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Utilizing health analytics in improving the performance of healthcare services: A case study on a tertiary care hospital

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Summary Among the most common and chronic problems in the healthcare system worldwide is the crowding of emergency rooms (ER); leading to many serious complications. King Faisal Specialist Hospital and Research Center utilized health analytics methods to identify areas of deficiency and suggest potential improvements to ER performance. The project implemented solutions and monitored two indicators; ER length of stay (LOS), reflecting efficiency, and percentage of patients leaving without treatment, reflecting effectiveness of the ER. A retrospective analysis of 26,948 ER encounters in 2014 was done in January 2015. Analytics techniques were used to suggest process redesign based on results. Two recommendations were implemented; a Fast-Track for lower acuity ER patients and an internal waiting area, for those patients who can stay vertical and spare an ER bed. 32.8% of ER patients had lower acuity levels and less than 0.5% of them were admitted to the hospital. After implementing the two solutions, the total ER LOS was reduced from 20 h in 2014 to less than 12 h in 2016; 40% improvement. The percentages of patients left without being seen stayed around 3.5%, while the percentages of patients left before complete treatment was significantly reduced from 13.5% in 2014 to 5.5% in 2016. Consequently, the total percentage of patients left without treatment was reduced from 17% in 2014 to 9% in 2016, with 50% improvement. All other factors were the same, including numbers of ER visits, Patient Acuity Level, working staff, working hours, and the count of ER beds. Health analytics methods can be used to identify areas of deficiency, potential improvements, and recommend effective

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solutions to positively enhance ER performance. More solutions should be examined such as team triaging, patients palmar scanning, and placing a physician in triage. Additionally, more indicators should be monitored, such as the effectiveness of ER treatment—including the rates of revisits.

Introduction

Healthcare organizations worldwide are interested in achieving better quality and performance; it is important to define healthcare performance and identify quality improvement dimensions and methods. Many studies discuss how healthcare performance improvement encompasses the combined and continuous efforts of all healthcare stakeholders; healthcare professionals, patients and their families, researchers, payers, planners, and educators, to make the changes that will lead to better patient outcomes, better system performance and better professional development [1]. Many criteria and measurable attributes can define healthcare performance and quality, such as safety, effectiveness, efficiency, availability, accessibility, timeliness, and equity. This is why healthcare professionals and organizations must take into account patient preferences as well as social preferences in assessing and assuring quality [2]. Among the most common and chronic problems in the healthcare system worldwide is the crowding of the emergency room; leading to many serious consequences and complications. This problem needs to be addressed with more innovative and unconventional solutions [3].

Emergency room crowding

Crowding in emergency rooms (ER) and the impaired performance of this essential service has become a major concern for both healthcare professionals and researchers. ER impaired performance is becoming a major barrier to receiving effective, efficient, and timely emergency care. Patients who present to the ER face long waiting times to be treated and those under treatment might even face longer treatment times until they are admitted to the hospital or discharged home [4]. Some researchers analyzed ER crowding and classified its related factors into three interdependent components: input factors, throughput factors and output factors [5]. Other researchers studying ER length of stay (LOS) divided this key performance indicator into three intervals; waiting time; which is the interval from patient's arrival to the ER until he or she is seen by an ER physician, treatment time; from starting the examination by the ER physician until a decision is made, whether to admit the patient to the hospital or to discharge them home, and boarding time; from making the decision of admission for some patients until they are physically moved to an inpatient hospital bed [6].

Using these conceptual models we can work on developing strategies and solutions to decrease ER crowding and improve performance. The problem of inadequate staffing, due to lack of physicians or nurses, low ER physicians and nurses' productivity, low efficiency of ER staff, and shortages of treatment areas are commonly studied throughput factors that may cause ER crowding and prolonged LOS [7]. Lower staffing levels or productivity of physicians and triage nurses predisposed patients to wait longer for care [8]. Competency of attending physicians in ER, in terms of skills and efficiency, and lack of, or slow, responsiveness of ER nurses has been associated, in many studies, with patients leaving without being seen or leaving before complete treatment. The use and/or delays of the ancillary services, including lab, radiology and other procedures, usually prolong the ER length of stay [9].

