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Simulation of the Emergency Department Care Process for Pediatric Traumatic Brain Injury

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Abstract

The treatment of patients in the emergency department (ED) with severe pediatric traumatic brain injury (TBI) is challenging, and treatment process strategies that facilitate good outcomes are not well documented. The overall objective of this study is to identify factors that can impact the care process associated with pediatric TBI. This objective is achieved using a discrete-event simulation model of TBI patients as they progress through the ED treatment process of a level I trauma center. This model was used to identify areas where the ED length of stay can be reduced. The number of patients arriving at any given time was also varied in the simulation model to observe the impact to bed allocation policies, and changes in staff and equipment. The findings showed that implementing changes in the ED (i.e., availability of two CT scan machines, formation of resuscitation teams that included eight staff personnel and modifying the bed allocation policy) could result in a 17% reduction in mean ED length of stay. The study outcomes would be of interest to those (e.g., health administrators, health managers, and physicians) who can make decisions related to the treatment process in an ED.

Keywords

Pediatric traumatic brain injury; emergency department; simulation model

INTRODUCTION

The overall quality of healthcare has been shown to impact patient outcomes.^{1–3} For children with severe traumatic brain injury (TBI), the timeliness of care directly impacts how quickly children can deteriorate.^{4–5} Decision makers (e.g., hospital administrators, hospital managers, physicians) need a way to consider alternatives for ED care without negatively disrupting the existing care process. Computer simulation provides a way to evaluate the effectiveness of the healthcare system and to find ways to optimize the overall system process without disrupting operations. They can be used to facilitate hospital planning and resource allocation, evaluating the likelihood of a favorable treatment outcome, and decreasing waste while increasing overall patient satisfaction.⁶ They are particularly useful for examining care in an emergency department (ED) given the complexity and dynamic nature of the environment and the myriad of activities that impact patient care

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(laboratory processing time, waiting time, examinations, complex information flow, unexpected patient arrivals, need for personalized treatments, and travel to diagnostic sites).⁷ Most simulation models of ED care focus on ED overcrowding,^{8–13} which does not necessarily consider the process flow associated with patient care. In this study, we use simulation to identify factors that can improve the care process of children with TBI in the ED.

TBI is a leading cause of morbidity and mortality and is associated with more than 630,000 ED visits, 60,000 hospitalizations, and 6,000 deaths in the United States annually among children under 19 years of age.¹⁴ High quality ED care of TBI patients includes timely access to evidence-based care, timely expert trauma response and expedient provision of rehabilitative services.^{15–17} Ajdari et al.¹⁸ showed that for every 10 minutes spent performing non-value added tasks in the ED, there is a 9% reduction in a favorable discharge outcome for children with TBI. Accordingly, reducing the non-value added times (NVAT) could greatly impact the overall efficacy of the treatment process. We hypothesize that this reduction in NVAT can be achieved with a reduction in the patient's overall ED length of stay (LOS). A computer simulation model is used to evaluate the factors that can impact the care process associated with pediatric TBI. Several scenarios (e.g. changes in the number of staff, ED equipment, and bed allocation) are considered to help visualize and assess the impact on the patient's ED LOS.

METHODS

We simulated the TBI pediatric care process in an emergency department at a level I trauma center, with an emphasis on patient flow and interactions with ED staff and equipment. IRB approval was waived for this study as no patient identifiers were collected.

Data Requirements

The simulation model requires data on real TBI patients and information on three major entities that exist in the ED: patients, staff, and equipment.

Patients—Patients were divided into two sub-categories: patients with suspected severe TBI and non-TBI patients. The ED staff and equipment are used to treat non-TBI as well as the TBI cases, and the care process of the non-TBI cases directly affect the availability of the ED equipment for the TBI cases.

Inclusion criteria for TBI cases included history of trauma, suspected severe TBI based on level 1 pediatric trauma activation, tracheal intubation either prior to or in the ED, and an ED admission Glasgow coma scale score < 9. The definitive diagnosis of TBI is made prior to the initial resuscitation efforts, and through diagnosis from a head computerized tomography (CT) scan.

