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Reducing Emergency Department Crowding Using Health Analytics Methods: Designing An Evidence Based Decision Algorithm

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Abstract

OBJECTIVE: The main objective of this study is to utilize health analytics methods in designing an evidence based decision algorithm to support healthcare professionals in identifying and safely diverting less risky emergency patients to ambulatory care settings or referring them to other hospitals in order to reduce emergency department crowding. METHODS: The study used retrospective analysis methods. Data were retrieved from the hospital data warehouse system including a total of 13,750 emergency encounters conducted over the first six months of 2014. Descriptive analytics were used to explore different variables and test for any relationships between these variables and admission probability of the patient to determine which variables could be used to build the suggested decision algorithm model. RESULTS: Three variables; acuity level, mode of arrival and age group were identified as the most influential factors on future admission status of emergency patients and were recommended as indicators for designing the decision algorithm. DISCUSSION: Based on the analysis and the suggested decision algorithm, 30% of emergency patients had a 0.2% admission rate; these were suggested to be diverted to urgent outpatient appointments within 24 hours. About 20% of patients can be safely referred to other hospitals, according to the conditions set in the decision algorithm while the remaining 50% of patients should continue their emergency treatment. CONCLUSION: Health analytics can support designing evidence based tools to guide the process of performance improvement, in our study reducing emergency department crowding at King Faisal Specialist Hospital and Research Center, Jeddah, Saudi Arabia.

Peer-review under responsibility of the Program Chairs

Keywords: Decision Algorithm, Decision Support, Evidence Based, Health Analytics, Reducing Emergency Department Crowding.

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1. Background and Significance

Emergency department (ED) crowding is a significant international problem, with an increasing research worldwide into this field. It has become a major barrier to receiving timely emergency care for patients all over the world[1]. Patients who arrive to EDs often face long waiting times to be treated and, for those who require admission, even longer waiting times are expected for an inpatient hospital bed. Because ED crowding is a reflection of a higher level supply and demand mismatches in the healthcare system, the problem cannot be solved by examining the ED in isolation. A conceptual model of ED crowding could help to understand its causes and develop potential solutions. This model classifies ED crowding into three interdependent components: input, throughput, and output. These components exist within an acute care system characterized by the delivery of unscheduled care. Using this conceptual model we can work on developing strategies and solutions to reduce ED crowding[2].

1.1. Factors affecting ED Crowding

According to Asplin's conceptual model, factors of ED crowding can be classified mainly into three categories; input factors, throughput factors, and output factors. Input factors usually reflect sources and aspects of increased patient inflow, throughput factors reflect bottlenecks and slow processes within the ED and output factors reflect bottlenecks in other next parts of the health care system that might affect the ED, such as availability of hospital inpatient beds for ED patients to be admitted[3, 4]. Input factors include the increased flow of patients on the ED, mainly due to increasing numbers of non-urgent visits, the frequently flyer patients and the effects of seasons of some infectious diseases such as influenza which might lead to increased ED crowding. Sometimes low acuity patients frequently seek non urgent care in the ED due to insufficient or untimely access to primary care. Frequent ED visitors, defined by four or more annual visits, account for 15% of the total ED visits in many hospitals, these patients usually do not have urgent complaints but yet they still come to the ED for treatment[5]. The closure of other hospitals and healthcare facilities might lead to increased ED crowding. Ambulance diversion from other hospitals due to acute, complicated or tertiary care cases also can lead to increased crowding. Recently discharged inpatients might not represent a huge percentage of ED visits but when they come to ED they usually have longer ED lengths of stay and more frequent hospital admissions than other patients. Some studies linked lower socioeconomic status with increased waiting times and ED length of stay[6].

