

An exhaustive review and analysis on applications of statistical forecasting in hospital emergency departments

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ABSTRACT

Emergency departments (EDs) provide medical treatment for a broad spectrum of illnesses and injuries to patients who arrive at all hours of the day. The quality and efficient delivery of health care in EDs are associated with a number of factors, such as patient overall length of stay (LOS) and admission, prompt ambulance diversion, quick and accurate triage, nurse and physician assessment, diagnostic and laboratory services, consultations and treatment. One of the most important ways to plan the healthcare delivery efficiently is to make forecasts of ED processes. The aim of this study is thus to provide an exhaustive review for ED stakeholders interested in applying forecasting methods to their ED processes. A categorisation, analysis and interpretation of 102 papers is performed for review. This exhaustive review provides an insight for researchers and practitioners about forecasting in EDs in terms of showing current state and potential areas for future attempts.

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1. Introduction

Time is a crucial factor that provokes serious problems in the performance of EDs. Time related metrics in ED operations make it possible to measure, monitor, and analyse ED performance in a meaningful way. Patient arrivals, overall LOS and admission, prompt offloading of ambulance patients, quick and accurate triage, nurse and physician assessment, diagnostic and laboratory services, consultations and treatment are common and important processes of an ED care (Eitel, Rudkin, Malvey, Killeen, & Pines, 2010; Gul & Guneri, 2015a; Wargon, Guidet, Hoang, & Hejblum, 2009). Overcrowding and long waiting times in ED processes have been common complaints for recent years. Both have impacts on the quality of ED patient care (Annual Report of the Office of the Auditor General of Ontario, 2010). Effective fulfilment of these processes has the potential to enhance ED throughput and patient satisfaction. Delays within these time related processes may exacerbate the overcrowding in the EDs. So, it becomes important to forecast and know the time metrics in terms of avoiding the delays. Statistical forecasting is considered as an OR method that uses time series data and a variety of statistical formulae and data mining techniques to forecast different types of ED processes. The development of forecasting models on ED processes indicates a need for planning more accurately, even if overcrowding is widely linked to other hospital units and outer world (Wargon et al., 2009). Therefore, we

present an exhaustive review and analysis on forecasting models and applications of ED processes. We aim to contribute to the ED stakeholders interested in applying forecasting methods in their facility.

The objective of this paper is to review the statistical forecasting models designed to improve ED processes. We do not deal with other departments of the hospitals such as outpatient clinic, radiology clinic, mammography clinic, intensive care unit, and operation room within the scope of this review. Our paper aims to present forecasting methods including regression, time series, data mining and some miscellaneous OR methods for ED stakeholders to help them in planning the processes efficiently and improving service quality. Our ultimate goal is to provide ED stakeholders a guide for statistical forecasting concepts that can be practically applied to various ED processes.

In Wargon et al. (2009), models for forecasting ED visits have been dealt as a systematic review by discussing the limitations and pointing advantages of nine identified studies. This study seems to be the only review for ED patient visits forecasting. Unfortunately, no systematic and exhaustive review has been provided that covers other various forecasting themes for EDs excluding ED patient visits such as ED admission, crowding, LOS and waiting times. Therefore, in this paper, we review the literature related to the ED forecasting models using academic databases of PubMed, Web of Science, Scopus and Google Scholar. A total of 102 papers were reviewed ranged from 2001 to 2017. Our contributions to the

knowledge are as follows: (1) to estimate and classify the ED forecasting themes, (2) to reveal forecasting methods used (regression, time series, data mining) that have further applied to mentioned themes, (3) to show the distribution of databases, journals and countries in which the papers are published, (4) to determine how the trend of these papers will continue in the future, (5) to show what data type and performance measures used, and (6) to foresee what open themes in ED processes can be for future work.

The study is structured as follows: Section 2 details material and article identification and selection methodology. Section 3 provides classification of papers in terms of applied forecasting themes. Section 4 offers a comprehensive summary of the review outcomes, graphical representations, and an overall assessment on existing themes, main challenges and open areas. Finally, Section 5 presents conclusion, limitations, and recommendations.

2. Material and method

2.1. Article identification and selection

We put together papers in notable databases that provide important insights to researchers and practitioners

studying forecasting of ED processes. To this end, we followed an article identification and selection process as shown in Figure 1.

First, we collect relevant papers from significant databases with suitable keywords (*emergency department/emergency room AND forecasting/predicting/estimating AND patient demand/arrival/visit/volume/presentation, LOS, admission, waiting time, ambulance diversion, etc.*). In this way, we conducted an extensive search in the title, abstract, and keywords of scholarly papers.

In the review process, the following main library databases cover most of the papers, namely: PubMed, Scopus, Web of Science, Google Scholar, Wiley, Elsevier, Springer, IEEE, BMJ Journals, Hindawi, Wolters Kluwer Health, Mary Ann Liebert, Oxford Journals, and Taylor & Francis. While some IEEE based conference proceedings were included, book chapters, thesis, and unpublished working papers were excluded from the review. The papers were analysed, classified, and recorded on an Excel sheet using the following dimensions, namely:

- Year: year of publication
- Database: title of database which the paper published in

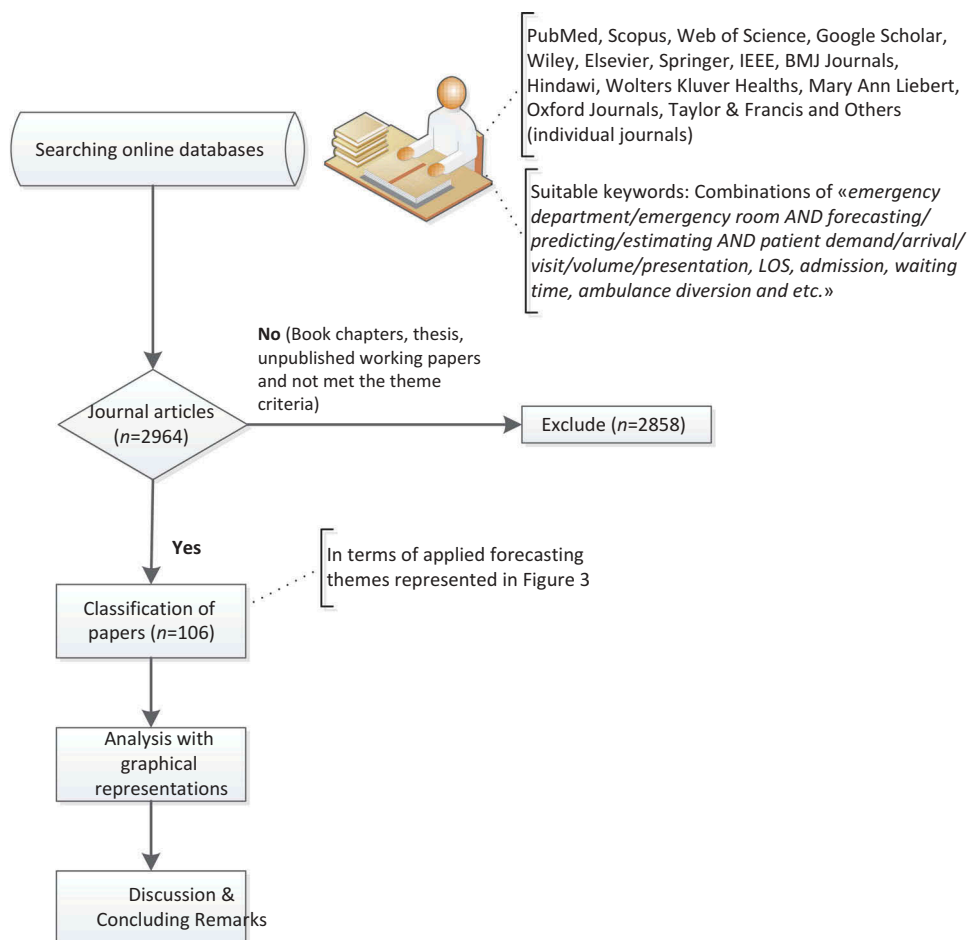


Figure 1. Article identification and selection process flow chart.

- Journal: title of journal in which the paper published
- Country: country where the study was being conducted (in general, country of the first author is considered)
- Application theme: applied forecasting themes are ED patient demand (in other words ED arrivals, visits, volume, presentations), ED patient admission, ED LOS, ED crowding, utilisation of ED resources, ED patient waiting time, ambulance diversion, inpatient admissions, and others
- Specific objective: short purpose of the study in a few words including applied area or methods used
- Method(s) used for forecasting: list of applied methods – as listed in Table 1 – classified under seven groups as time series, regression, data mining, regression + data mining, regression + time series, regression + time series + data mining and others (Markov chain, CUSUM & EWMA control charts, simulation, overcrowding scales such as NEDOCS, EDWIN and READI, queuing theory, principle component analysis, etc.)
- Data characteristics and data type (if the theme is related to ED patient demand): description of data collected and used for the study in terms of quantity and time period. Data type refers to the information whether the data is hourly, daily, monthly or annually
- Performance measures: They show the accuracy of the forecasting model reviewed

Second, a classification is carried out in terms of applied forecasting themes. Finally, we analyse the papers in terms of statistical results for distribution

Table 1. Acronyms used in the paper.

ACF	Auto-correlation function
ANN	Artificial neural network
ARIMA	Autoregressive integrated moving average
ARMA	Autoregressive moving average
CCMU	Clinical emergency department classification
CUSUM	Cumulative sum of the recursive residuals
EDWIN	Emergency department work index
ES	Exponential smoothing
EWMA	Exponentially weighted moving average
GARCH	Generalised autoregressive conditional heteroskedasticity
GEMSA	Multicentre emergency department study group
LR	Linear regression
MAE	Mean absolute error
MAPE	Mean absolute percentage error
MASE	Mean absolute scaled error
MSARIMA	Multivariate seasonal autoregressive integrated moving average
NEDOCS	National emergency department overcrowding scale
PACF	Partial auto-correlation function
PCA	Principle component analysis
READI	Real-time emergency analysis of demand indicators
RMSE	Root mean square error
ROC	Receiver operating characteristic curve
SARIMA	Seasonal autoregressive integrated moving average
SMHW	Seasonal multiplicative Holt-Winters
SVM	Support vector machine
WMAPE	Weighted mean absolute percentage error
<i>r</i>	Correlation coefficient

of the papers and concluding remarks for the future studies.