Staff—The trauma team at this facility consists of physicians and non-physicians. Physician entities include trauma trainees, ED attending, surgery attending, surgery resident, pediatric attending, pediatric resident, anesthesiology attending, anesthesiology resident, and neurosurgery resident. Non-physician entities include registered nurses and respiratory therapists. Pre-hospital personnel were not included as part of the typical trauma team

because they are not typically involved in hospital care after transfer and verbal report. The only clinicians included in the analysis and simulation model were those that were directly involved in patient care. Radiologists and other staff responsible for performing and interpreting the various tests (head CT scan, X-rays, etc.) throughout the ED treatment process were also included. ED staff with indirect involvement (e.g. social workers, unit coordinators, medics, etc.) was excluded.

Equipment—The model included large equipment that was directly used by the patients and included prep, process and wait time: head CT scan, X-ray, and ultrasound machines.

Data Collection

Detailed process flows were collected on 20 critically injured children with suspected severe TBI who received care in the ED (i.e., TBI cases). An iPad application¹⁹ was designed to collect time-stamped data from real patients as they progress through the ED treatment process. The iPad application was used by medical students who were staffed at the ED in 12-hour shift rotations for a period of three months. They were trained to collect data prospectively on the timing and sequence of each patient's interaction with the hospitals staff/resources from the time of ED admission until the time s/he was transferred out of the ED. The medical students were retrained if needed to achieve interrater reliability ($\kappa > 0.8$) using a codebook and in close coordination with a member of the research team. An aggregated value stream map (VSM) was then created from the acquired data (See Figure 1). Variations in care among patients are denoted with decision points and the percent requiring various tests or processes.

Simulation Model

This value stream map was used to create the computer simulation model and represents the essential process of the ED TBI care. The percent of patients requiring a specific test or process is used to compute the likelihood of a chosen path in the simulation model. As noted earlier, the study objective is to identify factors that can improve the care process associated with pediatric TBI. The factors examined should minimize NVAT. Because the simulation does not allow every instance of NVAT to be captured, the patient ED LOS is used as a proxy for NVAT. Past findings show that ED LOS and NVAT are positively correlated and can provide insights on patient clinical outcomes.¹⁸

The variables considered in the simulation model are those that (i) directly impact NVAT/LOS, and (ii) can be controlled by the decision maker to reduce NVAT/LOS. The decision makers are those that can make decisions related to the ED care process, and two factors that can be modified are ED staff and ED equipment.

Uncontrollable or observable variables such as patient arrival rate is imposed on the system externally but can be manipulated in the simulation model to examine its impact on the patients' ED LOS. We assumed a Poisson arrival rate with means of λ_1 and λ_2 for the cases and controls. The TBI patient arrival rate, λ_1 was set at one patient per week. This was based on data collected from the iPad application and confirmed based on interviews with hospital staff. The non-TBI patient arrival rate, λ_2 was set at 10 patients per hour, based on

interviews with hospital staff. The discrete-choice simulation model was developed with the academic version of the Simio software²⁰ (Figure 2).

Interdisciplinary clinicians from the study site verified that the simulation model was representative of the current ED process flow. The validity of the simulation model was assessed by comparing the mean LOS for a one-week period from 1000 simulated patients to 56 real patients collected from previous work.¹⁸

RESULTS

Most of the ED treatment processes occurred at the patient's bedside in the resuscitation room. The processes that occurred elsewhere were diagnostic tests and transferring the patient out of the ED. Four types of medical tests were identified: head CT scan, X-ray (pelvis, chest), ultrasound, and blood work. In the simulation model, the patient remains in the room unless s/he needs to leave the ED for discharge or additional tests. There are three resuscitation rooms in the ED, each containing four beds, or up to 12 patients at any given time. If the resuscitation rooms are at capacity, new arrivals are treated by using available beds in the ED that are not part of the resuscitation rooms, standing up, or in more extreme situations, lying down on the floor. This flexible strategy is consistent with the study trauma center's mission to provide the highest level of trauma care to children with severe TBI.

The distribution of the predicted ED LOS, based on 1000 simulated patients, was compared to the actual ED LOS (69.75 minutes) collected from our previous study (see Figure 3).¹⁸ The validity was also tested using an independent *t*-test for unequal sample sizes to compare the mean LOS obtained from the simulation model with those from the actual (or observed values). Statistical significance was assessed at $\alpha < 0.05$. No significant differences were observed between the actual and simulated model (*p*-value > 0.05). We therefore conclude that the simulation model is a reasonable representation of the real ED setting. Once the validity of the simulation model was confirmed, various simulated situations were examined for possible improvements to the ED treatment process. These simulated situations were grouped into two categories: (1) changes to the arrival rates and (2) changes in staff, equipment, and bed allocation policies.