The main throughput factors include inadequate staffing and shortages of treatment areas, which are the two commonly studied factors that may cause ED crowding. The average nurse should be caring for four patients and the average physician should be caring for six to seven patients simultaneously. Lower staffing levels of physicians and triage nurses predisposed patients to wait longer[7]. The training background of attending physicians in charge of an ED has been associated with patients leaving without being seen. The use and/or delays of the ancillary services, including lab, radiology and other procedures, usually prolong the ED length of stay[8]. The usual output factors that might increase ED crowding include mainly the slow inpatient boarding process and hospital bed shortages, which are identified as commonly studied output factors that may cause ED crowding. The increasing hospital occupancy rates and bed shortage are strongly correlated with increased ED patients' waiting times, ED occupancy level and ED patients' length of stay especially when the hospital occupancy levels exceeded 90%[9, 10].

1.2. Effect of ED Crowding

The effects of ED crowding can be classified generally into four main categories; adverse clinical outcomes, reduced healthcare quality, impaired access to care and healthcare provider losses. Adverse clinical outcomes reflect health related and clinical patient complications. Reduced healthcare quality reflects below benchmarks quality of care delivery process. Impaired access to care reflects the inability of patients to receive timely care at their preferred institutions. Healthcare provider losses reflect consequences borne by the health care system itself[11]. Patient mortality is a commonly studied adverse outcome of crowding. Many studies found a significant increase in mortality rates associated with increased ED crowding[12]. Transport delays and treatment delays are also effects of crowding and related to reduced quality. Patients who arrive at the ED during crowded periods will wait longer for an ED bed. Crowding is also associated with increased door to doctor and door-to-needle time for patients with suspected myocardial infarction. High ED occupancy levels can also be associated with delayed pain assessment and lower likelihood of pain documentation[13]. Ambulance diversion and patient leave are also effects of crowding related to impaired access. Patients are more likely to leave without being seen when ED occupancy approaches 100% of the total capacity. The rate of patients leaving without being seen is closely correlated with waiting times. Patients frequently cite long waiting times as a reason for leaving without being seen and many of them will seek other medical care. Patients who leave the ED without being seen are twice as likely to report worsened health problems[14]. The negative financial effect on hospitals due to ED crowding is documented. One study found that patients who boarded in the ED longer than a day also stayed in the hospital longer[15].

1.3. The Role of Health Analytics

Health analytics actually is a business driven term that encompasses a wide spectrum of aspects and dimensions of big data analysis. This analysis is based mainly on the availability and accessibility of data and information pooled through the good integration and interoperability of a wide range of technologies and tools such as electronic health record systems, data warehouses, web applications, clinical decision support systems and others operational systems[16]. The Healthcare Information and Management Systems Society, United States, and many other references define health analytics as "the process of systematic use of medical data and related clinical and business information through the application of analytical disciplines such as statistical, contextual, quantitative, predictive, and cognitive analyses to develop actionable insights and lead information based decision making for better healthcare provision, planning, management, measurement and learning"[17].

Health analytics applications and tools can be considered a collection of decision support systems for the healthcare providers enabling knowledge professionals such as physicians, nurses and health administrators, health policy makers and pharmacists to gain vision and make more effective and efficient evidence based healthcare decisions[18]. Health analytics can also be defined as a way of transforming data and information into plans and actions through analysis and insights in the context of the healthcare decision making and problem solving[19]. Typically, hospitals and healthcare organizations already have been implementing descriptive analytics to medical data and clinical cases. Using queries and reporting tools and technologies, healthcare professionals usually collect data and information on past performance, enabling classification and categorization of normally structured data[20]. Recently, healthcare data warehouses collects different data types from different sources to create operational healthcare dashboards, strategic scorecards and clinical data stores[21].

2. Study Objectives

At King Faisal Specialist Hospital and Research Center, Jeddah, Saudi Arabia, the emergency department crowding has been a chronic problem for several years. Despite the hospital expanded the ED space and increased its capacity bed count from 22 to 36 beds over the last few years, the problem of ED crowding was still resistant. More patients are visiting the ED and experiencing even longer waiting times, longer stays and longer boarding times. King Faisal Specialist Hospital and Research Center is a tertiary care, and recently became a central referral hospital, that specializes mainly in cancer treatment and organ transplantation, where the occupancy rates of inpatient departments were going higher and the average length of stay of inpatients were getting longer due to the increasing numbers of referred patients for tertiary care with more severe illnesses and complicated conditions and increased percentage of cancer and organ transplantation cases among other general cases.