3. Applied forecasting theme

The emergency care system is one of the most important components of the larger health care delivery system and of the even larger social safety net system (Committee on the Future of Emergency Care in the United States Health System, 2006). To better manage patient flow of this system, there are many operations management methodologies that could be applied including quality function deployment, failure-mode and effects analysis, human factors engineering, queuing theory, supply-chain management, statistical quality control, and forecasting. As a crucial tool among these, *forecasting* facilitates the understanding of ED systems and make it possible for ED managers to control and improve overall system performance. A usual conceptual ED patient flow diagram is demonstrated in Figure 2. From arrival at an ED to hospital admit or disposition, emergency care patients receive treatment at multiple points along the delivery process. Patient flow, defined as the movement of patients through this system, has many important indicators in terms of timeliness, safety, and quality of care such as ED patient throughput (the number of patients treated and discharged from the ED per day), ED LOS (the length of time a patient spends in the ED, beginning at the point when the patient sees a triage nurse and ending when the patient leaves the ED), utilisation of ED resources and ED patient wait time. Input/Throughput/Output (I/T/O) model of ED patient flow in Figure 2 allows for the identification of themes on forecasting of ED processes. Input component of the I/T/O model includes ED forecasting themes of patient demand of critically ill and injured patients, non-emergent and safety net patients. Also, forecasting of ambulance diversion is related to this component of the model. The throughput component of the I/T/O model demonstrates LOS in the ED and is comprised on triage, room placement, medical evaluation, diagnostic testing and ED treatment. ED boarding of inpatients is also featured in the throughput component. Also, forecasting of ED patient wait time in the abovementioned processes is related to the throughput component. The output component of the I/T/O model represents the disposition of ED patients. It includes both hospital admission, transfer to another facility, and patient discharge.

In this section, 102 papers are presented according to 9 main application themes as presented in Figure 3. The themes are:(1) ED patient demand/arrivals/visits/volume/presentations, (2) ED patient admission, (3) ED LOS, (4) ED crowding, (5) utilisation of ED resources, (6) ED patient wait time, (7) ambulance

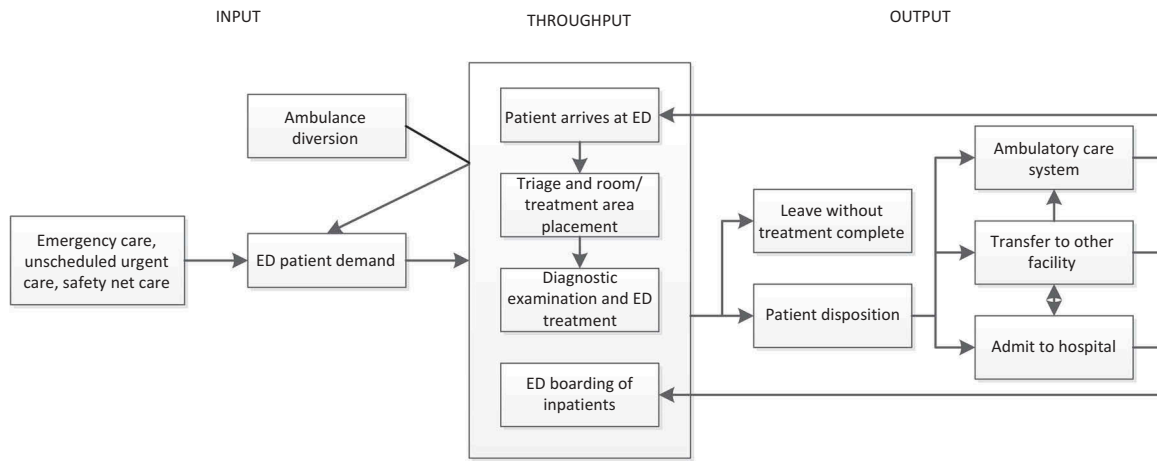


Figure 2. Input/Throughput/Output model of ED patient flow (Adapted from Committee on the Future of Emergency Care in the United States Health System, 2006).

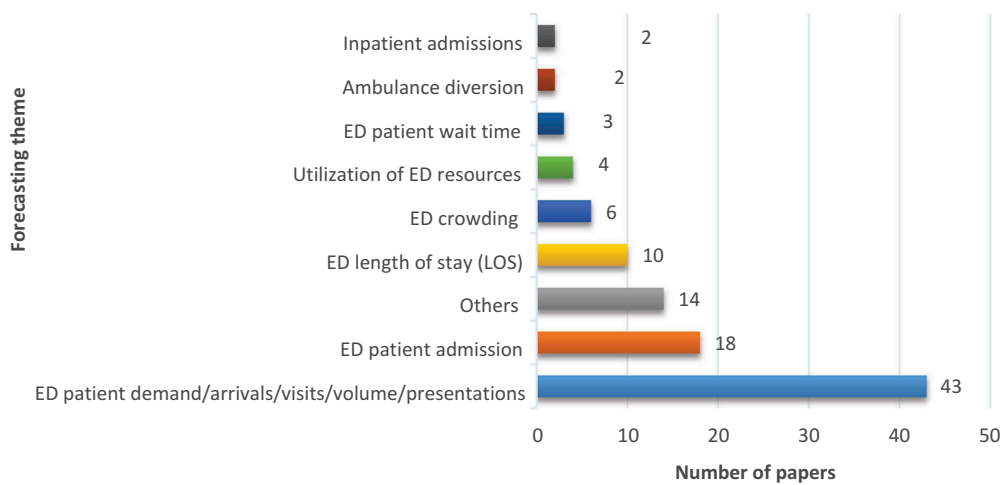


Figure 3. Distribution of papers according to forecasting theme for the EDs.

diversion, (8) inpatient admissions, and (9) others such as anomaly detection, posttraumatic stress disorder forecasting, triage forecasting, communication risks prediction, charge prediction, patient disposition prediction, 90-day mortality prediction, and forecasting of blood product transfusion requirements of trauma patients.

3.1. Forecasting ED patient demand

The service quality through the EDs, expressed by waiting time and LOS, is significantly related to the patient demand (Au-Yeung, Harder, McCoy, & Knottenbelt, 2009; Xu, Wong, & Chin, 2013). Increased patient arrivals may lead to prolonged waiting and overcrowding. In order to enhance ED processes, a better balance between ED resources (doctors, nurses, beds, medical equipment, etc.) and demand (patient arrivals) is required. Accurate forecasting of ED patient demand can provide managerial implications on long- and short-term staffing policies so that the EDs can be better prepared for the coming demand variations (Xu et al., 2013; Yucsan, Gul, &

Celik, 2018a; Yucsan, Gul, Mete, & Celik, 2018b). Regarding the theme of ED patient demand forecasting, 41 studies were retrieved. A detailed summary of papers regarding this theme was listed in Table 2. In the papers retrieved by our study, three main classes of methods were used to forecast ED patient demand.

The first class consists of regression-based forecasting models. They may be classified as linear, logistics and Poisson and consists of looking for correlations between patient demand and a series of independent variables, such as calendar or meteorological variables. The second class is time series-based forecasting models that view patient demand as a time series and predict future values from past values (Wargon et al., 2009). The last class is concerned with data mining-based forecasting models. Within the context of this class, ANNs, SVM, decision trees, and Bayesian networks can be mentioned.

Among the retrieved papers, many variants of regression models exist as linear (Araz et al., 2014; Aroua & Abdul-Nour, 2015; Batal et al., 2001; Cote et al., 2013; Ekström et al., 2015; Gul & Guneri, 2016; Jiang et al., 2018; Jones et al., 2008; Park et al., 2008;

Table 2. Summary of papers in terms of forecasting ED patient demand.