This study describes in details the processes implemented in the ER performance improvement at King Faisal Specialist Hospital and Research Center, Jeddah, Saudi Arabia. The executive management of the medical and clinical affairs of the hospital decided to utilize health analytics methods to identify areas of deficiency and suggest potential improvements then implement solutions and finally monitor ER using two main key performance indicators; the ER LOS for ER patients, reflecting the efficiency of performance [10], and the percentage of patients leaving the ER without treatment, including both patients who left without being seen and those who left before complete treatment, reflecting the effectiveness of ER performance [11].

What is health analytics?

Health analytics has emerged as an important area of research and application, reflecting the magnitude of influence of data and information based management on solving problems and making decisions in contemporary healthcare organizations over the past two decades. Typically, hospitals and other healthcare organizations have been implementing descriptive health analytics to medical data. Using queries; reporting tools and technologies, healthcare professionals usually collect data on the performance of different healthcare services. More recently, healthcare data warehouses collect different data types from different systems and sources to create operational healthcare dashboards, strategic scorecards and data stores [12]. The main objectives of health analytics are to explore performance gaps and to suggest best strategies and recommendations to solve them. Health analytics should help healthcare professionals and organizations monitor performance on an ongoing and regular basis and help them to troubleshoot bad performance and identify the root causes for problems. Health analytics help users to design, develop, implement, and evaluate different key performance indicators which can enhance continuous monitoring, identify reasons for performance deviations, and eventually improve performance [13].

Health analytics is a business driven term that encompasses a wide spectrum of aspects and dimensions of business intelligence applications and big data analysis. This new concept is based mainly on the availability and accessibility of data and information pooled through the good integration and interoperability of a wide range of systems and tools such as hospital information systems, electronic medical records, clinical decision support systems, and other specialized medical systems [14]. In all types of industries and all over the world, senior leaders of business organizations, as well as healthcare organizations recently, are always eager to know whether they are getting the full value from the massive amounts of data and information they already have within their organizations. New technologies are gathering even more data than ever before, yet many organizations are still looking for better ways to obtain value from their data to be able to sustain and compete in the marketplace. Their queries about how best to achieve value persist. Knowing what happened and why it happened is no longer enough. Organizations need to know what is happening now, what is likely to happen next and what actions should be taken to get the optimal results [15].

Types of health analytics?

The discipline of health analytics is now moving from the operational analytics level into the higher level of strategic analytics and from the simple descriptive analytics toward the more sophisticated diagnostic, predictive and prescriptive health analytics. In the very near future, hospitals and healthcare organizations that used descriptive and diagnostic analytics, to collect data on the performance of different healthcare services, will utilize the more advanced level of predictive and prescriptive health analytics to choose among different feasible alternatives. The most advanced or sophisticated type, discovery health analytics, typically supports users who are trying to discover new scientific facts. To do that, the analysis requires huge volumes of data with plenty of detail to discover new knowledge and relationships [16]. In light of studies discussing and describing different types of analytics we notice that health analytics can be classified into four main types; descriptive, diagnostic, predictive, and prescriptive analytics [17—24]. Other researchers add a fifth type to these four; the discovery analytics [16,25]. Fig. 1 describes the various types of health analytics.

Descriptive analytics is the easiest and simplest level—describing the data as is with no more inferential analyses, explorations, or correlations between data variables or information elements. Descriptive analytics is used to study different healthcare decisions and their implications on services performance, clinical outcomes and results [26]. The presentation of data is usually in simple graphs and tables that show hospital occupancy rates, discharges, average length of stay and many other healthcare services related indicators. Descriptive analytics uses a lot of data visualization to help answer specific questions or identify patterns of care, thus providing a broader view for evidence-based clinical practice. They allow organizations to manage real-time, or near real time data, what can be called operational content, and capture all patients' visual data. This method can identify previously unnoticed patterns in patients, for example, patterns related to hospital readmissions, and support a better balance between capacity and cost [15].

Diagnostic health analytics works on answering why something happened. It needs extensive exploration and directed analysis of the existing data using tools such as visualization techniques in order to discover the root causes of a problem and help

