Leveraging ED Efficiency with Machine Learning

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Abstract

Emergency department (ED) crowding is characterized by the shortage of medical resources and the prolonged patient waiting time. Here we analyzed the emergency department from a systemic point of view. We summarized the possible leverage points in the ED system, and reviewed previous studies targeting these critical points. In addition, we developed a decision forest-based machine learning classifier, which can be used for patient assessment. Our simulation showed adding this classifier into the ED system greatly reduced patient's waiting time. Our study suggested machine learning as a promising solution that leverages the ED efficiency at multiple points.

1 Review

1.1 Background

The emergency department provides medical care to the patients with urgent needs, severe pain or life-threatening conditions, especially when the hospitals are closed during weekends/holidays or at night. Every year, hundreds of millions of individuals entered the emergency department seeking urgent medical assistance. In 2011, CDC reported 136 million ED visits in the US[8], while Canadian Institute for Health Information (CIHI) showed an annual 16 million ED patients in 2012[9]. The amount of ED patients has been steadily increasing all over the world. From 2010 to 2015, Canadian ED visits increased at a speed of 1 million per year. Some countries like France were even faced with an increase of over 50% within 10 years [10]. Associated with the growing patient population is the longer waiting hours. ED waits before the care can range from a few minutes to more than a day. Based on the CIHI data of 2010-2011, the median waiting hours was around 4 hours in Canada, with 10% of patients waited for more than 8 hours [9].

The extreme long waiting reflects the huge imbalance between ED services and the patient's' demands, which is defined as ED overcrowding [6]. Despite increasing political, and public attention, this issue continues to rise in severity [4, 5]. ED overcrowding has been associated with negative patient outcomes, including low patient satisfaction, high risks of death, and patients leaving without being seen [11,12,13,14]. Using prospective cross-sectional studies and retrospective cohorts, Pines and his colleagues reported that long waiting time resulted in compromised medical service, lower patients' satisfaction and adverse outcomes for cardiac patients [13]. Cha group showed a significant higher mortality rate among pediatric patients who experienced ED crowding [14]. Richardson group reported a greater 10-day mortality of patients, who were exposed to crowding before the hospital admission [15]. Asaro conducted an observation study, showing that 14,170 patients left before being seen due to the long waiting time [16].

ED crowding has attracted significant amount of public attention. Many studies have been conducted to reduce the waiting time. In this study, we want to investigate the ED crowding from a systemic perspective. We will first analyze the ED as a system and identify the potential leverage points in the system. We will evaluate the effects of changing some of these leverage points in computational simulation. By studying the ED system, we hope to provide new insights the ED crowding problem.

1.2 Leverage points in the ED system

The ED crowding has been increasing since the recent decades. The politics, the health administrative, the research community and the general public have been trying to identify the key spots in an intuitive manner. From a system thinking perspective, these "key spots" play as the leverage points in the system – the points where small changes may lead to large improvement in the whole system. Here we will summarize the potential leverage points according to Donella Meadows' "12 places to intervene in a system" [18], and review the changes that have been proposed at some of the points.

Donella Meadows [18] frames a system into the following basic diagram (Figure 1). In the center is the state of the system, which can be interpreted as the quantity of importance. In our case, the state of the system is the ED efficiency. We have a goal to keep it at certain level - not too low to cause prolonged waiting, and not too high that it occupies unnecessary medical and financial resources. The discrepancy between the perceived ED efficiency and the expectation drives the feedbacks into the controls of the inflows (e.g. purchases of equipment, hiring of nurses and physicians) and the outflows (e.g. patients who consume ED resources, breakdown of equipment, personnel retirement), and thus adjust the system towards the targeted state.

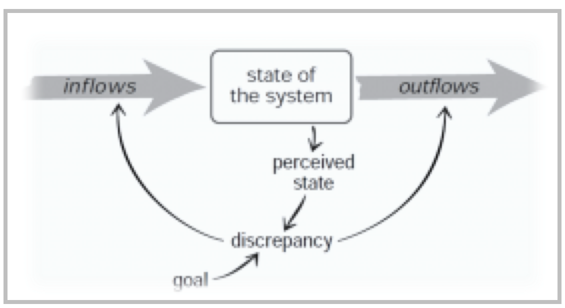

Figure 1: Donella Meadows' model of system (source: [18])

1.2.1 Constants, parameters, numbers

One of the most widely discussed parameters in the health system is the amount of annual investment. Taking Canada as an example, it is one of the very few countries that provide free basic health care. Since the hospital do not charge their patients, the costs are largely covered by income tax [19]. The total tax amount, the percentage of tax invested in public health, and the percentage of ED budget out of the total health expenses are the frequently debated by the politics and the public. It is straightforward to understand the important of these numbers in adjusting the capacity of ED system.

Another important parameters is the volume of patient flow [20]. However, this number can be hardly tuned, unless either the overall population decreases, or the mindset about ED usage is changed. We will discuss the possible change of mindset in "the mindset or paradigm out of which the system arises" in the following sections.