Authors (Year)	Method(s) used	Specific objective	Data characteristics	Data type	Performance measures
Rosychuk, Youngson, and Rowe (2016)	SARIMA	To forecast monthly rates of ED presentations with chronic obstructive pulmonary disease	Individual aged ≥ 55 years patients' data from April 1999 to March 2011	Monthly	Standard error, 95% confidence interval
Xu, Tsui, Jiang, and Guo (2016)	ARIMA, LR	To develop a hybrid ARIMA-LR approach	Two-year daily data from 1 January 2012 to 31 December 2013	Daily	RMSE, MAPE
Butler, Gu, Kenney, and Campbell (2016)	ACF, PACF, SARIMA	To use a time-series approach to assess whether current day and previous day is correlated	From January 2010 to May 2015	Weekly	<i>p</i> value
Afilal et al. (2016a)	ARIMA, CCMU, GEMSA	To forecast daily attendance at an ED using time series-based approach	January 2010 and 31 December 2014	Daily	RMSE
Calegari et al. (2016)	ES, SMHW, SARIMA, MSARIMA	To analyse the performance of forecasting models in predicting the demand for medical care	1 January 2013 until 31 May 2015	Daily	MAPE
Afilal et al. (2016b)	ARMA	To study the daily arrivals at an ED in France	1 January 2010–31 December 2014	Daily	RMSE
Gul and Guneri (2016)	Regression, ANN	To forecast ED arrivals for short, medium and long term considering calendar and ED specific variables	266,693 patient records between the dates 1 January and 31 December in 2012	Daily	Monthly, Yearly
Standard error, R-squared					
Rosychuk, Youngson, and Rowe (2015)	SARIMA	To forecast monthly patterns of asthma presentations to EDs in Alberta, Canada	362,430 ED presentations from April 1999 to March 2011	Monthly	Standard error, 95% confidence interval
Mai, Aboagye-Sarfo, Sanfilippo, Preen, and Fatovich (2015)	ARIMA, multivariate vector-ARIMA	To predict the number of ED presentations in Western Australia in the next 5 years, stratified by place of treatment, age, triage and disposition	Monthly ED data from 2006/7 to 2012/13 financial years	Monthly	95% confidence interval
Aboagye-Sarfo et al. (2015)	ARMA, Holt-Winters	To develop multivariate vector-ARMA models for predicting ED demand in Western Australia (WA) and compare them to ARMA and Winters' models	Seven-year monthly data (2006/07 to 2012/13)	Monthly	MAE, RMSE, MAPE
Petrou (2015)	ARIMA	To propose an ARIMA model to analyse official data from Cyprus' largest emergency room facility for three years	369,970 visits from January 2011 to December 2013	Monthly	R-squared, MAPE
Harrou, Sun, Kadri, Chaabane, and Tahon (2015)	ARMA, EWMA	To report the development of statistical method for enhancing detection of abnormal daily patient arrivals at the ED	From January 2011 to December 2011	Daily	R-squared
Zlotnik, Gallardo-Antolin, Alfaro, Pérez, and Martínez (2015)	Support vector regression	To apply SVM to forecast patient visit and allocate dynamic nursing staff	January 2006–December 2007	Daily	MAE
Kang and Park (2015)	Statistical analysis, histogram	To evaluate ED patient visit variability in order to determine if the average can be used to operate EDs	The year 2013	Daily	
Aroua and Abdul-Nour (2015)	LR, SARIMA, multivariate SARIMA	To explore the capability of forecasting techniques to predict ED visits based on Major Diagnostic Categories	The years 2008–2011	Weekly	MAE, MAPE, WMAPE
Ekström, Kurland, Farrokhnia, Castrén, and Nordberg (2015)	LR analysis	To investigate whether Web site visits could be used to predict the ED attendance for the coming day	From 13 August 2011 to 31 October 2012	Hourly	R-squared
Araz, Bentley, and Muelleman (2014)	SARIMA, Holt-Winters, LR	To forecast influenza-like-illness (ILI)-related ED visits	Weekly ED visits between 2008 and 2012	Weekly	RMSE
Kadri, Harrou, Chaabane, and Tahon (2014)	ARIMA	To develop models for forecasting daily attendances at a paediatric ED in France	Daily patient data from January 2012 to December 2012	Daily	RMSE, R-squared
Kim, Lee et al. (2014)	ARIMA, SARIMA, GARCH	To evaluate the predictability of patient volume in hospital medicine using a variety of known forecasting techniques	Patient volume data from January 2009 to June 2012	Daily, Hourly	MAPE
Bergs, Heerinckx, and Verelst (2014)	Automated ES	To evaluate an automatic forecasting algorithm in order to predict the number of monthly ED visits	A 6-year period data (2005–2011)	Monthly	MAE, MAPE, MASE
Menke et al. (2014)	ANN	To design an ANN and to test it retrospectively to determine if it may be used to predict ED volume	Patient registry data from 4 February 2007 to 31 December 2009	Daily	R-squared
Xu et al. (2013)	ANN, regression	To model ED daily patient arrivals and to quantify the relative importance of contributing variables	One year of data of patient arrivals	Daily	MAPE
Marcillo, Hajat, and Gouveia (2013)	Generalised linear models, generalised estimating equations, SARIMA	To develop different models to forecast the daily number of ED patients according to calendar variables and ambient temperature readings	1 January 2008 to 31 December 2010	Daily	MAPE
Cote, Smith, Eitel, & Akçali (2013)	Regression analysis	To apply regression-based forecasting models based on data obtained from a large teaching hospital's ED	1997–2006	Daily	Monthly, Yearly
R-squared					

(Continued)

Table 2. (Continued).

Authors (Year)	Method(s) used	Specific objective	Data characteristics	Data type	Performance measures
Chase, Cohn, Peterson, and Lavieri (2012)	Binary logistic regression	To investigate whether ED variables could be used in mathematical models to predict a future surge in ED volume based on recent levels of use of physician capacity	Information spanning July 2009 through June 2010	Hourly	CUR
Rosychuk, Klassen, Voaklander, Senthilselvan, and Rowe (2011) Boyle et al. (2011)	SARIMA CUSUM	To examine the monthly patterns of young children who made group-related visits to EDs in Canada To predict and track epidemics (and, potentially, pandemics) of influenza	27,355 group-related ED visits data from 1 April 1999 to 30 March 2005 5 years of historical data (2005–2009) on ED presentations and hospital admissions for influenza-like illnesses	Monthly Daily	standard error, 95% confidence interval MAPE
Kam, Sung, and Park (2010)	SARIMA	To develop and evaluate time series models to predict the daily number of patients visiting the ED of a Korean hospital	2 years of data from January 2007 to December 2008	Daily	MAPE
Wargon, Casalino, and Guidet (2010)	General linear model	To investigate whether mathematical models using calendar variables could identify the determinants of ED census over time in geographically close EDs	From 2004 to 2007	Daily	MAPE
Au-Yeung et al. (2009)	Structural time series	To forecast daily patient arrivals into an ED based on previous arrivals data	4 years of patient arrival data between 1 April 2002 and 31 March 2007	Daily	RMSE, r , 95% confidence interval
Jones et al. (2009)	ES, ARIMA	To study the temporal relationships between the demands for key resources in the ED and the inpatient hospital and to develop multivariate forecasting models	One-year hourly data from three diverse hospitals	Hourly	MAE
Sun, Heng, Seow, and Seow (2009) McCarthy et al. (2008)	ARIMA Poisson regression	To forecast ED attendances for micro and macro level planning To develop methodology for predicting demand for ED services by characterising ED arrivals	Daily data from July 2005 to March 2008 One-year hourly ED arrival data	Daily Hourly	MAPE 95% confidence interval
Schonwetter et al. (2008)	Logistic regression	To devise a model to predict the probability of hospice cardiac disease patients having ED visits and/or hospitalisations after hospice admission	65 patients	Hourly	Standard error, Wald statistic
Jones et al. (2008)	Regression, Time series, ANN	To explore and evaluate the use of several statistical forecasting methods to predict daily ED patient volumes at three diverse hospital EDs	Daily data from 1 January 2005 through 31 March 2007 from three EDs	Daily	MAPE
Park, Park, and Desai (2008)	Regression	To predict the number of patients arriving at ED and establish a forecasting model of number of ED patient arrivals	From 1 January 2005 to 30 September 2007	Monthly	R-squared
Champion et al. (2007)	ES, Box–Jenkins	To propose ES and Box–Jenkins methods for forecasting of ED crowding	Seven-year monthly data (2000 to 2005)	Monthly	RMSE
Zibners, Bonsu, Hayes, and Cohen (2006)	Box–Jenkins ARIMA	To predict the volume of patient visits to an academic paediatric ED based on short interval local weather patterns	76,702 records	Hourly	R-squared
Morzuch and Allen (2006)	Regression-based, ARIMA, ES	To forecast hourly arrivals for each day using standard Holt–Winters ES methods	11 November 1999 to 28 June 2002	Hourly	RMSE
Jones, Joy, and Pearson (2002)	ARIMA, GARCH	To develop a methodology for forecasting the number of beds occupied due to emergency admissions and the number of emergency admissions	From 1 April 1993 to 23 March 1999	Daily	RMSE
Batal, Tench, McMillan, Adams, and Mehler (2001) Jiang, Chirn, and Tsui (2018)	Stepwise LR ANN, Genetic algorithm, SARIMA, ARIMAX, Linear regression, SVM	To develop a prediction equation for the number of patients seeking urgent care To explore an integrated framework for predicting ED patient flow under different triage levels	Daily patient volume from February 1998 to January 1999 A total of 245,377 records from 1 July 2009 to 31 March 2011	Daily Daily	95% confidence interval MAPE, RMSE
Juang, Huang, Cheng, and Wann (2017)	ARIMA	To construct an adequate model and to forecast monthly ED visits	From January 2009 to December 2016	Monthly	MAPE

Xu et al., 2016, 2013), logistic (Chase et al., 2012; Schonwetter et al., 2008) and Poisson (McCarthy et al., 2008). The dependent variable in LR models which are used in ED patient demand forecasting is the number of patients arriving per time period. The independent variables or input variables can be day of the week, month of the year, temperature, etc.

In a logistic regression model, the dependent variable is categorical. Logistic regression is divided into two classes as binomial/binary and ordinal/multinomial. Binomial or binary logistic regression deals with situations in which the observed outcome for a dependent variable can have only two possible types (Schonwetter et al., 2008), “0” and “1” (e.g., “no emergency room visits and/or hospitalisations (ERVH)” vs. “yes ERVH”). Multinomial logistic regression deals with situations where the outcome can have three or more possible types (e.g., “disease A” vs. “disease B” vs. “disease C”) that are not ordered.

Poisson regression models are based on the assumption that the events in one time period are independent of the events in another time period (McCarthy et al., 2008). It is used to model count data and contingency tables. In McCarthy et al. (2008), a Poisson regression model was proposed to predict ED patient demand. One year of ED visit data were merged with local climate data. Poisson regression was selected to represent the count of hourly ED arrivals as a function of temporal, climatic, and patient factors. The appropriateness of prediction models by whether the data met key Poisson assumptions were evaluated. On conclusion of the study, patient demand of the observed ED was well approximated by the proposed Poisson regression model. It was shown that the expected arrival rate was characterised by a small number of factors and did not depend on recent number of arrivals.

