.* 2012 United States	People with ambulatory care-sensitive conditions	≥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
Colligan, E.M. *et al.* 2016 United States	Medicare beneficiaries	≥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
Colligan, E.M. *et al.* 2017 United States	Medicare beneficiaries	≥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

Cunningham, A. *et al.* 2017 United States	All	95th percentile ≥10 visits per year	To compare frequent and infrequent ED visitors' primary care utilization and perceptions of primary care access, continuity, and connectedness and to examine primary care utilization and perceptions as predictors of ED use	1,113	t-test Chi-square test Logistic regression
Das, L.T. *et al.* 2017 United States	Children with asthma	≥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	Wilcoxon rank-sum test Chi-square test LASSO logistic regression Regularized logistic regression Decision trees Random forests Support vector machines
Doran, K.M. *et al.* 2013 United States	All	2-4 visits per year 5-10 visits per year 11-25 visits per year ≥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	≥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	≥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	≥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
Flood, C. *et al.* 2017 United States	Children	≥4 visits per year	To identify factors associated with high ED utilization among children in vulnerable families	2,631	Chi-square test t-test Logistic regression
Freitag, F.G. *et al.* 2005 United States	People with chronic daily headache	≥3 visits per year	To examine the characteristics of chronic daily headache sufferers who use EDs and identify	785	Wilcoxon rank-sum test t-test Chi-square test Poisson regression

			factors predictive of ED visits		Negative binomial regression Logistic regression
Friedman, B.W. *et al*. 2009 United States	People with severe headache	≥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	≥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
Girts, T.K. *et al*. 2002 United States	People with a diagnosis of psychosis	≥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
Grinspan, Z.M. *et al*. 2015 United States	People with epilepsy	≥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
Gruneir, A. *et al*. 2018 Canada	Nursing home residents	≥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
Hardie, T.L. *et al*. 2015 United States	All	≥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
Hasegawa, K. *et al*. 2014 United States	People with acute asthma	≥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

			acute asthma and the associated hospital charges		
Hasegawa, K. *et al.* 2014 United States	People with acute heart failure syndrome	≥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
Hasegawa, K. *et al.* 2014 United States	People with chronic obstructive pulmonary disease	≥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
Huang, J.A. *et al.* 2003 Taiwan	All	≥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
Hudon, C. *et al.* 2016 Canada	All	≥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
Hudon, C. *et al.* 2017 Canada	People with diabetes	≥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.* 2006 United States	All	≥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.* 2016 Canada	People with substance use disorders	≥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
Kanzaria, H.K. *et al.* 2017 United States	Adults aged 18-55 years	≥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

			predictors of persistent frequent ED use		
Kerr, T. *et al.* 2004 Canada	Injection drug users	≥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. *et al.* 2018 Canada	Patients who received oesophagectomy	≥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. *et al.* 2018 Canada	All	99th percentile	To describe patient and visit characteristics for Canadian ED highly frequent users and patient subgroups with mental illness, substance misuse, or ≥ 30 yearly ED visits.	261	t-test Wilcoxon rank-sum test
Kirby, S.E. *et al.* 2010 Australia	People with chronic disease	≥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.* 2011 Australia	All	≥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. *et al.* 2018 United States	Adults who present to the ED repeatedly for acute alcohol intoxication	≥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. *et al.* 2015 Taiwan	All	≥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. 2006 Belgium	Psychiatric	≥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. *et al.* 2018 United States	Persons with systemic lupus erythematosus	≥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. *et al.* 2016 Italy	All	≥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. *et al.* 2016 Italy	All	90th percentile ≥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. *et al.* 2014 Singapore	People with asthma	≥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. *et al.* 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. *et al.* 2015 United States	Homeless people	≥3 visits per year	To examined 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. *et al.* 2013	People with mental health,	≥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. *et al.* 2000 United States	All	≥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
Mann, E.G. *et al.* 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. *et al.* 2016 Ireland	All	≥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	≥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	≥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	≥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 ≥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
Nambiar, D. *et al.* 2017 Australia	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
Nambiar, D. *et al.* 2018 Australia	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
Naseer, M. *et al.* 2018 Sweden	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
Neufeld, E. *et al.* 2016 Canada	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
Neuman, M.I. *et al.* 2014 United States	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
Ngamini-Ngui, A. *et al.* 2014 Canada	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
Norman, C. *et al.* 2016 United States	All	≥4 visits per year	To clearly define and describe characteristics of frequent emergency medical services users in order to provide	539	Logistic regression