1.2.2 The sizes of buffers and other stabilizing stocks, relative to their

flows

When the equipment breaks down, new ones are purchased, if the budget allows. When the nurses quit their jobs or retire, new medical graduates are hired by the department. Despite the dynamic inflow and outflow, existing ED facilities form the buffers of the system at a given time. Some research studies argue that the current buffers, especially the stocks of equipment and staff are too small, and hence play as the limiting factors for ED crowding. Wong's group observed that the limited bed capacity led to prolonged waiting time in the general internal medicine [21]. Duguay's simulation model identified the size of medical staff team as a leverage point [1]. Another simulation study suggested that increasing MRI and CT scan might reduce ED crowding [17]. Lack of buffering capacity results in frequent conflicts between demand and supply. Unfortunately, the buffer sizes are usually determined by the funding availability, and cannot be easily changed in reality.

1.2.3 The structure of material stocks and flows

Patients in ED require different resources and have different levels of acuity. One high impact solution to ED crowding is to restructure ED flow by adding fast tracks for patients with low acuity [21, 22]. The underlying rationale is that patients with low acuity usually require less examination and treatment time. Clearing these patients from the system quickly by fast tracks significantly saved 25% time for patients with minor issues, without negatively affecting severe patients [22]. Many hospitals have adopted this new design, and successfully reduced patient waiting time to some level [23].

1.2.4 The lengths of delays, relative to the rate of system change

There are multiple levels of delays in the ED and the whole health system. There is delay between the patient call the ambulance and the time he or she is sent to hospital [24]. There is delay between the moment a patient walks into the ED room and the time he or she receives medical care. There is also delay between an examination prescription and the time when the scanning device become available. Those observable delays are commonly rooted in the lack of buffering. Other delays may be caused by the nature of the system's working mechanisms. Draeger revealed the delay exists between the time when one physician shift finishes the last visit, and the time when the next shift starts visit his/her first patient [25]. The delay is caused by cleanup and transition work, and results in a very low patient visiting speed at the junction of two shifts. The author didn't provide any solution, but mentioned that the physician's' behavior might need to be taken into account during further studies of ED system.

1.2.5 The strength of negative feedback loops, relative to the impacts they are trying to correct against

ED and the related issues form a complex system with multiple feedback loops. Patient's' arrival increases ED crowding, especially when the medical resources are limited. ED crowding leads to lower care quality, including longer waiting hours, shorter assessment time by nurse and physicians, and patients receiving medical care in the hallway [26]. Poor care quality results in negative outcomes, which provokes anger and frustration. The negative emotions of patients, the excessive workload, the miscommunication under pressure and the lack of team collaboration together stress out ED staff, and lower ED efficiency in short term [27]. On the other hand, in the long run, expression of the frustration in the media attracts public attention, which pushes government to allocate more budget into the health system, and attracts academic interests in solution development. Increased government investment in emergency department allows hospitals to purchase additional medical equipment, such as the examination device or test reagents, and to expand their ED team. Investment in other part of the health system, such as preventive medicine, decreases the number of sudden sickness and reduces patient visits in ED. In addition, researchers develop new technologies and better design of ED structure (patient flow, room organization etc.). Increase in medical resources, decrease in the patient number, and the invention of new tools and designs tend to collaboratively alleviate ED crowding.

The strength of the negative feedback loop partially depends on the amount of attention from the government and the public. It can be distracted by other social problems, such as safety, education, care for kids and the elder, and fundamental constructions.