The hospital management decided to adopt a group of new procedures to reduce the ED crowding by working on the three categories of factors described above; the input, throughput and output factors. This study was dedicated to solving the problems of the first category; the input factors. In an attempt to utilize health analytics methods and tools in reducing the ED crowding, a suggested decision algorithm was designed based on retrospective analysis and findings of the ED flow. The main objective of this suggested decision algorithm was to support healthcare professionals at the ED in identifying less risky ED patients, who do not need to be admitted, and safely diverting them to ambulatory care settings and giving them urgent outpatient appointments within 24 hours or referring them to other affiliated less crowded hospitals. This way crowding should be reduced by only allowing patients who really need immediate emergency care, or most probably will need to be admitted to the hospital inpatient departments due to their more sever conditions, to go through the complete cycle of the emergency care.

3. Materials and Methods

Since this study planned to use retrospective analysis methods, the data for the study was retrieved from the hospital data warehouse system including all available data elements of all emergency encounters that were conducted over the first six months of 2014; from the 1st of January to the 30th of June 2014. A total of 13,750 patient encounters with valid data were retrieved from the data warehouse and were then subjected to multiple data analytics techniques, including data processing and analysis using MS Excel, MS Access and SPSS, in addition to the regularly available system reporting and analytics. Descriptive analytics techniques were used in the form of analyzing and calculating different variables and testing for any relationships between those variables and the admission status probability of the patient to determine which variables could be used to support healthcare professionals at the ED in identifying and safely diverting less risky ED patients to ambulatory care settings or to refer them to other affiliated less crowded hospitals. Three main types of patients and scenarios have been suggested, based on the CTAS – The Canadian Triage and Acuity Scale, the first is a seriously sick patient who needs immediate emergency care, such as CTAS levels 1 and 2, this patient needs to be treated in the hospital ED until a decision is made regarding admission to inpatient hospital departments, referral to other hospital services or discharging the patient home after complete treatment, the second is a completely non-urgent patient, such as CTAS levels 4 and 5, who is coming the ED for no specific reason other than not being able to access the ambulatory care services of the hospital due to long waiting lists or other eligibility or financial reasons, this patient needs to be diverted to an urgent outpatient appointment within 24 hours through an early decision and before completing the whole ED service cycle and the third is a patient who needs emergency care but still not very urgent, such as CTAS level 3, which can be medically stabilized through a rapid management team then safely referred to another affiliated hospital to continue and complete emergency treatment there.

4. Results

According to the analysis of the results, only 1,540 patients out of the total 13,750 patients were admitted to the hospital inpatient departments which mean 11.2%. Most of the emergency patients; 85% were discharged home after treatment, including a very small percentage, about 3%, left without being seen or left before completing treatment. Eight main variables could be identified for evaluation using health analytics; these were: Gender, Age Group, Nationality, Patient Acuity Level, Patient Mode of Arrival, Patient Discharge Destination, Day of Encounter and Session of Encounter. The three main variables that had statistically significant influence on the admission rates of emergency patients to the hospital inpatient departments were Patient Acuity Level, Patient Mode of Arrival and Patient Age Group. Other variables did not have any significant effect on the rate of admission. So the plan was to conduct further analysis on these three variables to guide building the suggested decision algorithm model.

4.1. Patient Acuity Level Analysis

The ED of the hospital uses the CTAS – The Canadian Triage and Acuity Scale to classify the acuity level of the emergency patients and their needs, where CTAS Level 1 – Resuscitation include patients who need to be seen by a physician immediately 98% of the time, CTAS Level 2 – Emergent are patients who need to be seen by a physician within 15 minutes 95% of the time, CTAS Level 3 – Urgent include patients who need to be seen by a physician within 30 minutes 90% of the time, CTAS Level 4 – Less Urgent include patients who need to be seen by a physician within 60 minutes 85% of the time and CTAS Level 5 – Non Urgent include patients who need to be seen by a physician within 120 minutes 80 % of the time. Out of the total 13,750 ED encounters, we had only 12,630 encounters classified by acuity level, the rest of the encounters were not assigned acuity levels. 3 patients out of the admitted 1,540 were not assigned an acuity level.