			suggestions for efficient and cost-effective interventions that address the healthcare needs of these users		
O'Toole, T.P. *et al.* 2007 United States	Substance users	≥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
Palmer, E. *et al.* 2014 Canada	All	≥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
Panopalis, P. *et al.* 2010 United States	People with systemic lupus erythematosus	≥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
Pasic, J. *et al.* 2005 United States	Psychiatric	2 SD above the mean number of visits ≥6 visits per year ≥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
Paul, P. *et al.* 2010 Singapore	All	≥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
Peltz, A. *et al.* 2017 United States	Medicaid-insured children	≥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
Pereira, M. *et al.* 2016 United States	All	≥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
Pines, J.M. & Buford, K. 2006 United States	People with asthma	90th percentile ≥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
Quilty, S. *et al.*	People without	≥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. *et al.* 1998 United States	All	≥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. *et al.* 2017 Germany	All	≥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. *et al.* 2018 United States	Persons with substance use	≥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. *et al.* 2017 United States	All	≥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. *et al.* 2018 United States	Patients with asthma exacerbation	≥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. *et al.* 2018 United States	Children	≥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

Schlichting, L.E. *et al.* 2018 United States	Children	≥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
Schmoll, S. *et al.* 2015 France	Psychiatric	≥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
Soler, J.J. *et al.* 2004 Spain	People with chronic obstructive pulmonary disease	≥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
Street, M. *et al.* 2018 Australia	Adults aged ≥65 years	≥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
Sun, B.C. *et al.* 2003 United States	All	≥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
Supat, B. *et al.* 2018 United States	Children	≥6 visits per year	To assess pediatric ED utilization in California and to describe those identified as frequent ED users	690,130	Logistic regression
Tangherlini, N. *et al.* 2010 United States	All	≥4 visits per year	To identify the factors that lead to increased use of emergency medical services (EMS) by patients ≥65 years of age in an urban EMS system	10,918	Kruskal-Wallis test Chi-square test Logistic regression
Thakarar, K. *et al.* 2015 United States	Homeless	≥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	≥5 visits per year	To explore the population profile and associated socio demographic,	536	Hosmer-Lemeshow test Logistic regression

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. *et al.* 2014 United States	Chronic diseases and mental health	≥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.* 2015 Switzerland	Mental health and substance users	≥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. *et al.* 2012 United States	All	≥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. *et al.* 2015 Japan	Adults with asthma	≥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. *et al.* 2018 United States	Patients with colorectal cancer	≥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. *et al.* 2018 Singapore	Patients with cancer	≥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

Woo, J.H. *et al.* 2016 Korea	All	≥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
Wu, J. *et al.* 2016 United States	All	≥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
Zook, H.G. *et al.* 2017 United States	Native american children	≥4 visits per year	To determine differences in emergency department ED use by Native American children in rural and urban settings and identify factors associated with frequent ED visits	39,220	Logistic regression Hierarchical model Multiple imputations

Fig 2. Number of studies by country.