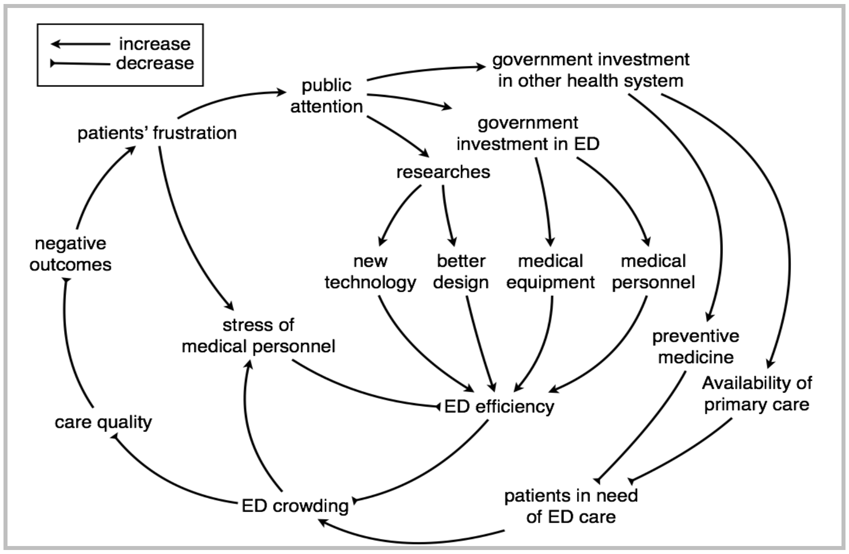

Figure 2: Feedback loops in ED system

1.2.6 The gain around driving positive feedback loops

ED Nurses and physicians are often reported to experience high level of stress [28]. The stress can be attributed to heavy workload, lack of staff and resources, poor management support and violent patients [29, 30, 31]. Prolonged exposure to the highly stressful working environment may cause burnout, which is characterized by depersonalization, exhaust of emotion, fatigue and threatened self-imaging [32]. Stress and burnout have an adverse impact on ED efficiency in terms of decreased performance, lack of care, conflicts among the staff, and high staff turnover [31, 33].

Many studies suggest intervening this positive feedback loop as protection of the staff wellbeing, which may ultimately improves the working environment and efficiency. Most of the suggestions are preventive training to the staff, such as the wellness education and cope style training [34, 35].

1.2.7 The rules of the system

Many ED rules can be changed to improve efficiency and reduce crowding. These rules include who is supposed to give triage assessment, what should be the triage assessment criteria, whether the processes of assessment and treatment should be coupled or separated, how the boarding policy is implemented, and etc. In Khurmer's simulation study, security guard idles for most of the time, while triage nurses are always highly occupied. He suggested that the policy can be changed that security guards should be considered as a backup for patient liaison [4]. Ashour's group invented a new triage algorithm to reduce assessment bias and mistakes in decision making [36]. Davies' simulation study compared two policies - "See and Treat" versus "See" and "Treat", and showed that "See" and "Treat" policy, which separates the two processes, reached higher patient throughput and lower cost [37].

One successful example of rule changing is Britain's "Four-hours rule", which demands 96% of patients to be properly handled within four hours of arrival. The policy is monitored by the government, and the hospital leaders take responsibility if the target is not met [39]. This new rule significantly improved the inpatient planning without too much increase in cost, and was followed by other countries including Australia, Canada and New Zealand [40].

Changing rules can be an effective leverage point to smooth the whole system. However, comprehensive real life analysis is still needed in addition to the simulation studies, before any of the above policies can be put into practice. Moreover, how to make sure new policies are fully implemented is another difficult problem. Legislation and the collaboration among the leaders of the health system may be required to guarantee the full adoption of new rules [38].

1.2.8 The mindset or paradigm out of which the system — its goals, structure, rules, delays, parameters — arises

According to the definition by CIHI, "Emergency departments (EDs) are intended to provide care in emergency and life-threatening situations, to offer urgent medical attention for serious conditions and injuries, and to provide access to a wide range of health care specialists and diagnostic equipment" [41]. However, different mindset drives people to the ED, even if the primary care clinics are more suitable for their needs. In 2013, 41% adults in Canada reported to visit ED within 2 years, while over 20% of the visits were actually avoidable. One reason of the non-urgent visits is rooted in the nature of public health system. In Canada, health care is considered as a basic human right, and is sponsored largely by the government [41]. However, it also exhibits the low efficiency that is observed in many public systems: Canadian patients have the longest waiting time to see their family doctors, not even mention the appointments with the specialists [42]. Without timely access to primary care, patients and their worrying relatives naturally see the ED as a fast and convenient alternative [43, 44]. Some patients may even go to the ED to avoid the long waiting time of referral [45]. This mindset may be changed by identifying the underlying cause for misuses, providing patient education on the appropriate use of ED, extra charges to inappropriate use of ED, and most importantly, improving the efficiency of primary care in the health system [46].

2 Simulation Study

In a previous study, we developed a decision forest-based machine learning classifier (MLC) for ED assessment. This MLC is an algorithm taking multiple measurement of a patient as inputs and predict whether the patient should be admitted to hospital. It considers over 20 different parameters, including gender, age, allergy, family history and several tests on the patients' medical records, and it is designed to be able to deal with missing data. It can also be used to predict the acuity at triage given a different set of inputs. Using machine learning classifier for triage and assessment would be a cost-effective complement to the nurses and physicians. A combined use of machine and staff equals to the expansion of the staff buffering size. Moreover, machine needs no rest, and hence eliminates the "delay between shifts". Hence, we hypothesize that our machine learning classifier can be a powerful leveraging game changer. We expect that our machine learning classifier may significantly reduce the patient waiting time by expanding the medical resource buffer, restructuring the interaction with patients, and reducing the delays.

2.1 Simulation system description

Part of the data used in this study is based on the administrative data of The Dr. Georges-L. Dumont Regional Hospital [1], a Canadian community hospital in Moncton. The ED is responsible for triage and basic assessment of patients arriving at the hospital, and the ED is open 24 h a day. At The Dr. Georges-L. Dumont Regional Hospital, there are 6 beds and 5 medical physicians in ED at any given time of a day.