Table 1. Admitted ED Patients compared to Total ED Patients Sorted by Acuity Level.

Code	Acuity Level	Admitted Patients	%	All ER Patients	%	% of Admitted to All
1	1-Resuscitation	40	2.6%	44	0.3%	90.9%
2	2-Emergent	410	26.7%	1,069	8.5%	38.4%
3	3-Urgent	1,078	70.1%	7,411	58.7%	14.5%
4	4-Less Urgent	8	0.5%	3,489	27.6%	0.2%
5	5-Nonurgent	1	0.1%	617	4.9%	0.2%
Total		1,537	100%	12,630	100%	12.2%

We have five sequential acuity levels and we have two final patient statuses; admission and discharge. To test the effect of different patient acuity levels on the status of being admitted to the hospital or discharged home, we assigned numerical values, from 1 to 5, for acuity levels and assigned code 1 for admission and code 2 for discharge to analyze the effects and relationships. Using the ANOVA, one-way analysis of variance, the acuity level of the patients had a statistically significant effect on their admission status. Different acuity levels had different admission status. To test for the correlation between acuity level, which has an ordinal variable now, and admission; we used the Pearson correlation coefficient test, where the acuity level of the patient had a moderately positive statistically significant correlation with the admission status. Since the acuity level is lower from 1 to 5 (1 is the highest and 5 is the lowest acuity level) and the admission is coded 1 and the discharge is coded 2, this is why the relationship was positive; it means that when patients have lower acuity levels 4 & 5 they are more likely to be discharged than to be admitted. Higher acuity level patients have more tendencies to be admitted.

High acuity level patients tend to be admitted more than low acuity levels, especially patients on acuity level 1-Resuscitation and 2-Emergent with an admission percentage of 90.9% and 38.4% respectively. The acuity level 4 and 5 both had the least, if not negligible, admission percentage out of their own population which represents 32.5% of the total emergency encounters, where only 0.2% of them were admitted; only 8 patients out of 3,489 Less Urgent and 1 patient out of 617 Non Urgent patients have been admitted. We can easily recommend these patients with those two acuity levels to be diverted to outpatient appointments with confidence that rarely any of them will be under significant risk. The next candidate group for the referral of patients to other hospitals would be the acuity level 3-Urgent, which has the majority of ED encounters, 7,411 cases representing 58.7% of the total emergency encounters, and only 14.5% of them were admitted. If this decision is to be made, it should be done after considering other variables and with full caution.

4.2. Patient Mode of Arrival Analysis

Out of the total 13,750 ED encounters, we had only 13,159 encounters with patient mode of arrival, the rest of the encounters were not assigned a mode of arrival. All of the admitted 1540 patients were assigned a mode of arrival.

Table 2. Admitted ED Patients to Total ED Patients Sorted by Mode of Arrival.

Code	Mode of Arrival	Admitted Patients	%	All ER Patients	%	% of Admitted to All
1	Family or Relatives	997	64.7%	8,692	66.1%	11.5%
2	Walking	216	14.0%	3,533	26.8%	6.1%
3	Wheelchair	48	3.1%	311	2.4%	15.4%
4	Stretcher	228	14.8%	246	1.9%	92.7%
5	Ambulance	30	1.9%	155	1.2%	19.4%
6	Helicopter	3	0.2%	11	0.1%	27.3%
7	Others	18	1.2%	211	1.6%	8.5%
Total		**1,540**	**100%**	**13,159**	**100%**	**11.7%**