Apart from regression-based models, several authors or investigators proposed time series methods to forecast ED patient demand (Tandberg & Qualls, 1994). Wargon et al. (2009) pointed out that time series models in forecasting of ED patient demand focus on the net result of three components: (1) long-term trends; (2) short-term and often seasonal changes; and (3) the effects of unexpected events. The simplicity and effectiveness, and attractiveness for practical applications are main advantages of time series models (Kadri et al., 2014). Time series forecasting models are classified under two main classes as univariate and multivariate. In the knowledge of ED patient demand forecasting, various time series models were applied. ARIMA model is the most widely used time series method proposed by Jones et al. (2002), Morzuch and Allen (2006), Zibners et al. (2006), Jones et al. (2008), Jones et al. (2009), Sun et al. (2009), Kadri et al. (2014), Kim, Lee et al. (2014), Petrou (2015), Afilal et al. (2016a), Xu et al. (2016) and Juang et al.

(2017). ARIMA models were demonstrated as (p, d, q) where p is the number of AR terms, d is the number of non-seasonal differences needed for stationarity, and q is the number of lagged forecast errors in the prediction equation (Xu et al., 2016).

A number of variations on the ARIMA models are commonly employed by researchers such as ARMA (Afilal et al. 2016b; Aboagye-Sarfo et al., 2015; Harrou et al., 2015), SARIMA (Araz et al., 2014; Aroua & Abdul-Nour, 2015; Butler et al., 2016; Kam et al., 2010; Kim, Lee et al. 2014; Marcilio et al., 2013; Rosychuk et al., 2011; Rosychuk et al., 2015; Rosychuk et al., 2016), MSARIMA (Aroua & Abdul-Nour, 2015), multivariate vector-ARIMA (Mai et al., 2015), Box-Jenkins ARIMA (Champion et al., 2007; Zibners et al., 2006).

ES is also one of the most important time series method applied mostly by researchers in the field of ED patient demand forecasting. This method is based on weighted moving average formulae (Champion et al., 2007). Among the retrieved studies in our review, Morzuch and Allen (2006), Champion et al. (2007), Jones et al. (2009), Araz et al. (2014), Bergs et al. (2014), Aboagye-Sarfo et al. (2015) and Calegari et al. (2016) used and successfully applied ES method to their data regarding ED patient arrivals.

The data mining-based models applied in the reviewed studies cover ANN, SVM, decision tree, and Naïve Bayes. ANNs are machine learning algorithms that work to solve computational processes in specific areas by using many interconnected processing elements (Onat & Gul, 2018). They are mainly applied for prediction, clustering, classification, and detection of abnormal patterns in healthcare domain and specifically in ED processes. SVM is a machine learning technique that can be widely used for regression analysis and classification in different research areas of EDs. Unlike traditional methods that aim to minimise the training error, SVM aims to minimise an upper bound of generalisation error by maximising the margin between the separating hyperplane and the data which can be considered as an approximate application of the structure risk minimisation principle (Salah, 2017). Decision trees are non-parametric learning algorithm which can be applied to both regression and classification problems of EDs. Given data variable, decision trees implement a set of *if-then-else* rules to predict class variable. Naïve Bayes assumes that each variable is independent of other variables. Bayes theorem is used in this learning method to calculate the probability of a certain class given a certain variable.

The above-mentioned data mining-based models are used to forecast patient demand in the context of ED operations. ANNs are frequently applied to forecasting ED patient arrivals (Gul & Guneri, 2016; Jones et al., 2008; Menke et al., 2014; Xu et al., 2013). Zlotnik et al. (2015) applied support vector

regression and M5P tree model to forecast patient visit and allocate dynamic nursing staff for an ED system. On conclusion of the current study, these models were found to be superior to the stratified average model with a 95% confidence interval.

Unlike abovementioned methods used in forecasting of ED patient demand, Boyle et al. (2011) predicted and tracked epidemics of influenza with an adaptive CUSUM methodology. This analysis pointed out the value of health departments performing surveillance monitoring to forewarn of disease outbreaks. Au-Yeung et al. (2009) forecasted daily patient arrivals into an ED based on previous arrivals data. They proposed a structural time series model to characterise each arrival stream. On conclusion of the current study, it was clearly seen that this model assisted ED managers at the observed hospital to best use the resources available and anticipate periods of high demand.

3.2. Forecasting ED patient admission

The second most important theme among forecasting concepts is ED admission process. Optimal utilisation of the ED includes the timely evaluation, management, and stabilisation of all patients. Boarding of admitted patients in the ED leads to lower service quality, reduced timeliness of care, and reduced patient satisfaction. The ED should not be utilised as an extension of the intensive care units and other inpatient units for admitted patients, because this unfavourably affects patient safety, quality, and access to care (American College of Emergency Physicians, 2008). Because of all these reasons, ED admission process has been addressed by researchers in the literature (Table 3). Golmohammadi (2016) developed a prediction model capable of estimating the likelihood of admission of each ED patient to the hospital (as inpatient) using logistic regression and ANN methods. On conclusion of the study, it was proved that an ED admission forecasting model based on demographic and clinical variables accurately estimated the likelihood of patient admission, thus decreased ED boarding and crowding. As in Sun, Heng, Tay, and Seow (2011), Peck et al. (2013) and Golmohammadi (2016) applied logistic regression in their forecasting models. Peck et al. (2013) tested the generalisability for predicting the probabilities that ED patients will be admitted to a hospital inpatient unit. Results of the accuracy of ED patient admission likelihood prediction models showed that they were generalisable across hospitals of different sizes, populations, and administrative structures. Sun et al. (2011) developed a predictive model to assess whether a patient was likely to require inpatient admission at the time of ED triage.

Data mining-based methods such as ANN (Andersson et al., 2011; Leegon et al., 2006; Luo et al., 2016; Meng et al., 2015; Zhang et al., 2017),

SVM (Luo et al., 2016), Bayesian networks (Barak-Corren et al., 2017; Leegon et al., 2005), decision trees (Azari et al., 2013; Luo et al., 2016), and time series-based methods such as ES and ARIMA (Boyle et al., 2012; Moriña et al., 2011) were also applied to forecast ED admission process. On the other hand, while Boyle et al. (2008) forecast patient admission data using LR analysis, logistic regression is studied by many scholars (Andersson et al., 2011; Barak-Corren et al., 2017; Dent et al., 2007; Kim, Li et al., 2014; Lucke et al., 2018; Ng et al., 2016; Zhang et al., 2017).

3.3. Forecasting ED LOS

LOS, in another name patient throughput time, is described as the length of time that passes from the patient's time of arrival at the ED until time of discharge or transfer to another department of the hospital. Starting from patient arrivals at the EDs it becomes important have to be known the overall LOS in terms of efficient resource allocation (Gul & Guneri, 2015b). For this purpose, forecasting of LOS for the EDs has gained importance through the knowledge and studied by many researchers. We have retrieved seven papers regarding ED LOS forecasting in our review. Table 4 shows a summary of these papers in terms of method(s) used, specific objective(s), data characteristics, and performance measures.

In ED LOS forecasting, data mining-based methods are used more compared to regression and time series-based methods. Chaou et al. (2017) predicted LOS among patients discharged from an ED in Taiwan using an accelerated failure time model. They identified and quantified the causing variables on the ED LOS in the current study. On conclusion, it was proved that the forecasted ED LOS might be useful for ED stakeholders to better anticipate an individual's LOS and to help the administrative level plan its staffing policy. Azari et al. (2015) and Combes et al. (2014) used logistic and LR in their forecasting models. ANN was mostly preferred by researchers in ED LOS forecasting (Gul & Guneri, 2015b; Hachesu et al., 2013; Launay et al., 2015; Wrenn et al., 2005). Launay et al. (2015) forecasted prolonged LOS in older patients hospitalised in acute care wards after an ED visit. Gul and Guneri (2015b) proposed two ANN-based models by a base model that includes all variables and an alternative model that takes into consider all the variables except variables with weak or medium correlation on LOS. Hachesu et al. (2013) forecasted the LOS of heart patients using ANN, SVM and decision tree. In their proposed model, LOS was the target variable, and 36 input variables were used for prediction. All three algorithms were able to predict LOS with various degrees of accuracy. The findings demonstrated

Table 3. Summary of papers in terms of forecasting ED admission.