There are also nurses for triage and registrations. In this study, we regard physicians and nurses as medical personnel to decrease the model complexity. Similarly, we do not include the shift of medical personnel into account to have a better focus in a larger picture.

2.1.1 Patient flow

The patient arrival is based on a schedule derived from the data that changes hourly. An exponential distribution is used to model the hourly patient arrivals. Previous studies indicated that patient arrivals increase from 0800h to 1300h of a given day and drop after 1600h [1]. Figure 3 could confirm this observation because it shows the arrival data from a study on 163 Canadian hospitals [2].

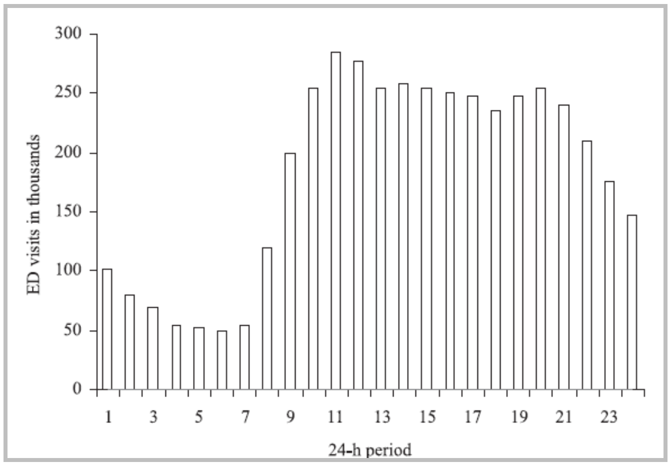

Figure 3: Patient arrival pattern over a 24-h period for 163 Canadian hospitals (Source: [2])

2.1.2 Triage code

Triage code is important in ED and patients are triaged into one of five categories [1] according to the Canadian Triage and Acuity Scale (CTAS). Level one is the most severe and level five is the least urgent. We redesign the triage codes into three levels: acute, subacute and minor. Acute patients have the highest priority in triage and assessment, and minor patients have the lowest priority though.

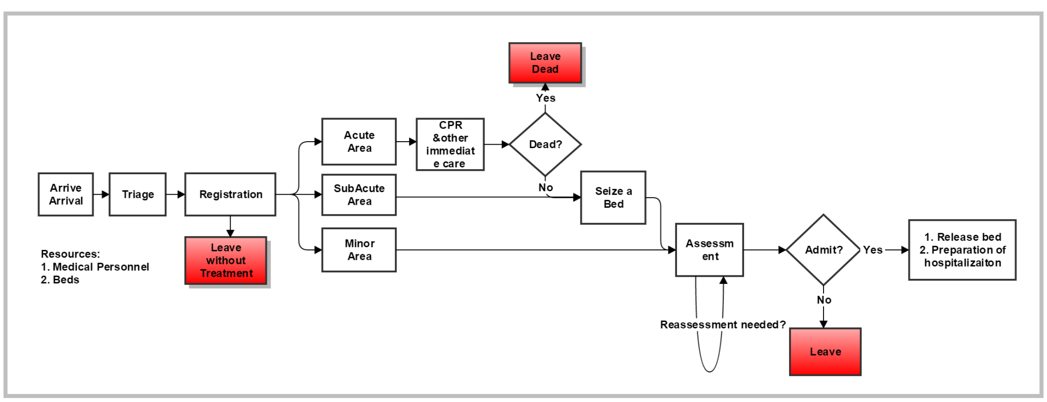

Figure 4: Hospital ED patient flowchart

2.1.5 Process Overview

Figure 2 presents a typical patient flow through ED. A regular patient enters the system and picks a number to wait for the triage and registration [17]. During this process, some patients may choose to leave without been seen. The people deciding to wait will be then directed to different areas based on the condition.

If a patient is found to be in critical condition, he is moved to acute area and cardiopulmonary resuscitation (CPR) or other resuscitation methods will be performed. According to previous studies [2], 0.1% of the ED patients may be dead and leave ED. Patients in both acute and subacute area need to get a bed and then all patients (including minor patients) will be directed to the assessment area. In this area, medical personnel would check patient's' condition and decide the admission to ED. Some patients may need additional examination/reassessment, e.g. lab tests, if necessary. After the second assessment, the patient may be discharged or transferred to admission.

2.2 Proposed methodology

In this study our goal is to improve the care process by reducing patient waiting time, decreasing the patient length of stay in ED, and improving medical personnel's efficiency. Several scenarios are designed for different variable setting and the models are built using the Arena Simulation Software, version 14.0. We want to understand how to use MLC in the system to improve the scenarios. There are four main steps of the proposed methodology.

1. Collect data and extract probability distribution.
2. Verify simulation models and discuss limitations.
3. Use MLC in multiple positions of the system.
4. Evaluate the simulated models.