Regression

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

Out of the four categories (regression, hypothesis testing, machine learning, and other tools), the most reported tool was the logistic regression (90 studies [3-5, 15-101], two of which are regularized by LASSO or elastic net techniques), followed by the binomial regression (13 studies [18, 46, 55, 73, 76, 77, 82, 89, 102-106], 2 of which are zero-truncated). To a lesser extent, the Poisson regression (seven studies [77, 107-112], one of which is zero-truncated), the linear regression (six studies [74, 76, 102, 113-115]), 131 the analysis of variance (six studies [44, 59, 73, 96, 103, 104]), the Cox regression (four studies [87, 93, 105, 116]), and hierarchical models (one study [90]) were also used. In those studies, the results are often associated with odds-ratios. The mixed-effects models were mentioned three times [39, 91, 117]. Regression parameters were estimated by generalized estimating equations in four studies [18, 103, 106, 118] while parameter confidence intervals were estimated by the bootstrap procedure (two studies [25, 67]) and the Clopper-Pearson method (one study [25]). The receiver operating characteristic curve (ROC), or equivalently the sensitivity, specificity, or area under the curve ("c-statistic"), was computed in ten studies [4, 36, 48, 64, 75, 83, 88, 107, 117, 119]. Finally, two studies performed imputation to account for missing data (Markov chain Monte Carlo and multiple imputations [78, 90]).

Hypothesis testing

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

The most common statistical tests were the chi-square test (53 studies [17, 28, 31, 34, 36-38, 40-42, 47, 49, 52, 54, 56, 58, 60, 62-69, 72-74, 76, 77, 79-82, 85, 88, 89, 94, 96, 97, 101-104, 109, 110, 112, 115, 119, 121-124]) and the t-test (24 studies [40, 45, 47, 49, 62, 63, 65, 66, 74, 77, 79, 81, 85, 89, 94, 95, 97, 98, 109, 114, 115, 122, 124, 125]), which measured associations between variables and goodness-of-fit. As an alternative to the chi-square test for association, five studies used the Fisher exact test [63, 72, 94, 98, 119]. Sample mean differences were assessed by 23 studies with the Mann-Whitney U test (also called the Wilcoxon rank-sum test [20, 23, 31, 47, 58, 66, 77, 98, 110, 119, 121, 123-125]), its variant for dependent samples the Wilcoxon signed rank test [40, 101], or the Kruskal-Wallis test [23, 37, 42, 68, 73, 76, 102]. The difference in proportions test [126], Mantel-Haenszel test (test for differences in contingency tables, two studies [44, 117]), the likelihood ratio test (significance test for nested models, two studies [64, 67]), the Hosmer-Lemeshow test (goodness-of-fit for logistic regression, two studies [67, 70]), the Wald test (significance test for regression coefficients, two studies [30, 96]), and the Breslow-Day test (test for homogeneity in contingency tables odds ratio [53]) were also used to a lesser degree. Finally, one study checked the assumption of normality with the Kolmogorov-Smirnov test [66].

Machine learning

Machine learning tools are a set of algorithms that can learn and adapt to data in order to classify or predict, for instance [127]. In the selected studies, the machine learning tools aimed mainly at classifying users (frequent versus non-frequent).

Two studies used random forests [31, 36] along with support vector machines. Decision trees, which include classification and regression trees, were implemented by five studies [5, 31, 36, 61, 113]. Adaptive boosting, or AdaBoost, is a meta-algorithm that combines with other algorithms and helps for better performances. It was computed in two studies [36, 61].

Other tools

Two studies used survival analysis [50, 116], while another one fitted a nonparametric distribution to their data [25]. Finally, maximum likelihood monotone coarse classifier algorithm was used as a binning method [91] and non-negative matrix factorization as a clustering technique [115].