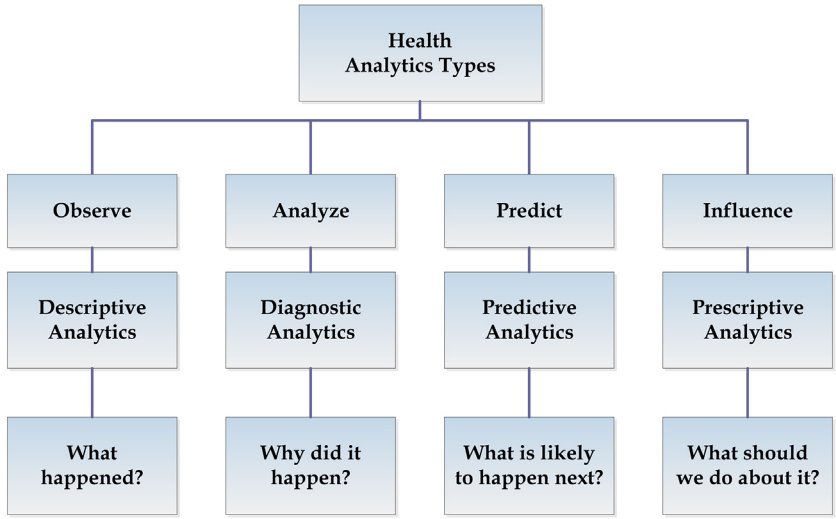

Figure 1 Types and functions of health analytics [16,22—26].

users realize the nature and impact of the problem. This may include better understanding the impact of input factors and operational processes on performance indicators. For example, increased waiting time while providing certain healthcare services could be tracked down to any or all of multiple influential factors including patient related, provider related, or organization related factors [22—24].

Predictive health analytics work in a more complex way than simple descriptive analytics; it focuses on the use of information rather than simple data. It examines existing past readings and indicators to predict future performance. A pharmacist may need to expect the amounts of a drug to stock in anticipation of an outbreak of an epidemic disease. Certain changes or outcomes could be predicted and evaluated based on the huge amounts of previously collected data, such as patients length of stay; patients who might choose surgery; patients who likely will not benefit from surgery or would have complications [27].

The role of prescriptive health analytics comes into action when decisions have to be made regarding a wide range of feasible alternatives, it enables executives not only to look into consequences and expected results of their decisions and see the opportunities or problems, but it also provides them with the best course of action to take advantage of that foresight in a timely manner. The success of prescriptive analytics depends mainly on the adoption of five basic elements; utilizing hybrid data, including both structured and unstructured data types, integrating predictions and prescriptions, taking into account all possible side effects, using adaptive algorithms that can be tailored easily to each situation in addition to the importance of robust and reliable feedback mechanisms [28].

We have a fifth type of health analytics; the discovery health analytics, which utilizes knowledge more than information, or what can be considered as wisdom; to use data and information in discovering new medications or alternative treatments or detect new symptoms, signs or diseases or unknown side effects [29]. Hospital information systems and electronic medical records provide horizontal clinical information at the individual level. Analyzing patient level data can yield population level inferences and results, such as the strength of association between medical product exposure and subsequent outcomes. It is important to understand the value of knowledge discovery methods and the challenges in extracting clinically relevant knowledge from big medical data [25].

Materials and methods

King Faisal Specialist Hospital and Research Center in Jeddah planned this study and performance improvement project on two phases; the first phase was to perform a retrospective analysis of all available ER data, which was conducted in early January 2015. The study data was retrieved from the data warehouse system of the hospital including all data elements of all emergency encounters of the last year; 2014. A total of 26,948 encounters with valid data were retrieved. Descriptive, diagnostic and prescriptive analytics techniques were used in the form of identifying and calculating different

ER data variables and testing for any relationship between those variables and the admission status probability of the patient to determine which variables could be used to support executive management decisions regarding suggesting changes or recommending process redesign in order to improve the ER performance. Variables definitions are in the next results section.

The second phase of the study started in mid-January 2015, immediately after getting the full results of the analysis of the ER data and a preliminary vision on the prescribed solutions. This phase included implementing two suggested recommendations; a Fast-Track for lower acuity level ER patients; dedicating 20% of the ER bed capacity, in addition to an added internal waiting area for those patients who can stay vertical instead of occupying an ER bed. Two consultant family medicine physicians were assigned to manage those patients with lower acuity levels according to the currently used Canadian Emergency Department Triage and Acuity Scale (CTAS), which has five acuity levels from 1 to 5; decreasing in severity and composed of Resuscitation, Emergent, Urgent, Less Urgent and Non Urgent levels [30]. The main objective was to assign ER physicians only to patient cases with higher acuity levels; CTAS Levels 1—3, and in the same time to reduce the demand for other resources by less acute patients, without any change in the manpower, working hours or in the total number of the ER beds or capacity. The internal waiting area was dedicated to less acute patients who can stay vertical, and to spare ER beds to more acute patients. The ER performance was then monitored for any potential improvement using two main indicators; ER LOS, and related intervals, and percentages of patients leaving ER without treatment. The first indicator reflects mainly the throughput and efficiency of work processes while the second reflects the input process and patients' crowding. Both are interrelated and they have mutual effects on each other, when crowding and input increase the throughput and workflow will slow down and ER LOS will be longer, and on the other hand, when the throughput processes improve the intake will also improve, waiting time will decrease and percentage of patients leaving ER without treatment will be reduced.