2.2.1 Data collection and input analysis

The probability used in this model is based on the data from Duguay's studies on Canadian ED systems [1]. Duaugy's data is derived from the hospital administrative database with information on each patient that arrives in the ED at Dr. Georges-L. Dumont Hospital in Moncton. In the first step, the data of ED patient including patient arrival time, triage time, and assessment time, is directly extracted from [1]. Then, CPR time, Dead Rate, Leave without Seen Rate, Reassessment Rate and Admit Rate are from [2,3]. TRIA, POIS are abbreviation for Triangular and Poisson respectively. Table 1, 2 and 3 show the detailed specifications of the model.

Resources	**Number of resources**
Medical Personnel	5
Beds	16

Table 1: Number of resources

Process	**Statistical distributions**
Triage	POIS(6)
Registration	TRIA(3,5,7)
CPR	UNIF(11, 45)
Assessment	TRIA(25,30,40)
Reassessment	TRIA(6,10,15)

Table 2: Fitting statistical distributions (in minutes)

Events	Statistical distributions
Leave without Seen	3.2%
Leave Dead	0.1%
Reassessment	23%
Admitted	10.8%
Triage Result	Acute (7%) Subacute (72%) Minor (21%)

Table 3: Rate and probabilities of events

According to the data analysis, the patient arrival can be model as a schedule. Figure 5 shows the average number of patient arrivals by hours.

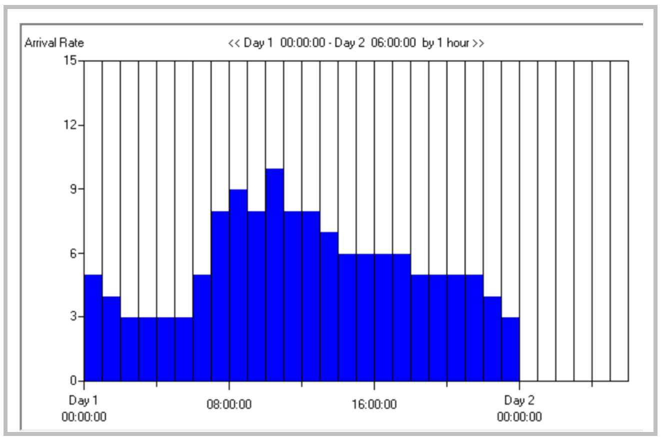

Figure 5: Patient arrival pattern over a 24-h period

2.2.2 Model Verification and Limitations

Model verification is the task ensure that the model behaves as intended [7]. It is important to validate that the model is built correctly based on the conceptual model and assumption.

We verified the effectiveness of the simulated model through Arena animation and the comparison with the actual ED statistics in Canada [2].

Multiple assumptions are made to define the model due to the limitation of data. These assumption are as followings.

1. Medical personnel: to control the number of variables in comparison, we do not take the difference between physicians and nurses into account. In our model, medical personnel are responsible for triage, CPR, assessment and reassessment.
2. Time delays: in this model, we only consider the delay for waiting for medical personnel and beds. Patient transferring time in ED is not considered.
3. Patient arrival schedule: in this model, we use the same arrival schedule for both weekdays and weekends. However, there should be variations [2, 3].

2.2.3 Design of alternatives using machine learning classifiers

MLC is an alternative way to analyze patient's' condition. We built a MLC called ED Screen to do the analysis of patient’s condition. The classifier proves to have more accurate and faster prediction on patient's severity than the traditional ED diagnosis. There are two places in the system we could add ED Screen as an additional resources: triage process and assessment process. In practice, patients are be able to answer some questions, such as "do you have any family history" on ED Screen. Then ED Screen terminal could generate a triage code if it is used in triage process. In assessment process, a similar evaluation report on patients could be generated to make admission decision.

Patients may be not familiar with ED Screen and we choose to have medical personnel intervene when that is necessary. This could also happen when ED Screen result is not statistically significant. According to the result we gathered for ED Screen, the accuracy is 93.1% which means 93.1% patients could get valid results without the necessity of being seeing by a medical personnel. 6.9% of the patients will be directed to a medical personnel for a regular check. Table 4 presents the technical specification of the MLC.

Item	**Value**
Predication accuracy	93.1%
Process Time in Minutes	TRIA(3,5,10)

Table 4: MLC specifications

The design of the alternatives is based on considering use ED Screen in different places: triage process and assessment process. In our design, a patient would first try to access a MLC. If all MLCs are busy, the patient would try to consult with a medical personnel.

Events	**Number of ED Screen in triage**	**Number of ED Screen in Assessment**	**Number of Additional Medical Personnel**
Original	0	0	0
ML Triage	1	0	0
ML Assessment	0	1	0
ML Shared	1	1	0
Extra Personnel	0	0	1

Table 5: Original model and alternatives

In table 5, we show the design of alternatives. As the foundation of all alternatives, Original is the model that simulated the scenario depicted in Figure 4. As shown in Figure 6, MLCs in blue can be used for both triage and assessment process. ML Triage is the model that has an additional MLC in triage.