4. Discussion

The most exploited statistical tools arguably came from regression analysis. This may be because regression is well established in medical statistics or also because it is the most natural tool when trying to find significant variables to explain a dependent variable (in this case, to be a frequent user). Moreover, it allows predicting easily the risk of a new user becoming a frequent user, depending on its covariates. Other tools from hypothesis testing or machine learning also proved to be popular, albeit to a much lesser extent. Combining these statistical techniques may help in discovering significant and complementary patterns, compared to using tools from one class only. In our scoping review, two studies mixed statistical tools from regression, hypothesis testing, and machine learning [31, 36]. In those studies, the author evaluated various performance criteria. While logistic regression performed well, other techniques such as random forests or LASSO regression were also competitive. Besides the fact that logistic regression can display modest performances [128], random forests and LASSO regression can complete logistic regression. The first technique can be used to assess the importance of each independent variable in the model, while the second technique can be useful for automatic selection of features. Likewise, using a variety of statistical tools can help complete or confirm results obtained with established methodologies. Different tools from one class can also be mixed in order to achieve different stages of the analysis (for instance, different types of regression [82]).

The analysis of frequent ED users could benefit from using more machine learning techniques. Those were found to be not as common as regression or hypothesis testing, although they are especially appropriate when dealing with classification, prediction, or big data. Tools such as support vector machines (which were used by two studies in this scoping review [31, 36]), artificial neural networks, or Bayesian networks are common classifiers and predictors in the artificial intelligence community [129]. They are popular for instance in cancer diagnostic and prognosis, which strongly rely on classification and prediction [130-132]. In particular, support vector machines, decision trees or self-organizing maps can deal with binary outcomes, which is usually the case for frequent use outcomes. They usually require large datasets in order to overcome overfitting, but this is becoming less and less of an issue in health sciences [133]. Nevertheless, machine learning tools often use a black box approach as there are many intermediary steps leading to the final solution. While each step usually consists of simple arithmetic operations, their multiple interactions can be more difficult to interpret. In spite of this opacity, they still display good performances in classifying and predicting. In some cases, they may be more accurate than the widely used logistic regression [134]. Those methods would thus turn out to be less useful in data exploration [135]. Machine learning tools are getting popular in other fields in health sciences, such as critical care [136], cardiology [137] or emergency medicine [138]. The authors state that their fields would benefit from this growing popularity, though results need to be analyzed and interpreted in collaboration with clinicians.

Other tools exist that may also be suitable for describing the associated variables or the prediction of frequent ED users but were not reported in the literature. Among those, principal component analysis (PCA) is a dimensional reduction and visualization technique, sometimes used with cluster or discriminant analysis [139]. Based on all the original explanatory variables, PCA constructs new ones by summing and weighing them differently. More weight is given to relevant variables so that those latter become dominant in the new constructions while still including all variables. For instance, Burgel *et al*. (2010) built chronic obstructive pulmonary disease clinical phenotypes by constructing new relevant variables with PCA and by grouping similar subjects in this new space with cluster analysis [140]. Moreover, PCA has already been used for the construction of questionnaires and diagnosis tools in a medical context [141, 142], both of which can prove useful in the identification of frequent users.

As mentioned, regression techniques were common in the selected studies. Yet, quantile regression (QR, [143]) was not mentioned. QR is a generalization of mean regression in the sense that its focus is not only the mean of the dependent variable distribution (such as in classical linear regression) but any quantile of it. QR thus represents an alternative to define frequent users by the high quantiles of ED visit distribution (e.g. the 90th quantile). Eight studies [25, 27, 46, 48, 51, 54, 62, 121] defined frequent users with quantiles, but they did not use QR. QR would allow for finer investigations in the different quantiles of ED users in relationship to the explanatory variables. For instance, the association between age and the number of ED visits may be significantly different across the 10th (low users) and 90th (frequent users) quantiles. Such a heterogeneous association would be uncovered by QR, while usually unseen with a classical mean regression. Ding *et al*. (2010) used QR to characterize waiting room and treatment times in EDs [144]. They explored the lowest, median and highest of those times and highlighted predictors that were significant only in particular quantiles. Usually, QR requires a continuous dependent variable as opposed to a logistic regression, though it is possible to combine these two regressions [145]. Furthermore, defining frequent users by quantiles would allow for better comparison between studies as there is no common definition for frequent users.