Results

After being retrieved from the hospital data warehouse system, ER data was cleaned and validated then processed and analyzed; exploring different variables that could predict any significance, deficiency or room for potential improvement. Eight main variables could be identified for evaluation using health analytics; these were: Patient Gender (male or female), Age Group (8 age groups are used; less than 2 years old, 2—5 years, 6—13 years, 14—18 years, 19—44 years, 45—64 years, 65—79 years and 80 years or older), Nationality (Saudi & Non-Saudi), Patient Acuity Level (following the CTAS—Canadian Emergency Department Triage and Acuity Scale; 1—Resuscitation, 2—Emergent, 3—Urgent, 4—Less Urgent and 5—Nonurgent), Patient Mode of Arrival (by ambulance, carried by people, assisted by family or relative, police custody, on a stretcher, on a wheel chair and walking), Patient Discharge Destination (dead, discharged home or admitted to hospital), Day of ER Encounter (day of the week) and Session of ER Encounter (morning, evening and night). Three variables only had statistically significant influence on the admission rates of ER patients to the hospital inpatient departments and services; those 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, where the most influential variable among these three was the Patient Acuity Level. The acuity level of all ER patients during 2014 were analyzed and categorized, counting total patients visiting the ER in each acuity category and number of patients admitted from ER to inpatient departments and services in each category and the percentage of admission on each of those categories. The results are summarized in Table 1. As the acuity level goes down; become less severe, the percentage of admission becomes less, which is logical. About a third of the cases, 32.8%, were of the acuity levels CTAS 4 and 5 and 0.9% of those patients were eventually admitted to the hospital.

The explanation of this, after investigation, was that many eligible patients might have problems accessing their primary care or long waiting for an outpatient appointment, so they come to the ER instead of their clinic appointments when they feel sick. The decision of the executive management of the hospital was to redesign part of the ER into a Fast-Track area that contained 20% of the ER bed capacity and to dedicate this area to receiving only patients of the least two acuity levels; CTAS Level 4—Less Urgent and CTAS Level 5—Nonurgent and in the same time to dedicate two consultant family physicians, who worked primarily in the ER, to manage only patients of these two acuity levels on a 24 h basis, in addition to adding an internal waiting area for those patients who can stay vertical instead of occupying an ER bed, and then to monitor the performance of the ER over the next year after

Table 1 Patients admitted through ER compared to total ER patients sorted by Patient Acuity Level according to the CTAS during 2014.

Code	Acuity level	Admitted patients	%	All ER patients	%	% of admitted to all
1	Resuscitation	95	2.6%	145	0.5%	65.5%
2	Emergent	913	24.8%	2470	9.2%	37.0%
3	Urgent	2636	71.5%	15,489	57.5%	17.0%
4	Less Urgent	38	1.0%	7575	28.1%	0.5%
5	Non Urgent	5	0.1%	1269	4.7%	0.4%
Total		3687	100%	26,948	100%	13.7%

this major redesign change. Starting from January 2015 the ER performance was monitored for both detailed ER LOS and percentage of patients leaving ER without treatment, including both categories of patients who left without being seen and those who left before complete treatment.

To study the first performance indicator; the detailed components of the ER LOS were monitored; six indicators were reported; (1) the average of Arrival to Triage interval measured in minutes, (2) Triage to ER Bed interval measured in minutes, (3) Bed to Doctor interval measured in minutes and (4) Doctor to Discharge interval measured in hours, in addition to monitoring (5) the average of ER waiting time, including the first three intervals, from patient arrival till seen by the ER physician measured in minutes and (6) the total ER LOS measured in hours. Table 2 shows a comparison of the four quarters of 2014, four quarters of 2015 and the first quarter of 2016, which revealed that the average of Triage to ER bed interval was significantly reduced from around 95 min in 2014 to only 22 min in 2016 and the average of ER waiting time was also significantly reduced from 2.5 h in 2014 to only 1 h in 2016. Treatment time; Doctor to Discharge interval, shows also a significant reduction from 17.5 to 10.8 h and the total ER LOS is now reduced from around 20 h in 2014 to less than 12 h in 2016, which is a 40% improvement. Fig. 2 shows the comparison of the ER waiting time and Fig. 3 shows the comparison of the ER LOS through the 9 quarters.