1. Similarly, ML Assessment model has a MLC that is specifically assigned to assessment process.
2. Based on ML Triage and ML Assessment, ML Shared has a MLC that could be used for both triage and assessment.
3. To compare the result of adding a MLC with that of having an additional medical personnel, we have Extra Personnel model with an additional medical personnel available in both triage and assessment.

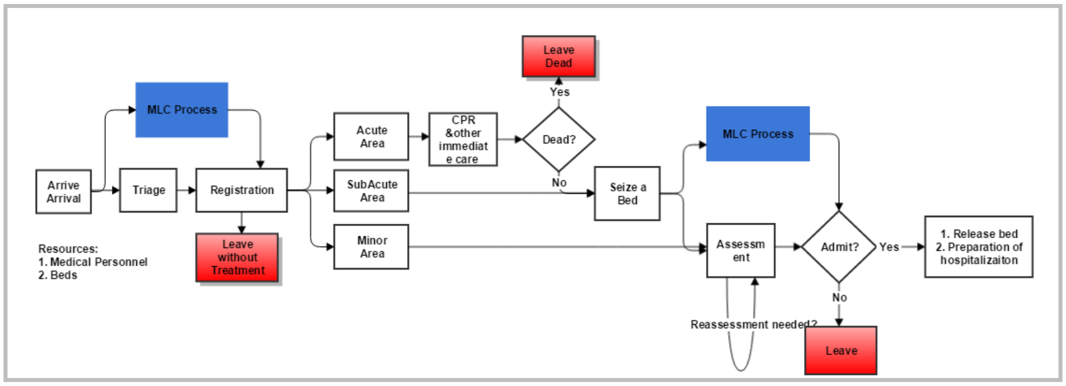

Figure 6: Hospital ED patient flowchart with MLC

2.2.4 Key performance measures

Three performance measures – patient waiting time (PWT), patient length of stay (PLOS) and resource utilization (RU) – are chosen as our criteria. PWT is defined as the length of a patient waiting for resources (beds or medical personnel). PLOS is defined as the time between a patient's arrival and his departure, including all steps such as waiting for resources, having a triage and going through CPR. PWT and PLOS have direct influence on patients' satisfaction of an ED visit: patients would expect to have low PWT and PLOS. The third index we choose is RU – the time-average number of units of resources that are busy, divided by the time-average number of units of the resources that are scheduled [7]. We examine RU to see how resources are utilized: higher RU stands for better efficiency in arranging the resources.

2.3 Simulation results and discussion

In this section, we compare the results of key performance measures – PWT, PLOS and RU – of each simulation scenarios. For each three measures, we then calculate the average and the 95% confidence interval based on the 10 replications' data for each scenario. Each replication is 720 hour long and the first 48 hours are warm-up periods.

2.3.1 Model Comparison: PWT

Figure 7 shows the patient waiting time (PWT) under 5 different scenarios. We present the PWT for different types of patients separately and the average PWT for all patients is also provided. From Figure 7 we find that minor patients have the longest waiting time and acute patients have the shortest waiting time, in all scenarios.

For acute patients, subacute patients, minor patients and the average for all patients, ML Shared yields the lowest PWT, which is 0.0862(half width = 0.01) hours, 0.0702(half width = 0.01) hours, 0.0984(half width = 0.01) hours and 0.0772(half width = 0.01) hours respectively. All scenarios show significant improvement of PWT over the Original. A decrease of up to 2.2 hours can be achieved by these models compared to actual situation in ED for all patients.