Strengths and limitations

To the best of our knowledge, this scoping review is the first to list statistical tools that are used in the identification of variables associated with frequent ED use and the prediction of frequent users. Besides, it was conducted following a well-defined methodological framework. The search strategies were designed with an information specialist in three different databases. Two independent evaluators selected the articles and extracted the data while a third independent evaluator settled disagreements, ensuring that all included studies were relevant. One limitation of our study is that quality assessment is not performed in a scoping review. However, this should not alter the results, since the aim was to list which statistical tools have been applied in the literature. Moreover, the majority of articles were in English, which may introduce a selection bias (for instance, one excluded article was in Spanish). More than half of the reviewed studies were indeed conducted in the USA, making the results difficult to compare to other countries.

5. Conclusions

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

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Authors contributions

YC and CH designed the study with FRH, ID, and AV. YC, ID, CH, and MB collected and analysed the data. YC and CH wrote the first draft of the manuscript. FRH, ID, AV, MCC, and MB contributed to the writing of the manuscript. All authors read and approved the final manuscript.

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Competing interests

The authors declare that they have no competing interests.

Data sharing statement

No additional data are available.

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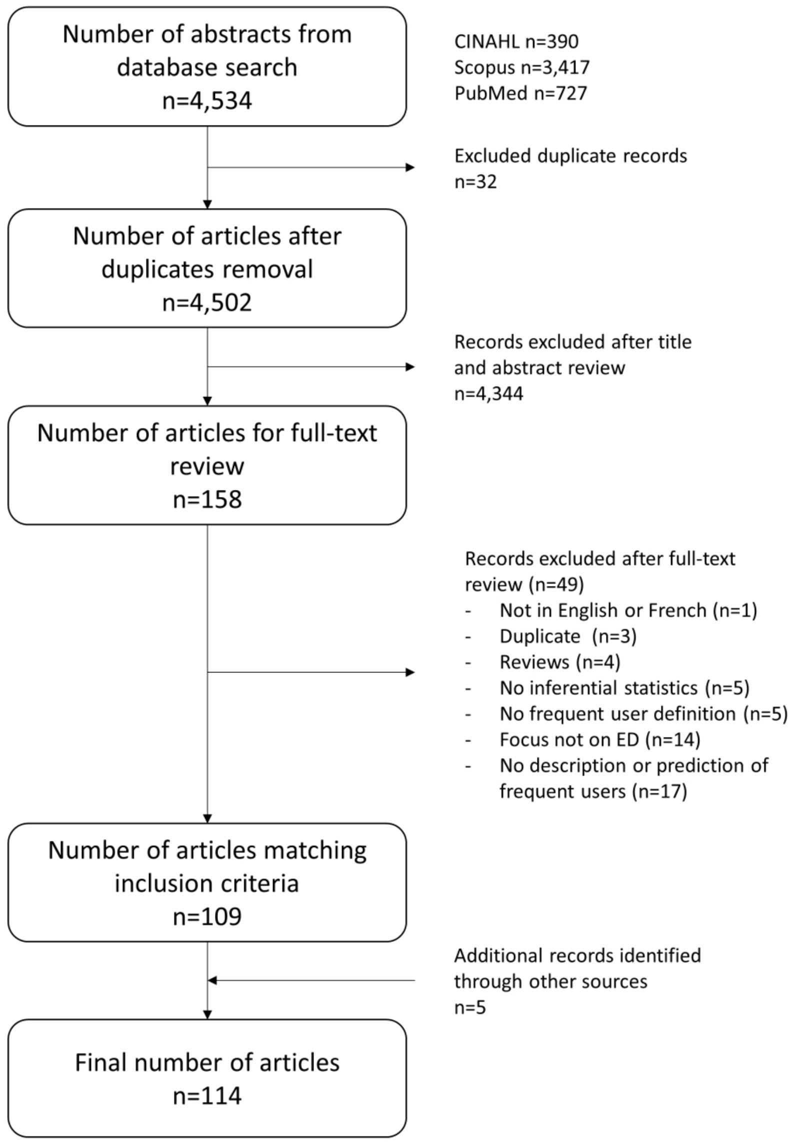

Fig 1. PRISMA flow diagram.