N.B. arrival is the ER patient check-in to the service and registering his/her arrival using medical record or ID number. Triage is the process of classifying the severity and assigning the patient an acuity level according to nurses' assessment of vital signs, pain level and physical condition to prioritize treatment. Assigning an ER bed is the check point at which a bed in the ER is assigned to a patient. Discharge is the process of sending the patient outside the ER, whether to be discharged home or to be discharged from ER and admitted to the hospital. Total ER LOS is the total time interval or duration elapsing from the first arrival of the patient to the discharge from the ER.

Looking at the second performance indicator; the ER patients who left without treatment, as illustrated in Table 3 and Fig. 4, we find that the

Table 2 ER LOS and related intervals (2014, 2015 and first quarter 2016).

Quarters	Arrival to triage mean (min)	Triage to bed mean (min)	Bed to doctor mean (min)	ER waiting mean (min)	Doctor to discharge mean (h)	ER LOS mean (h)
2014—Q1	14	93	33	140	18.3	20.7
2014—Q2	10	73	30	113	17	18.9
2014—Q3	10	97	31	138	16.5	18.8
2014—Q4	10	123	35	168	18.4	21.2
2014	**11**	**95**	**32**	**139**	**17.5**	**19.9**
2015—Q1	10	75	30	115	16	17.9
2015—Q2	11	39	29	79	11.6	12.9
2015—Q3	11	33	27	71	9.9	11.1
2015—Q4	14	38	34	86	12.7	14.1
2015	**12**	**44**	**29**	**85**	**12.2**	**13.6**
2016—Q1	14	22	26	62	10.8	11.8
2016	**14**	**22**	**26**	**62**	**10.8**	**11.8**

Bold values indicates collective figures for the whole year (4 quarters together).

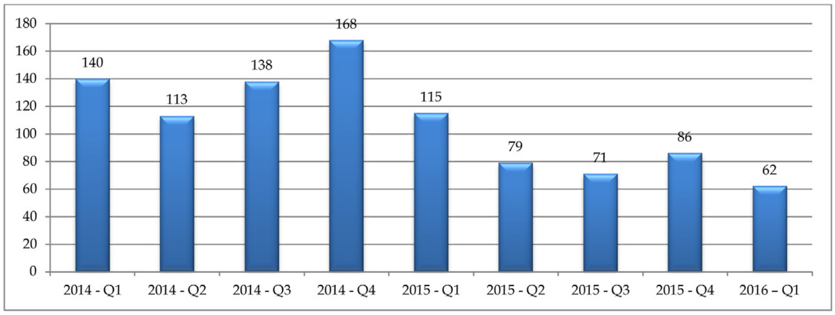

Figure 2 ER waiting time in minutes (2014, 2015 and first quarter 2016).

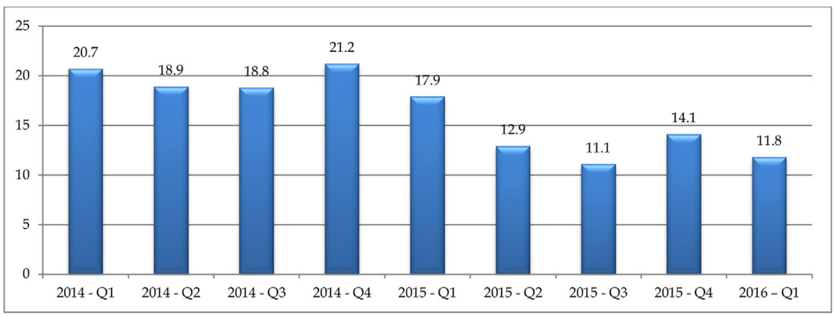

Figure 3 ER LOS in hours (2014, 2015 and first quarter 2016).