Authors (Year)	Method(s) used	Specific objective	Data characteristics	Performance measures
Golmohammadi (2016)	Logistic regression, ANN	To predict hospital admissions in order to reduce ED boarding	15,050 visits data from January 2012 to August 2012	MSE, r, MAE
Luo, Stone, Johnson, and Nkoy (2016)	SVM, ANN, decision tree	To develop a predictive model to guide appropriate hospital admission for ED patients with bronchiolitis	26,701 bronchiolitis patients' data	ROC
Meng et al. (2015)	ANN	To predict the emergency admission of elderly stroke patients in Shanghai by using a multilayer perceptron (MLP) neural network	Patients (> 60 years) with first-ever stroke registered from January 2012 to June 2014	Validity
Azari, Janeja, and Levin (2013)	Decision tree	To predict ED admissions to reduce boarding and LOS	120,000 visits from ED over a 24 months' period	Accuracy, precision, recall
Peck et al. (2013)	Logistic regression	To test the generalisability of a previously developed method for predicting the probabilities that ED patients will be admitted to a hospital inpatient unit	2007, 2010–2012	R-squared
Boyle et al. (2012)	ARIMA, regression, ES	To develop and validate models to predict ED presentations and hospital admissions for time and day of the year	5 years' retrospective analysis (1 July 2002–30 June 2007)	MAPE
Sun et al. (2011)	Logistic regression	To develop and validate a predictive model to assess whether a patient is likely to require inpatient admission at the time of ED triage	Patient visits at the ED from January 2007 to December 2008	95% confidence interval, ROC
Boyle et al. (2008)	LR	To forecast patient admission data using regression	5 years of ED admissions data (1/7/02–30/6/07) from two hospitals	R-squared, MAPE
Andersson, Andersson, Ohlsson, and Nilsson (2011)	ANN, Logistic regression	To construct and validate an ANN model for early prediction of the severity of acute pancreatitis	Acute pancreatitis patient data from 2002 to 2005 (n = 139) and from 2007 to 2009 (n = 69)	ROC
Barak-Corren, Fine, and Reis (2017)	Logistic regression, Naive Bayes	To develop a model for early prediction of hospitalisations	From 1 July 2014 to 30 June 2015	ROC
Dent, Weiland, Vallender, and Oettel (2007)	Binomial logistic regression	To determine the accuracy of predictions of the need for hospital admission	Between 11 July and 27 October 2004	Odds ratios and likelihood ratios
Kim, Li et al. (2014)	Logistic regression	To determine the importance of certain factors in predicting the need of hospital admission for a patient in the ED	Between January 2010 and March 2012	ROC
Leegon, Jones, Lanaghan, and Aronsky (2005) Leegon, Jones, Lanaghan, and Aronsky (2006)	Bayesian Network ANN	To predict hospital admission for ED patients using a Bayesian Network To predict hospital admission for ED patients using ANN	Between 4/10/04 and 6/30/04 3077 paediatric ED encounters' data	ROC ROC
Lucke et al. (2018)	Multivariable logistic regression	To develop models that predict hospital admission to ED of patients younger and older than 70 and compare their performance	10,807 patients' data	ROC
Morfiña, Puig, Rios, Vilella, and Trilla (2011)	Two-order integer valued autoregressive time series	To model the number of hospital admissions per week caused by influenza	From January 2004 to December 2007	N/A
Ng et al. (2016)	Multiple logistic regression	To identify risk factors for predicting the subsequent hospitalisation of non-urgent emergency patients	2 months data from January 2013 to December 2013	ROC
Zhang et al. (2017)	Logistic regression, ANN	To describe and compare logistic regression and ANN strategies to predict hospital admission or transfer following initial presentation to ED triage with and without the addition of natural language processing element	47,200 patients' data	ROC

Table 4. Summary of papers in terms of forecasting ED LOS.

Authors (Year)	Method(s) used	Specific objective	Data characteristics	Performance measures
Chaou et al. (2017)	Accelerated failure time model	To identify and quantify the influence of different patient-related or diagnostic activities-related factors on the ED LOS of discharged patients	106,206 patients' data	95% confidence interval
Launay, Rivière, Kabeshova, and Beauchet (2015)	ANN	To forecast prolonged LOS in older patients hospitalised in acute care wards after an ED visit	1254 participants' data in the year 2012	Sensitivity, specificity, positive predictive value, negative predictive value, likelihood ratios, ROC
Gul and Guneri (2015b)	ANN	To present an ED LOS forecasting model using ANNs	October and November 2010	<i>r</i> , absolute error
Azari, Janeja, and Levin (2015)	Logistic regression models	To present a framework that predicts patients with prolonged ED stays (> 14 h) from data available at triage	1 May 2011 and 1 June 2013	<i>p</i> value
Combes, Kadri, and Chaabane (2014)	LR	To identify the factors (variables) characterising the LOS in EDs in order to propose models to predict the LOS	2498 patients' data (period January–June, 2012)	Standard error
Benbelkacem, Kadri, Chaabane, and Atmani (2014)	Naive Bayes, BayesNet, SVM, Decision trees	To present an approach based on supervised classification methods in order to predict the patient LOS at the paediatric emergency department	6135 patients' data between three months (January–March 2012)	Accuracy, precision, recall, kappa statistic, ROC
Hachesu, Ahmadi, Alizadeh, and Sadoughi (2013)	Decision tree, SVM, ANN	To predict LOS of heart patients	4,948 patients' data who had suffered coronary artery disease	accuracy, specificity, sensitivity
Gill et al. (2018)	Gradient boosting machine	To predict ED fast track patients who stayed longer than 4 h in the ED	1 July 2014 and 30 June 2015	ROC
Wrienn, Jones, Lanaghan, Congdon, and Aronsky (2005)	ANN	To estimate patient's LOS in the ED with an ANN	9729 consecutive patients' data (4/1/04–6/30/04)	ROC
Zhu, Luo, Zhang, and Shen (2018)	Coxian phase-type distributions	To model of respiratory patients in ED using coxian phase-type distributions with covariates	894 respiratory diseases patients' data in the year 2014	Standard error

that the SVM was the best fit. Benbelkacem et al. (2014) presented an approach based on supervised classification methods in order to predict the patient LOS at a paediatric emergency department. Results of the study indicated that BayesNet and Naïve Bayes provided the best results. However, decision tree methods obtained comparable results and could successfully be suitable for the prediction of ED patient's LOS. Zhu et al. (2018) proposed a Coxian phase-type distribution model with covariates as an alternative method for ED LOS. The models were applied to 894 respiratory diseases patients' data in the year 2014 from ED of a Chinese public tertiary hospital. Results of the study show that ED LOS data can be modelled by the Coxian phase-type distribution model. Distributions of ED LOS differ significantly with respect to patients' gender, arrival mode, and treatment area. Using the fitted Coxian PH model assists ED stakeholders in identifying patients who are most likely to have an extreme ED LOS and in predicting the forthcoming workload for resources. Gill et al. (2018) determined the relative importance and estimated marginal effects of patient and system-related variables in predicting ED fast track patients who stayed longer than 4 h in the ED.

3.4. Forecasting ED crowding

ED crowding threatens service quality and access to care (Hoot et al., 2009). Therefore, accurate forecasting of ED crowding can provide stakeholders to handle this problem. ED crowding causes many troubles such as delayed treatment, patient leaves without seen by a doctor, prolonged transport and waiting, increased mortality, and financial losses (Hoot et al., 2008, 2009; Zhang et al., 2013). Papers in the literature forecasted ED crowding using ED crowding measures such as NEDOCS, EDWIN, READI, and statistical methods, simulation, and Markov chain. The formula for each of these three ED crowding measures considers various patient, ED, and hospital information, and yields a numerical value that indicates whether an ED is running smoothly, is crowded but effective, or is overcrowded at a given point in time (Ahalt, Argon, Ziya, Strickler, & Mehrotra, 2018). The NEDOCS score is based on a linear regression model which is computed using the ratio of total numbers of ED patients and beds, the ratio of the numbers of "hold" and inpatient beds, the most recent waiting time for an ED bed, the longest current boarding time, and the number of ED patients on a ventilator. The EDWIN is an algebraically simple, clinically sensible measure of ED busyness and crowding. It exhibits face and content validity and, at one institution, was associated with nurse and physician assessment of ED crowding and initiation of diversion and weakly associated with quality-of-care

measures (Bernstein, Verghese, Leung, Lunney, & Perez, 2003). It is based on a weighted sum of the number of patients from all five triage categories present in the ED, the total ED capacity as a product of the number of attending physicians and the total number of available beds (excluding the “hold” beds). The READI is calculated using the bed ratio, the provider ratio and the acuity ratio (Ahalt et al., 2018). Table 5 presents a summary of papers in terms of forecasting ED crowding.

3.5. Other forecasting papers for ED processes

This “Others” section includes forecasting themes about utilisation of ED resources, ED patient waiting time, ambulance diversion, inpatient admissions, and some miscellaneous applications such as anomaly detection, posttraumatic stress disorder forecasting, triage forecasting, communication risks prediction, charge prediction, discharge disposition prediction, and 90-day mortality prediction and forecasting of blood product transfusion requirements of trauma patients. Table 6 represents an overall summary of papers in terms of these mentioned forecasting themes. Sprivulis (2003), Stout and Tawney (2005), Schweigler et al. (2009) and Burns, Chernyak, and Scheinfeld (2016) focused on utilisation of ED resources. Burns et al. (2016) identified weather and calendar variables in order to forecast daily ED imaging volume to aid appropriate scheduling of imaging resources for efficient ED function.

Schweigler et al. (2009) studied to generate accurate short-term forecasts of ED bed occupancy using time series models. Both a sinusoidal model with AR-structured error term and a seasonal ARIMA model were found to robustly forecast ED bed occupancy 4 and 12 h in advance at three different EDs.

Another studied forecasting theme for EDs is waiting time. Waiting times are considered as performance measures and monitored to find delays in the service. Few researchers proposed models in order to forecast ED patient waiting time. Lin et al. (2014) applied queuing theory to estimate the average waiting time across patients as well as the necessary ED and IU resources. Similarly, Wiler et al. (2013) used queuing theory to derive and validate a model that predicts the effect of various patient crowding scenarios on patient left without being seen rates. Ding et al. (2010) characterised service completion times (waiting room times, treatment times and boarding times) by patient, clinical, temporal, and crowding factors for different phases of emergency care using quantile regression.

Peck et al. (2012) and Abraham et al. (2009) studied forecasting of inpatient admissions. Peck et al. (2012) proposed models that use information gathered during triage to predict, in real time, the number

Table 5. Summary of papers in terms of forecasting ED crowding.

Authors (Year)	Method(s) used	Specific objective	Data characteristics	Performance measures
Skinner (2016)	Dixon Forecasting Model, Bed Ratio, NEDOCs	To assess the development, use, and implementation of a predictive two-hour forecasting tool for ED overcrowding.	From June 17 until June 30 2015	r
Skinner and Higbee (2015)	Dixon Forecasting Model, Bed Ratio, NEDOCs	To study used the Dixon Forecasting Model (DFM), a Bed Ratio (BR), and the NEDOCs to establish a reliable 2 h overcrowding forecasting tool within the ED	17 June until 30 June 2015	Standard error
Hoot, Zhou, Jones, and Aronsky (2007)	EDWIN, NEDOCs, READI, Work Score	To monitor current and near-future ED crowding by using 4 measures	An 8-week period data (21 June 2006–16 August 2006)	Positive likelihood ratio, negative predictive value, negative predictive value, positive predictive value, specificity
Zhang et al. (2013)	Markov chain model	To suggest a patient flow network for supporting Markov chain model that forecasts ED patient flow rule	N/A	N/A
Hoot et al. (2008)	Simulation	To design and implement the discrete event simulation that uses patient flow to predict near-future ED operational measures	2006	r
Hoot et al. (2009)	Simulation	To implement and validate the previously developed Forecast ED discrete event simulation for real-time forecasting of emergency department crowding	(5/1/07–8/1/07)	R-squared

Table 6. Summary of papers in terms of other forecasting themes.