We have seven different and nominal modes of arrival and we have two final patient statuses; admission and discharge. To test the effect of different patient modes of arrival on the status of being admitted to the hospital or discharged home, we assigned numerical values, from 1 to 7, for modes of arrival and assigned code 1 for admission and code 2 for discharge to analyze the effects and relationships. Using the ANOVA - one-way analysis of variance, the modes of arrival of the emergency patients had a statistically significant effect on their admission status. Different modes of arrival have different admission status. Here we could not calculate a correlation between the patient mode of arrival and the admission rate, since the modes of arrival are nominal categories not ordinal, they have no specific order of increasing or decreasing pattern like acuity levels or age groups. So we will have to depend on the results of the Kruskal Wallis test plus the percentage of the admitted patients out of the total emergency patients for each mode of arrival. About 93% of total emergency patients arrived either walking or assisted by a family members or a relative, while only 7% of the total emergency patients arrived on a wheelchair, a stretcher or by an ambulance. 11.5% of the patients arriving assisted by a family member or a relative are admitted to the hospital inpatient departments and only 6.1% of the patients arriving walking are admitted to the hospital inpatient departments. These two categories, with only 10% admission rate together, are good candidates for being either diverted to an outpatient clinical appointment, within 24 hours, or referred to other hospitals, taking into consideration other variables.

4.3. Patient Age Group Analysis

Table 3. Admitted ED Patients to Total ED Patients Sorted by Age Group.

Code	Age Group	Admitted Patients	%	All ER Patients	%	% of Admitted to All
1	Less than 2 Years	130	8.4%	885	6.4%	14.7%
2	2 to 5 Years	121	7.9%	1,116	8.1%	10.8%
3	6 to 13 Years	110	7.1%	1,151	8.4%	9.6%
4	14 to 18 Years	75	4.9%	557	4.1%	13.5%
5	19 to 44 Years	349	22.7%	4,723	34.3%	7.4%
6	45 to 64 Years	408	26.5%	3,306	24.0%	12.3%
7	65 to 79 Years	277	18.0%	1,632	11.9%	17.0%
8	80 and Older	70	4.5%	380	2.8%	18.4%
Total		**1,540**	**100%**	**13,159**	**100%**	**11.7%**

We have eight sequential age groups and we have two final patient statuses; admission and discharge. To test the effect of different patient age groups on the status of being admitted to the hospital or discharged home, we assigned numerical values, from 1 to 8, for age groups and assigned code 1 for admission and code 2 for discharge to analyze the effects and relationships. Using the ANOVA - one-way analysis of variance, the age group of the patients had a statistically significant effect on their admission status. Different age groups have different admission status. To test for the correlation between age and admission we used the Pearson correlation coefficient test, the age group of the patient has a weak negative but statistically significant correlation with the admission status. Since the admission is coded 1 and discharge coded 2, this is why the relationship is negative; when patients are older they are less likely to be discharged. Older patient groups have more tendencies to be admitted. Older patients tend to be admitted more than younger patients, especially patients above 65 years of age. The age group number 5 (19 to 44 years) represents the greatest percentage of patients visiting the ED (4,723 out of the 13,750 = 34.3% of the total emergency encounters) while this group has the least admission percentage (only 349 patients were admitted out of the 4,723 = 7.4%) which makes this group a perfect candidate to be diverted to outpatient appointments or to be referred to other hospitals with confidence that they will not be under significant risk of being very sick or in need of admission there, since 92.6% of them will probably be discharged home. The second best age group to be diverted and referred is number 3 (6 to 13 years) which represents 8.4% of the total emergency patients (1,151 patients) and only 9.6% of them were admitted.

5. Discussion

According the analyses of the main three variables selected, showing the effects of emergency patient acuity level, mode of ED arrival and age group on the patient hospital admission status, we can conclude that these are the three most reliable and important variables that we can depend on as indicators to design our suggested decision algorithm, shown in figure 1, to support identifying and safely diverting less risky emergency patients to ambulatory care settings or referring them, after stabilizing their medical conditions, to other hospitals in order to reduce emergency department crowding. Based on the analyses, the suggested decision algorithm will classify emergency patients into three groups; 1) 30% of emergency patients, mainly less-urgent and non-urgent acuity level patients, could be diverted to an urgent appointment in the outpatient department clinics within 24 hours to complete their treatment, after being initially checked and medically stabilized in the ED by a suggested small rapid assessment and management team. 2) 20% of emergency patients could be safely referred to other hospitals, according to the conditions set in the decision algorithm and after being initially checked and medically stabilized in the ED by the suggested small rapid assessment and management team. 3) The remaining 50% of emergency patients should be continuing their ED treatment, including mainly resuscitation and emergent acuity levels in addition to very old, very young and sick patients on the urgent acuity level. The percentage values here can be modified according to the inclusion or exclusion of conditions in the three variables used in this decision algorithm.