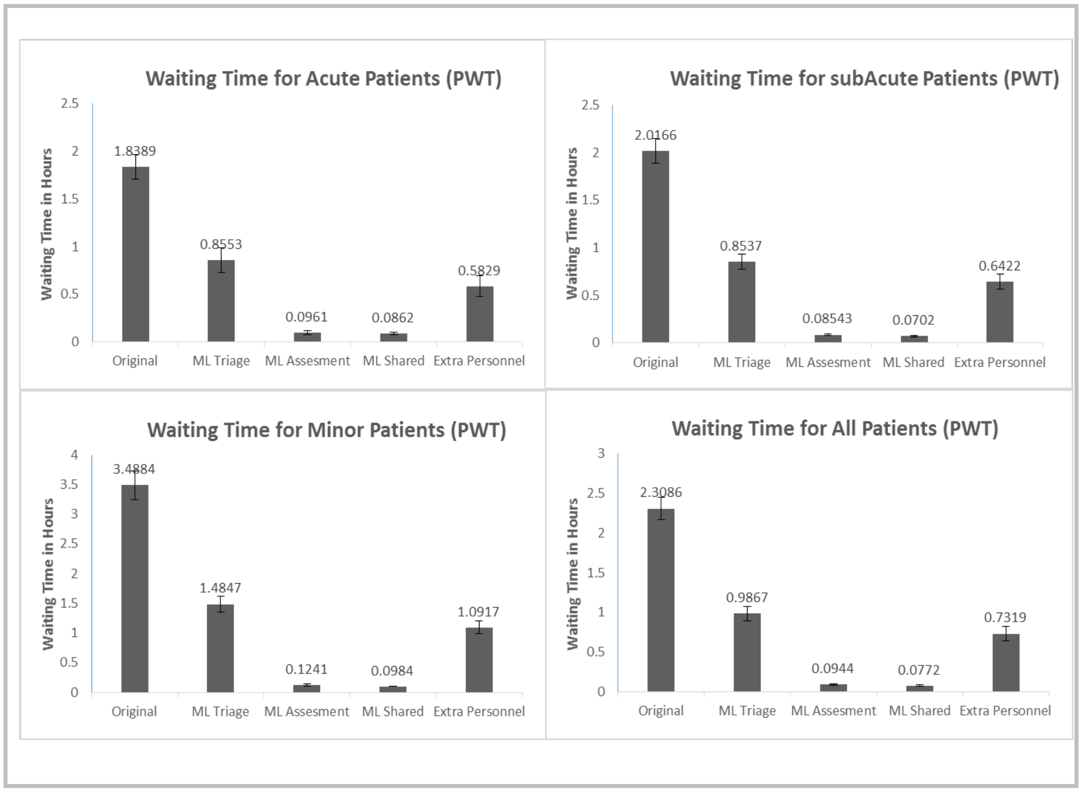

Figure 7: Waiting times for different types of patients under different scenarios

We also notice that Extra Personnel, adding an additional medical personnel, has less significant improvement than ML Assessment and ML Shared. However, Extra Personnel, is better than ML Triage that adds a MLC in triage only. This reason might be a MLC takes similar length of time as a medical personnel in triage. Therefore, this is totally different in assessment, where MLC is much faster than a medical personnel. Another possible explanation is that the additional medical personnel in Extra Personnel model could work in both triage and assessment, although the additional MLC in ML Triage could only work in triage.

Therefore, if the MLC could only be used at either triage or assessment, using it in assessment or make it shared resource could yield more improvement over PWT. This observation reveals that MLC may not be superior in all aspects unless we use it in the right place of the system. If a process takes similar length of time for machine and human beings, the superiority of MLC is not obvious. That is, we assume that using MLC in assessment is more meaningful than using it in triage.

2.3.2 Model comparison: PLOS

Patient length of stay (PLOS) in different scenarios are shown in Figure 8. Similarly, we present the result for acute patients, subacute patients, minor patients and the average for all patients separately.

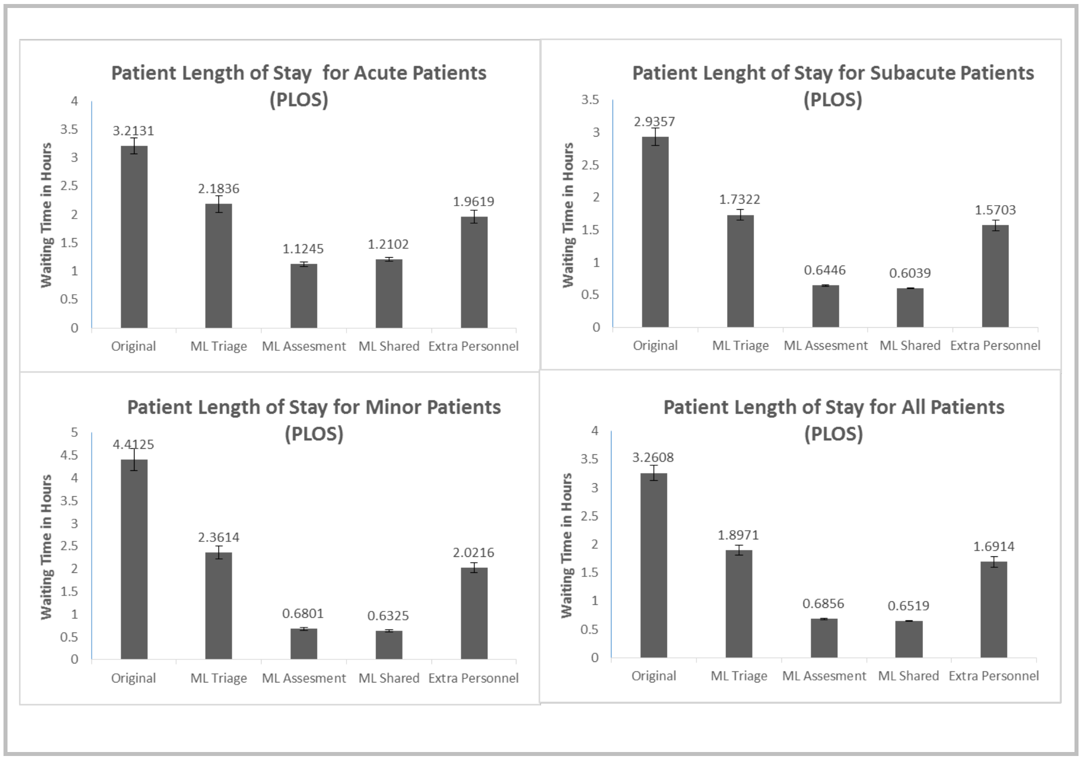

Figure 8: Length of stay for different types of patients under different scenarios