Authors (Year)	Method(s) used	Forecast theme	Specific objective	Data characteristics	Performance measures
Kadri, Harrou, Chaabane, Sun, and Tahon (2016)	SARMA	Anomaly detection	To use SARMA as a modelling framework and EWMA for anomaly detection	From November 2011 to March 2012	R-squared, MAPE
Burns et al. (2016)	Student's <i>t</i> tests and chi-squared tests	Utilisation of ED resources	To identify weather and calendar factors that would enable prediction of daily ED imaging volume	From 1 January 2011 through 31 December 2013	<i>p</i> value
Bagnasco, Siri, Aleo, Rocco, and Sasso (2015)	ANN	Communication risks	To describe the utility of ANN in predicting communication risks in the ED	March–May 2011 by observing 840 nurses' interactions	MSE
Galatzer-Lavy, Karstoft, Statnikov, and Shalev (2014)	SVM	Post-traumatic stress disorder forecasting	To forecast posttraumatic stress disorder from early trauma responses	957 participants	ROC
Lin, Patrick, and Labeau (2014)	Queuing theory	ED patient wait time	To employ queuing theory to estimate the average waiting time across patients as well as the necessary ED and IU resources	Fiscal year 2011/2012	
Peck, Benneyan, Nightingale, and Gaehde (2012)	Expert opinion, naive Bayes, logit-linear regression	Inpatient admissions	To evaluate models that use information gathered during triage to predict, in real time, the number of ED patients who subsequently will be admitted to a hospital inpatient unit	Data between 22 September 2010 and 26 November 2010	ROC, R-squared
Wiler, Bollandfar, Griffey, Poirier, and Olsen (2013)	Queuing theory	ED patient wait time	To derive and validate a model that predicts the effect of various patient crowding scenarios on patient left without being seen rates	87,705 visits in calendar year 2008	95% confidence interval
Wang (2013)	PCA and SVM	Triage prediction	To combine PCA and SVM to analyse anomaly detection	109,360 patient visits in 2010	MAPE
Abraham, Byrnes, and Bain (2009)	ARIMA, SARIMA	Inpatient admissions	To develop daily emergency inpatient admissions and occupancy	10 April 2004–25 March 2007	RMSE, MAPE
Au et al. (2009)	Continuous-time Markov chain	Ambulance diversion	To predict the onset of ambulance bypass	199,480 records between 1 January 2001 and 18 April 2005	Goodness-of-fit test
Schweigler et al. (2009)	SARIMA	Utilisation of ED resources	To generate accurate short-term forecasts of ED bed occupancy	ED bed occupancy data from July 2005 through June 2006	RMSE
Bennett, Moore, and Probst (2007)	LR	Charge	To develop a national estimate of uncompensated care from patients utilising the ED in rural hospitals	From 1999 to 2000	<i>p</i> value
Epstein and Tian (2006)	Logistic regression	Ambulance diversion	To develop a real-time instrument that might accurately predict the need for ambulance diversion	46,164 patient visits from 1 January 2003 to 31 December 2003	ROC
Stout and Tawney (2005)	Queuing theory	Utilisation of ED resources	To develop Excel spreadsheet model that is a dynamic, visual illustration of how variation in individual process times can affect total process capability	N/A	
Walczak (2005)	ANN	Blood product transfusion requirements of trauma patients	To evaluate the efficacy of ANNs to predict the transfusion requirements of trauma patients using readily available information	1016 patient records	MAE
Ding et al. (2010)	Quantile regression	ED patient wait time	To characterise service completion times by patient, clinical, temporal, and crowding factors for different phases of emergency care using quantile regression	1-year visit data	<i>p</i> value
Sprivilis (2003)	Retrospective analysis	Utilisation of ED resources	To estimate the number of, and costs associated with, low acuity presentations to an ED	24 December 1999–21 June 2000	95% confidence interval
Bradman, Borland, and Pascoe (2014)	Logistic regression	ED patient disposition	To predict patient disposition in a paediatric ED	A total of 1223 patients data	ROC
Derose, Gabayan, Chiu, Yiu, and Sun (2014)	Regression analysis	ED patient wait time	To assess patient transit times and ED system crowding measures based on their associations with outcomes	136,740 patients' data from January 2008 to December 2010	First and fourth quartiles
Goto, Maeda, and Goto (2013)	Decision tree	Outcomes after out-of-hospital cardiac arrest	To develop a simple and generally applicable bedside model for predicting outcomes after cardiac arrest	390,226 adult patients' data for 2005 through 2009	Survival probability

(Continued)

Table 6. (Continued).

Authors (Year)	Method(s) used	Forecast theme	Specific objective	Data characteristics	Performance measures
Hofman et al. (2016)	Cox regression analyses	90-day mortality	To predict 90-day mortality in older patients after discharge from an ED	The year of 2012	Hazard ratio
Keogh, Culliford, Guerrero-Ludueña, and Monks (2018)	Univariate and multivariate linear regression analysis	ED 4-hour target performance and cancelled elective operations	To explore ED 4-hour target performance and cancelled elective operations	142 patients' data between 2012 and 2016	R-squared
Leegon, Hoot, Aronsky, and Storkey (2007)	Gaussian process	Ambulance diversion	To predict ambulance diversion in an adult ED using a Gaussian process	1 March 2005–30 November 2005 data	ROC
Liu et al. (2014)	Random forest algorithm	Adverse cardiac events	To predict adverse cardiac events in ED patients with chest pain using machine learning for variable selection	A total of 702 chest pain patients	ROC
Riordan et al. (2017)	Logistic regression	Patient discharge disposition	To derive and validate a model capable of predicting patient discharge disposition using variables present on arrival to the ED for ESI 3 patients	Nearly 50,000 patients' data	ROC

of ED patients who subsequently will be admitted to a hospital inpatient unit using expert opinion, naive Bayes, logit-LR. Abraham et al. (2009) focused on daily emergency inpatient admissions and occupancy using time series models.

One of the major concerns that EDs faced is ambulance diversion (or bypass). It is described as diversion of ambulances to other hospitals except in urgent cases where the ED is judged to be so busy. Ambulance diversion theme was investigated by three researchers (Au et al., 2009; Epstein & Tian, 2006; Leegon et al., 2007). Epstein and Tian (2006) developed a logistic regression model that might accurately predict the need for ambulance diversion. Leegon et al. (2007) evaluated the accuracy of a Gaussian process for prediction of ambulance diversion. Au et al. (2009) studied prediction of the onset of ambulance diversion using continuous-time Markov chain model.

4. Analysis and results

This section presents distribution of papers by the following points of view: (1) forecasting themes, (2) methods used to forecast ED processes, (3) data characteristics and type used for forecasting of ED processes and (4) study objectives and performance measures, (5) publication trend, (6) published journal, database, and country of origin.

4.1. Themes and methods used to forecast ED processes

Regarding the forecasting themes, “ED patient demand” constitutes nearly a half of the total papers. About 42% of total papers ($n = 43$) are concentrated in this application theme (Table 7). Another most studied application themes are “ED patient admission,” “ED LOS,” and “ED crowding” by 18% ($n = 18$), 10% ($n = 10$), and 6% ($n = 6$) of total papers. “Utilisation of ED resources,” “ED patient wait time,” “inpatient admissions,” and “ambulance diversion” are probably in the most delicate disciplines.

From the summary of forecasting methods used for each application themes, the following important findings can be extracted: (1) the time series-based models play a dominant role among all methods with a rate of 27% ($n = 28/102$). The most widely applied modelling approach among all application themes is time series in ED patient demand area. (2) Regression, time series and data mining-based hybrid approaches are the least applied among all application themes. This hybrid approach is only applied in ED patient demand forecasting. (3) Regression is applied to most of all application themes excluding inpatient admissions, utilisation of ED resources and

Table 7. Summary of forecasting methods used for each application themes.

Forecasting theme for the EDs	DM	TS	Reg	Reg+ DM	Reg+ TS	Reg+ TS+ DM	Oth	Total
ED patient demand	1	23	7	3	4	2	3	43
ED length of stay (LOS)	7	1	2					10
Inpatient admissions		1		1				2
Utilisation of ED resources		1					3	4
Ambulance diversion			1				2	3
ED crowding							6	6
ED patient admission	5	1	7	4	1			18
ED patient wait time			1				2	3
Others	6	1	6					13
Total	19	28	24	8	5	2	16	102

DM: Data mining, Reg: Regression, TS: Time series, Oth: Others.

ED crowding while time series modelling is applied to six of the nine application themes.

4.2. Data characteristics and data type used for forecasting of ED processes

Data used for forecasting of ED processes have characteristics in terms of period and quantity. In ED patient demand forecasting studies, type of data can be classified into annually, seasonal, monthly, weekly, daily, and hourly. Figure 4 shows distribution of data type in ED patient demand forecasting studies. Daily data were used in 20 papers and monthly data in 9 papers. The data collection period varied widely, from one-year data to nearly 12 years. Detailed data characteristics for each paper were given in Tables 2–6.