190x275mm (300 x 300 DPI)

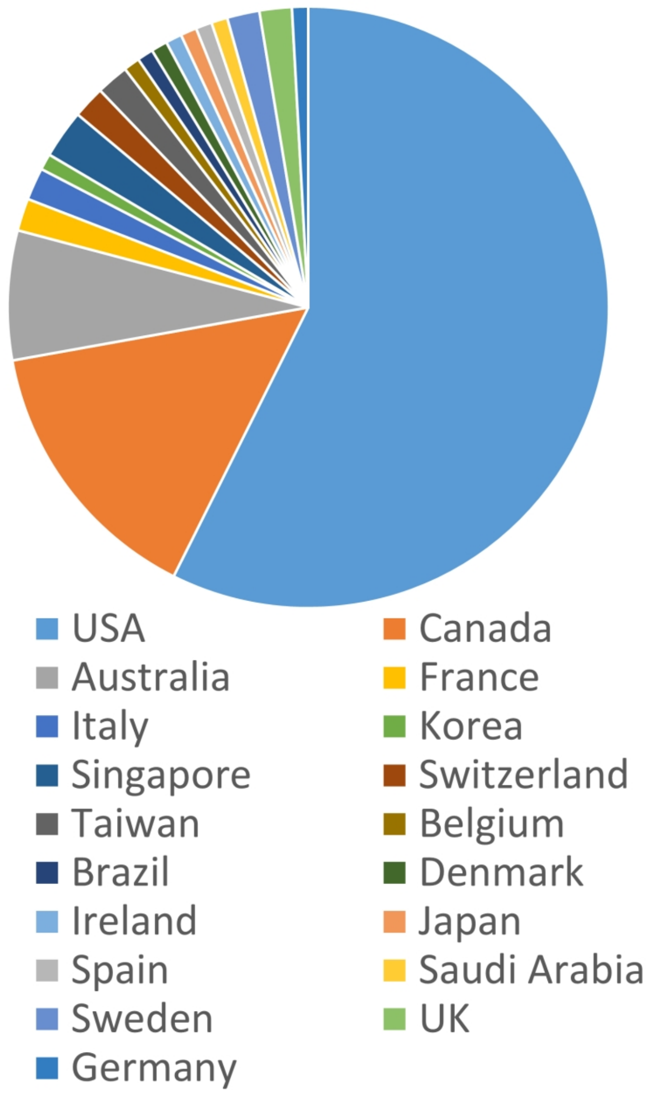

Fig 2. Number of studies by country.

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

user" OR "frequent users" OR "frequent utilisation" OR "frequent utilization" OR "high consultation" OR "high consultations" OR "high consultant" OR "high consultants" OR "high consult" OR "high consults" OR "frequent hospitalisation" OR "frequent hospitalisations" OR "frequent hospitalization" OR "frequent hospitalizations" OR "repeat hospitalisation" OR "repeat hospitalisations" OR "repeat hospitalization" OR "repeat hospitalizations" OR "revolving door")) AND ("Statistics"[Mesh] OR "predictive" OR "univariate" OR "multivariate" OR "prediction" OR "model" OR "models" OR "modeling" OR "modelization" OR "modelling" OR "modelisation" OR "regression")

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 #
TITLE			
Title	1	Identify the report as a scoping review.	1
ABSTRACT			
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
INTRODUCTION			
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
METHODS			
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

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SECTION	ITEM	PRISMA-ScR CHECKLIST ITEM	REPORTED ON PAGE #
RESULTS			
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
DISCUSSION			
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
FUNDING			
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

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