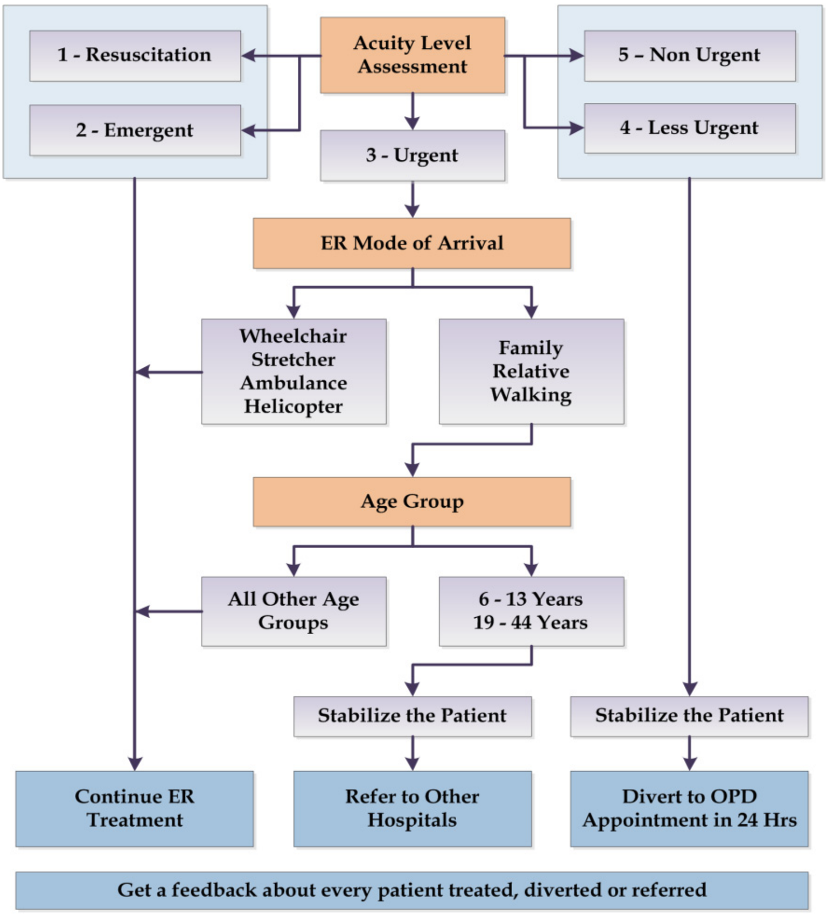

Fig 1. The Suggested Diversion & Referral Decision Algorithm (Designed by the researcher).

6. Conclusion and Recommendations

The main contribution of this work is to demonstrate a practical experience of using health analytics methods in supporting evidence based decision making, such as designing and using an evidence based emergency department diversion and referral decision algorithm which should help healthcare professionals to identify and safely divert less risky emergency patients to ambulatory care settings or refer them to other hospitals in order to reduce emergency department crowding at King Faisal Specialist Hospital and Research Center, Jeddah, Saudi Arabia. This suggested algorithm should be presented as a decision support tool that provide advice and recommendations to the emergency healthcare professionals and should not oblige them to follow the advice as a mandatory procedure, in all cases the healthcare provider is the ultimate and accountable decision maker. The compliance and adherence rate of healthcare providers to using and following the algorithm and the feedback on treated, diverted and referred patients should be recorded for future analysis and evaluation of the usefulness and effectiveness of this suggested algorithm.