4.3. Study objectives and performance measures

When reviewing measures used for assessing model accuracy and performance, 23 different groups of performance measures were identified as shown in Figure 5: MAPE, RMSE, R-squared, 95% confidence interval, MAE, ROC, standard error, r , MASE, WMAPE, MSE, Wald statistic, and some combination of these. In Sanders (1997), common used forecasting error measures are divided into two groups as follows: standard and relative error measures. While standard error

(bias), MAE, MSE and RMSE are defined under the first group, MAPE and WMAPE are investigated in the second group. Apart from this evaluation by Sanders (1997), R-squared corresponds to the percentage of explained variability by the model. A higher R-squared value means a better model accuracy. MAPE is the percentages of mean of the absolute differences between predicted and actual values. RMSE is the root squared mean of the squared differences between predicted and actual values. A lower value of RMSE and MAPE indicates good model performance; that is, a good balance between predicted and actual values. In the ED forecasting literature, it is indicated that MAPE is easier to understand for comparison (Wargon et al., 2009). Among our reviewed papers, ROC and MAPE were mostly preferred performance measures nearly by 21% and 15% of total papers ($n = 17$ and $n = 12$). It was followed by R-squared (8; 10%), RMSE (7; 9%), 95% confidence interval (6; 7%), and MAE (3; 4%).

4.4. Publication trend

The reviewed papers to forecast the ED processes are handled in time, by adjusting the distribution of the number of papers during the period of 2001–2018 in Figure 6. From Figure 6, it can be easily seen that

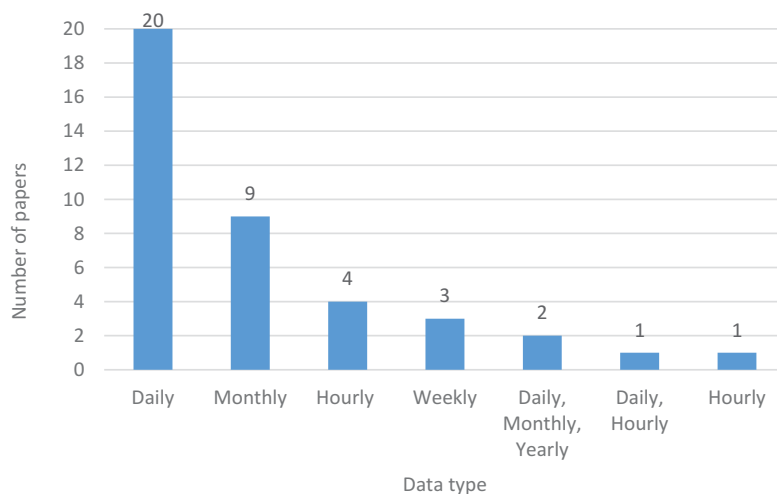


Figure 4. Distribution of ED patient demand forecasting papers in terms of data type.

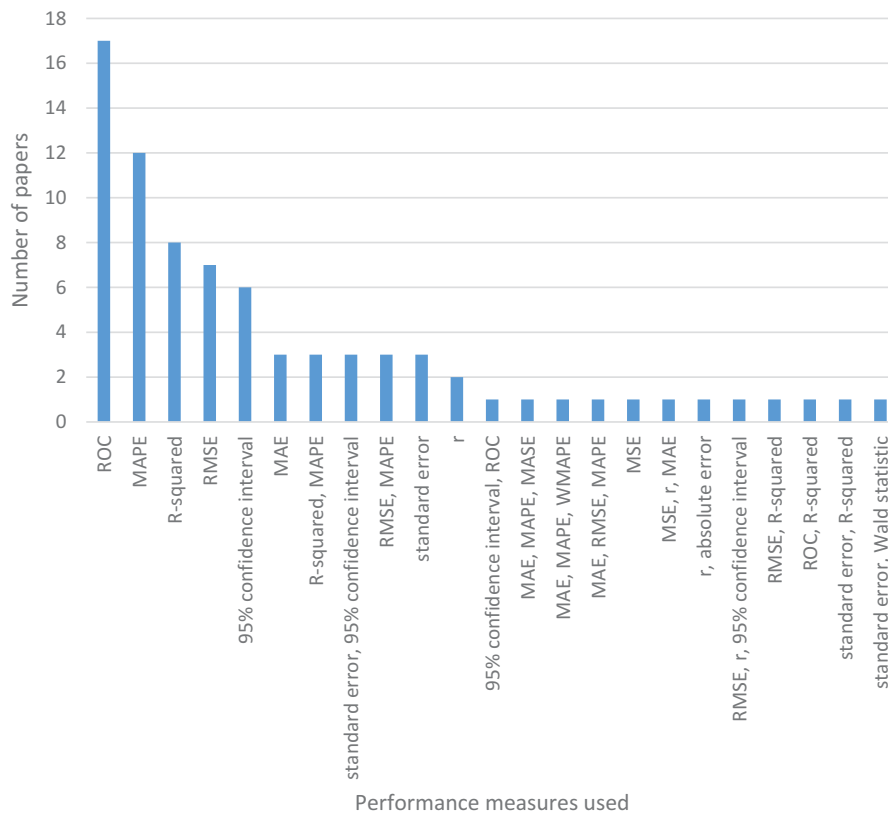


Figure 5. Distribution of papers in terms of performance measures used.

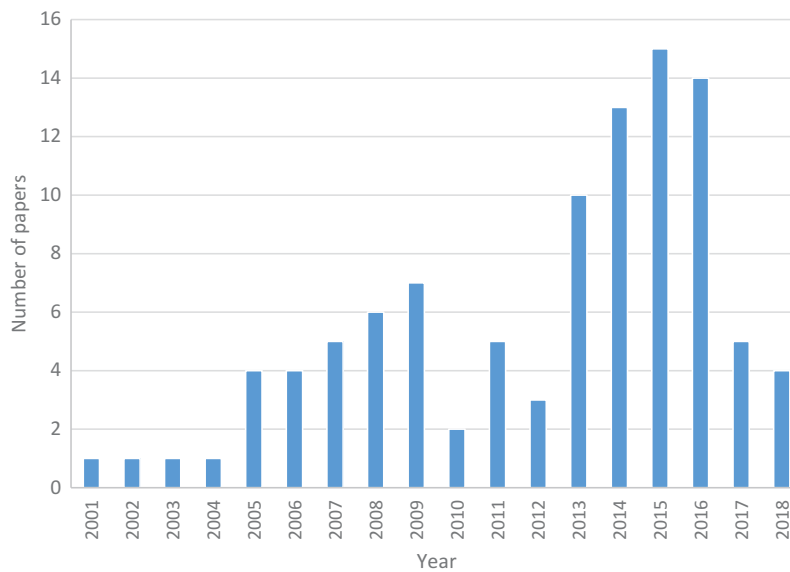


Figure 6. Distribution of papers by publication year.

there are two important increases in the production of papers from 2001 to 2009 and from 2013 to 2015. These two intervals have a high R^2 value (86% and 97%) indicating that the papers have increasingly better reception within the ED forecasting literature.

4.5. Published journal, database, and country of origin

Table 8 provides the list of journals ordered based on the number of papers (from that journals) that have

been reviewed and integrated to our review study ($n = 102$, and associated percentage % = 100, standing for the total number of papers). Academic Emergency Medicine has the most publications on ED forecasting models (13; 13%), followed by Annals of Emergency Medicine and Journal of Medical Systems (3; 3% per each). Of the journals, American Journal of Emergency Medicine, Emergency Medicine Journal, Health Care Management Science, Healthcare informatics research, IEEE Transactions on Information Technology in Biomedicine, Journal of Biomedical Informatics,

Table 8. Distribution of papers in terms of published journals.

Publication journal name	No. of papers	Percentage
Academic Emergency Medicine	13	13%
Annals of Emergency Medicine	3	3%
Journal of Medical Systems	3	3%
American Journal of Emergency Medicine	2	2%
Emergency Medicine Journal	2	2%
Health Care Management Science	2	2%
Healthcare informatics research	2	2%
IEEE Transactions on Information Technology in Biomedicine	2	2%
Journal of Biomedical Informatics	2	2%
Neurocomputing	2	2%
Pediatric Emergency Care	2	2%
BMJ Open	2	2%
Emergency Medicine Australasia	2	2%
1 papers from each of 33 journals	48	47%
Proceeding paper	15	15%

Neurocomputing, Pediatric Emergency Care, BMJ Open and Emergency Medicine Australasia have two papers (2% per each). Other journals contain one entry (totally 48, 47% per each). Also, 15 proceeding papers are retrieved that corresponds to 15% of total number.

When the database where the reviewed papers published investigated, it is seen that Wiley (22; 22%) and Elsevier (19; 19%) are forefront followed by Springer (8; 8%) and IEEE (7; 7%) (see Figure 7).