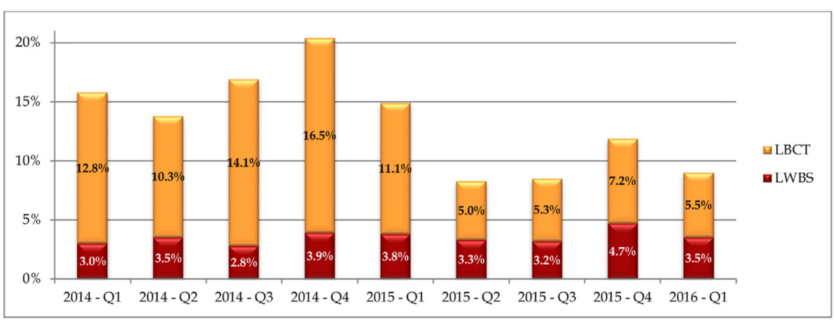

Figure 4 Percentages of LWBS—left without being seen and LBCT—left before complete treatment (2014, 2015 and first quarter 2016).

Table 3 ER total patients, numbers and percentages of LWBS—left without being seen and LBCT—left before complete treatment (2014, 2015 and first quarter 2016).

Quarters	Count	LWBS	%	LBCT	%	LWBS + LBCT	%
2014—Q1	7778	233	3.0%	995	12.8%	1228	15.8%
2014—Q2	6001	209	3.5%	621	10.3%	830	13.8%
2014—Q3	6812	189	2.8%	958	14.1%	1147	16.8%
2014—Q4	7480	290	3.9%	1235	16.5%	1525	20.4%
2015—Q1	7005	269	3.8%	778	11.1%	1047	14.9%
2015—Q2	7110	238	3.3%	352	5.0%	590	8.3%
2015—Q3	7611	240	3.2%	400	5.3%	640	8.4%
2015—Q4	8221	389	4.7%	596	7.2%	985	12.0%
2016—Q1	8407	297	3.5%	460	5.5%	757	9.0%

percentages of patients left without being seen did not significantly change but stayed around 3.5%, while the percentages of patients who left before completing treatment was significantly reduced from an average of 13.5% in 2014 to only 5.5% in 2016. Consequently, the total percentage of patients left without treatment was significantly reduced from 17% in 2014 to only 9% in 2016, which is almost a 50% improvement. To make sure that this significant improvement is due to the implemented changes, and not due to a change in the workload; or in the numbers of patients visiting the ER or in their acuity levels, a statistical analysis was done and found that the numbers of patients visiting the ER over the last quarter of 2015 and the first quarter of 2016 had actually significantly increased, which should have affected the two indicators negatively not positively, while the acuity level averages were the same for all quarters. The number of working staff; physicians and nurses, the working hours and the total number of ER beds were the same, which indicates that the achieved improvement was solely due to the two implemented redesign changes made in the workflow of the ER.

Discussion and conclusion

Timeliness is considered an essential quality indicator for many healthcare services, especially for emergency conditions [31]. The Institute of Medicine defines six domains of quality of care: safety, patient-centeredness, timeliness, efficiency, effectiveness, and equity. ER crowding is associated with increased mortality or complications and morbidity in patients with time sensitive conditions or those who leave without treatment. At least two domains of quality of care, safety and timeliness, are compromised by ER crowding [32]. Many studies investigated the association between increased hospital occupancy rates and the increased ER crowding and prolonged ER LOS or increased percentage of patients leaving without treatment [33,34]. Our study examined the utilizing health analytics methods; mainly descriptive, diagnostic and prescriptive analytics, in identifying areas of deficiency, potential improvements and recommending effective solutions to positively enhance ER performance and succeeded in this task. Our experience shows that data and analysis can be used for process improvement through identifying variables, conducting measurements, and exploring areas and methods of potential improvement. Our health analytics methods identified the importance of classifying ER patients into higher and lower acuity levels and managing them separately; dedicating ER resources only to higher acuity levels through managing lower acuity patients in a special Fast-Track, in addition to adding an internal waiting area for those patients who can stay vertical to spare ER beds for higher acuity patients.

This study has two main limitations; (1) it examined the effect of only two solutions on the performance of the ER—implementing a Fast-Track area for low acuity ER patients and adding an internal waiting area. (2) It examined the improvement of ER performance along only two indicators.

More solutions need to be examined for their effects on improving ER performance, such as team triaging, palmar scanning for patients or placing a physician in triage [35,36]. Additionally, in future research, more indicators should be monitored, such as effectiveness of ER treatment, including rates of revisits to ER department or patient satisfaction.

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