References

1. Higginson, I. (2012). Emergency department crowding. Emergency Medicine Journal, 29(6), 437-443.
2. Asplin, B. R., Magid, D. J., Rhodes, K. V., Solberg, L. I., Lurie, N., & Camargo Jr, C. A. (2003). A conceptual model of emergency department crowding. Annals of emergency medicine, 42(2), 173-180.
3. Wiler, J. L., Griffey, R. T., & Olsen, T. (2011). Review of modeling approaches for emergency department patient flow and crowding research. Academic Emergency Medicine, 18(12), 1371-1379.
4. Jan, F. A., Malik, A., Manhas, A., Hakim, A., Saeed, A., & Yatoo, G. H. (2012). Patient Flow at Emergency Department–The Safety Net of Health Care System. Journal of Medical Sciences, 15(2), 132-35.
5. Hunt, K. A., Weber, E. J., Showstack, J. A., Colby, D. C., & Callaham, M. L. (2006). Characteristics of frequent users of emergency departments. Annals of emergency medicine, 48(1), 1-8.
6. Horwitz, L. I., Green, J., & Bradley, E. H. (2010). US emergency department performance on wait time and length of visit. Annals of emergency medicine, 55(2), 133-141.
7. Schneider, S. M., Gallery, M. E., Schafermeyer, R., & Zwemer, F. L. (2003). Emergency department crowding: a point in time. Annals of Emergency Medicine, 42(2), 167-172.
8. Polevoi, S. K., Quinn, J. V., & Kramer, N. R. (2005). Factors associated with patients who leave without being seen. Academic Emergency Medicine, 12(3), 232-236.
9. Forster, A. J., Stiell, I., Wells, G., Lee, A. J., & Van Walraven, C. (2003). The effect of hospital occupancy on emergency department length of stay and patient disposition. Academic Emergency Medicine, 10(2), 127-133.
10. Hwang, U., McCarthy, M. L., Aronsky, D., Asplin, B., Crane, P. W., Craven, C. K. & Bernstein, S. L. (2011). Measures of crowding in the emergency department: a systematic review. Academic Emergency Medicine, 18(5), 527-538.
11. Hoot, N. R., & Aronsky, D. (2008). Systematic review of emergency department crowding: causes, effects, and solutions. Annals of emergency medicine, 52(2), 126-136.
12. Richardson, D. B. (2006). Increase in patient mortality at 10 days associated with emergency department overcrowding. Medical Journal of Australia, 184(5), 213.
13. Schull, M. J., Vermeulen, M., Slaughter, G., Morrison, L., & Daly, P. (2004). Emergency department crowding and thrombolysis delays in acute myocardial infarction. Annals of emergency medicine, 44(6), 577-585.
14. Weiss, S. J., Ernst, A. A., Derlet, R., King, R., Bair, A., & Nick, T. G. (2005). Relationship between the National ED Overcrowding Scale and the number of patients who leave without being seen in an academic ED. The American journal of emergency medicine, 23(3), 288-294.
15. Sun, B. C., Hsia, R. Y., Weiss, R. E., Zingmond, D., Liang, L. J., Han, W., ... & Asch, S. M. (2013). Effect of emergency department crowding on outcomes of admitted patients. Annals of emergency medicine, 61(6), 605-611.
16. Madsen, L. (2012). Healthcare Business Intelligence: A Guide to Empowering Successful Data Reporting and Analytics. John Wiley & Sons.
17. Ellaway, R. H., Pusic, M. V., Galbraith, R. M., & Cameron, T. (2014). Developing the role of big data and analytics in health professional education. Medical teacher, 36(3), 216-222.
18. Kohn, M. S., Sun, J., Knoop, S., Shabo, A., Carmeli, B., Sow, D. & Rapp, W. (2014). IBM's Health Analytics and Clinical Decision Support. Yearb Med Inform, 9, 154-162.
19. Chen, H., Chiang, R. H., & Storey, V. C. (2012). Business Intelligence and Analytics: From Big Data to Big Impact. MIS quarterly, 36(4), 1165-1188.
20. Bates, D. W., Saria, S., Ohno-Machado, L., Shah, A., & Escobar, G. (2014). Big data in health care: using analytics to identify and manage high-risk and high-cost patients. Health Affairs, 33(7), 1123-1131.
21. Nugawela, S. (2013). Data warehousing model for integrating fragmented electronic health records from disparate and heterogeneous clinical data stores.