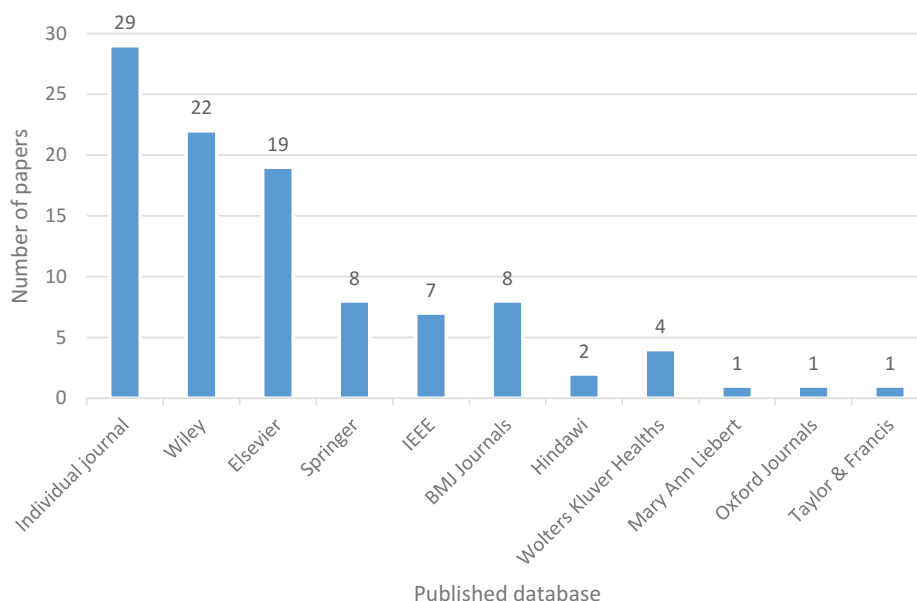
The literature review is, also, classified by country of origin for each study, resulting in the 21 portions and represented in the bar chart (Figure 8). The United States accounts for almost 36 (35%) of the all papers. Australia, France, the United Kingdom, and Canada are also prolific in the use of ED forecasting models (13; 13%, 7; 7%, 7; 7%, 6; 6%, respectively). The remaining countries have a rather testimonial presence (Canada, China, Singapore, Brazil, Taiwan, Turkey, Hong Kong, Spain, Sweden, Netherlands, Brazil, and Korea) with 6 (6%), 5(5%), 3(3%), 3(3%), 2(2%), 2(2%), 2(2%), 2(2%),

2(2%), 2(2%), and 2(2%), respectively. The other countries include Algeria, Arabia, Belgium, Cyprus, Iran, Israel, Italy, and Japan ($n = 1$ per each).

5. Discussion

5.1. Overall assessment and main challenges

Studies of ED patient demand forecasting models used generally the daily number of patient visits over a period ranging from 1 to 5 years. Dependent variables used in the developed models include hour of the day, day of the week, month, season, whether the day was a non-workday or the day after a non-workday and vacation days. Especially, in time-series based studies, additional variables are used like meteorological data consisted of maximum or minimum temperature, precipitation and wind speed. The historical data in the reviewed studies includes the linear and non-linear parts because of the complexity of and the randomness of ED demand. Forecasting accuracy depends on the choice of forecasting model. Hybrid models (e.g. ANN and ARIMA) have different advantage and disadvantage for the historical data. ARIMA models are very flexible and it can represent AR, MA and combined AR and MA (ARMA) series. ARIMA models very good when dealing with the linear part but it is weak when working with non-linear data. ANN model is good at dealing with the non-linear parts. But it is hard to decide how many input variables should to be used. When using hybrid model, the estimated values and residuals of the ARIMA model as input variables can solve this problem. Also, combination of ARIMA and ANN models can get better forecasting accuracy.

**Figure 7.** Distribution of papers by published database.

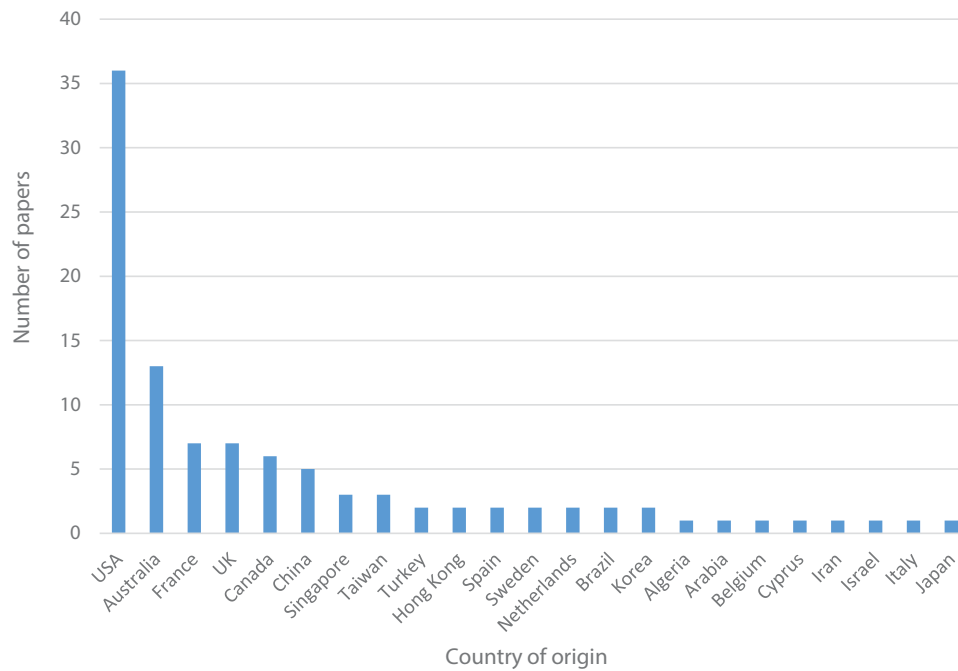


Figure 8. Distribution of papers in terms of country of origin.

5.2. Open areas for future work

Even though ED forecasting literature covers the themes of ED patient demand, ED patient admission, ED LOS, ED crowding, utilisation of ED resources, ED patient waiting time, ambulance diversion, inpatient admissions, and some other miscellaneous examples, there are still open themes for future work.

One of the open themes is consultation. It is a common and important process of ED care (Chan, Orlich, Kulasegaram, & Sherbino, 2013; Geskey, Geeting, West, & Hollenbeak, 2013; Wiler et al., 2015; Woods et al., 2008). In this process, emergency physicians request other specialists (consultants) to participate in the care of the ED patient and provide one of the following: admission, discharge or, consultation for another specialty (Woods et al., 2008). The performance measure of this process that significantly affects ED length of stay and overcrowding is consultation response time (Cho et al., 2011; Geskey et al., 2013). It is defined as the placement of an order for an ED consult until the initial consultant recommendation is communicated to the ED provider (Wiler et al., 2015). Reducing consultation response time enables ED executive and medical staff to decrease overall length of time patients remain in the ED and provide better patient satisfaction. In 2010, annual report of the Office of the Auditor General of Ontario, Canada, it is indicated that limited hours and types of specialists' consultations and diagnostic services available on-site were key barriers to efficient patient flow (Annual Report of the Office of the Auditor General of Ontario, 2010). It is also recommended in this report that to

better allow EDs to assess the impact that timely specialist consultation has on patient care, especially for high-acuity patients, EDs should track targeted and actual wait times for specialist consultation for emergency patients, so that the impact of these wait times on providing timely and appropriate patient care can be periodically assessed. One of the best ways is to predict this key performance measure to avoid delays in the whole processes considering related predictors. Predicting and determining consultation response time in EDs can be very useful for ED executive, particularly for prioritising health care policies and promoting health services, comprising the appropriate allocation of health care resources according to differences in patients' LOS (Gul & Guneri, 2015b).

From the method point, while different methods are applied to forecast ED, ANN-based models provide better results than regression-based models (Gul & Guneri, 2016). For improving the performance of forecasting, different metaheuristic approaches (ANN-ant colony optimisation (Song, 2012), ANN-genetic algorithm (Kuo, Chen, & Hwang, 2001), ANN-particle swarm optimisation (Chau, 2006), ANN-artificial bee colony optimisation (Hsieh, Hsiao, & Yeh, 2011), ANN-tabu search (Aladag, 2011), ANN-simulated annealing (Liao & Tsao, 2006), etc. should be integrated with ANN. To the best of our knowledge, while these approaches are successfully applied to different application areas, it is not applied in ED forecasting.

This review study highlights that most of the studies related to ED forecasting is being done in ED

patient demand, ED patient admission and ED LOS. Ambulance diversion, impatient admission and patient wait time have not attracted attention to a significant extent regarding development of methods for forecasting. Moreover, implementation of forecasting approaches has not been yet adapted to the auxiliary processes of EDs such as X-ray, tomography, ultrasound, laboratory tests and so on. However, these processes are considered as connections of EDs to the other departments of hospitals.

6. Conclusion

In this paper, a representative and systematic review of 102 papers on ED forecasting is presented. Recently, statistical forecasting concept has gained popularity in ED problems due to its ability on providing ED stakeholders planning their processes efficiently and improving service quality. These papers were classified under nine forecasting themes. In addition, all papers were classified by publication trend, published journal, database and country of origin, forecasting themes, methods used to forecast ED processes, data characteristics, and type used for forecasting of ED processes and study objectives and performance measures. It is aimed to present forecasting methods including regression, time series, data mining and some miscellaneous OR methods in ED-related problems. The ultimate goal is to provide ED stakeholders with a background on the ED as a service business and an overview of statistical forecasting concept that can be practically applied to various ED processes.

It should be acknowledged that this review has some limitations. The first is about exclusion of master's thesis, doctoral dissertations, and book chapters in this literature review. Second potential limitation is concerned with the languages of the papers. We did not include any papers written in a language other than English.



A number of significant arguments with respect to the applications can be derived from this literature review. Results of the literature review shows that: (1) Usage of forecasting concept in the ED problems is following an increasing trend. (2) Academic Emergency Medicine (Wiley) has the most publications on ED forecasting with 13%. (3) The United States ranks first by accounting for almost 35% of the all papers related to the ED forecasting models. (4) The time series-based models play a dominant role among all approaches with a rate of 27%. (5) ED patient demand is the area where the most papers carried out and constitutes nearly a half of the total papers by 42%. (6) Researchers mostly prefer ROC and MAPE as key performance indicators with 21% and 15%, respectively. We expect and observe that, in the future, the number of applications and approaches related with forecasting methods will raise in the ED literature.

Future directions for ED patient flow forecasting are motivated by gaps found within the two sets of literature. First concerns the ED patient flow processes which have not been studied in the field of forecasting before such as consultation and ED auxiliary processes. Therefore, it would be beneficial to develop forecasting models for these processes. Considering the above, another useful direction would be to develop hybrid models using time-series and data-mining-based methods for these ED processes. Moreover, decision support systems, demand/capacity matching models would be straightforward future venues in ED forecasting.

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No potential conflict of interest was reported by the authors.

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