For acute patients, ML Assessment yields the lowest PLOS, 1.12(half width = 0.045) hours. For subacute, minor and the average of all patients, ML Shared yields the lowest PWT, which is 0.6039(half width = 0.01) hours, 0.6325 (half width = 0.02) hours, 0.6519 (half width = 0.01) hours, respectively. All alternatives show a significant improvement of PLOS over Original. A decrease of up to1.5 hours can be achieved by these models compared to actual situation in ED for all patients. For different types of patients, acute patients have the longest length of stay in all scenarios. This is foreseeable because acute patients need to go through resuscitations, e.g. CPR that takes more time.

Similarly to the observations for PWT, Extra Personnel, adding an additional medical personnel, has more improvement than ML Triage, adding a MLC in triage. Meanwhile, Extra Personnel is not as good as either ML Assessment or ML Shared. Unlike PWT that we could see ML Shared has a clear edge, PLOS results show that different scenarios have varied advantages for different types of patients. Another character of PLOS is that there is no scenario could achieve a similar time for all types of patients—acute patients generally have larger PLOS. This makes sense because acute patients need to go through CPR and other urgent cares. By no means, the time for urgent cares can be eliminated by MLC. This also brings the insight MLCs could eliminate all barriers in a system.

2.3.3 Model Comparison: RU

Medical personnel and bed usage rate are presented in Figure 9. From the comparison of Original and Extra Personnel, we could see adding one medical personnel decreases the usage of medical personnel and beds. So simply adding medical personnel may not be bring improvement for resource usage in such a complex system. We could also find that the usage of MLC in ML Triage, ML Assessment, and ML Shared further bring the usage of medical personnel and beds down. This is a sign that the current ratio between medical personnel and beds in ED is not the best setting and has the space for optimization. We assume if we have right combination of medical personnel, beds and MLCs, the usage rate for all these resources could be significantly improved.

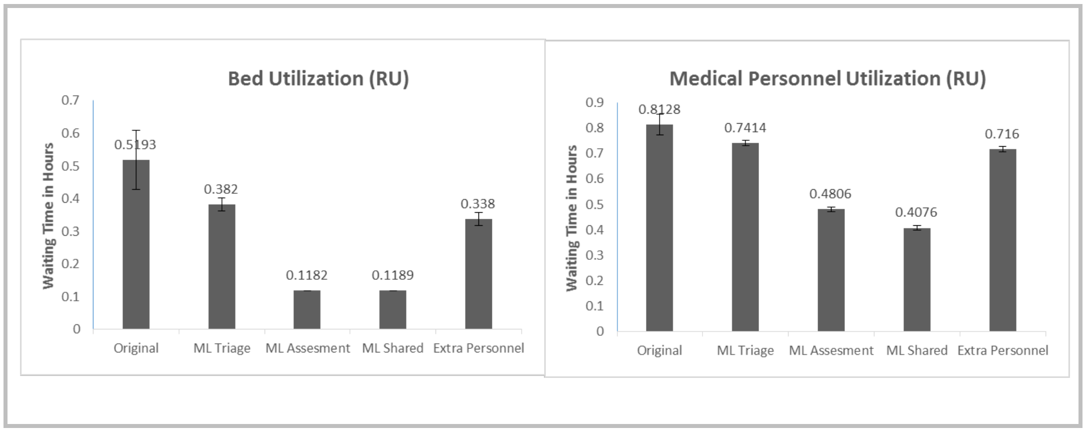

Figure 9: Resource utilizations under different scenarios

3 Conclusion

Machine learning has proved its value in many aspects of the health system, including health informatics, diagnosis classification, fraud insurance claim detection, and epidemiological forecasting [47, 48, 49, 50]. To our knowledge, our simulation study, for the first time, showed that the crowdedness in the ED system can be significantly reduced by simply adding a machine learning algorithm. It is a much cheaper and more effective solution than adding a human labor. The simulation result revealed that the place to use MLC decided its effectiveness in the system. Clearly, the points where the solution is applied to is as important as, if not more important than the solution itself. Our study is a starting point showing how modern technology can potentially become the new leverage point for the old problem, and how system thinking can be applied to solve the issue of health care. However, utilization of MLC could not eliminate all barriers in the complex system. Future studies will be needed to identify other leverage points.

Acknowledgments

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