Arrival rates—We observed changes in arrival rates by controlling the number of staff ($n=10$), CT scanners ($n=2$), and bed allocation policy to the existing configuration. The current policy has patients allocated to room #1 first (which is closest to the reception area), and if all beds in this room are at capacity, they are then assigned to room #2, and room #3 thereafter (see left side of Figure 2). The arrival rates for patients with suspected TBI (cases) was varied from the current arrival rate of one TBI patient per week (or 0.006 patients per hour) to 50 TBI patients per hour, with the latter simulating a hypothetical mass casualty scenario. For each arrival rate, the simulation was run for 100 simulated patients. A mean ED LOS was computed for the arrival rate λ_{ji} for each simulation run *i*. As observed in Figure 4, the mean ED LOS remained relatively stable until the arrival rate increased to 20 patients per day (mean ED LOS=112.7 minutes) with a substantial increase in ED LOS after an arrival rate of 5 patients per hour (mean ED LOS=602.7 minutes).

Changes in staff (S), CT scan machines (C), and the bed allocation policy (B)

—We examined the impact of changes in number of staff, number of CT scan machines, and bed allocation policies by fixing the pediatric TBI patient arrival rate to 5 patients per hour. This arrival rate was selected based on the changes in mean ED LOS observed earlier (Figure 4). We varied the number of ED staff between 1 and 10; number of available CT scan machines between 1 and 5, and considered three different bed allocation policies, B1 (current policy), B2, and B3. The differences among the bed allocation policies were in the relative ordering of patient placement in the resuscitation rooms, which does not require any facility redesign. Each bed allocation policy changes the travel time to and from the testing, reception, and discharge areas. Bed allocation policy B2 assigns patients to room #2 first, followed by #1 and #3. The third bed allocation policy (Policy B3) assigns patients to room #3 first, then #2 and #1.

There were 150 simulated scenarios and each was run with 100 simulated patients. A summary of the outcomes is provided in Table 1, with the optimal combination denoted with an asterisk. The optimum combination provided the lowest ED LOS and included 2 CT scan machines, 8 treating physicians/nurses in the ED resuscitation team, and bed allocation policy B2. Under this scenario, the mean ED LOS was 57.43 minutes per patient, which is a 17.66% reduction compared to the current ED LOS of 69.75 minutes per patient with the existing configuration (2 CT scanners, 10 physicians/nurses, and bed allocation policy B1).

A one-way analysis of variance (ANOVA) showed a significant difference in the bed allocation policies ($F(2,297)=6.438$, $p=0.002$), with a significantly lower mean ED LOS for policy B1 when compared to policy B1 and B3. Bed allocation policy B2 provides the shortest walk distance to the CT scanner, ultrasound machine, and X-ray machines. There were no significant difference in ED LOS between bed allocation policy B1 and B3 ($p > 0.05$).

LIMITATIONS

The small number of pediatric trauma patients ($n=20$) may impact the outcomes of the simulation model, and the generalizability to other ED processes. That said, each patient's arrival time is independent of one another and therefore, can be resampled in a simulation model to provide insights on this specific sub population of children with severe TBI. Hence, the study framework, collection of data using a tablet application, and the simulation model can be easily modified to accommodate additional patient data as they become available.

The diagnosis of TBI was made only after the ED resuscitation processes were initiated. It is therefore possible that some of our patients did not have severe TBI. Our case scenario is based on real world care, where patients with suspected TBI often receive initial ED care similar to those with confirmed TBI. We did not include appointment scheduling even though it has been considered in other studies.^{22–23} This is because critically injured trauma patients do not make appointments in an ED setting.

DISCUSSION

The objective of this study was to identify factors that can impact the care process associated with pediatric TBI in an ED setting. TBI is the leading cause of pediatric trauma.²⁴ A simulation model is needed to capture changes in bed allocation policy, staffing and equipment, without negatively impacting the real world care of injured children, who can deteriorate very quickly and have different physiology from adults.

The results of the simulation indicate that the current arrival rate of children with suspected severe TBI patients (approximately 1 TBI patient per week), and current ED capacity (i.e., number of available beds, equipment, and physicians/nurses) is sufficient to meet the current patient flow. The mean ED LOS does not change substantially even if the number of TBI patients increased to 10 per day as long as the arrival rate for the non-TBI patients remained stable. A substantial increase in ED LOS will be observed if the arrival rate surpasses 20 TBI patients per day. At this point, the overall quality of healthcare at this Trauma I center will be impacted as staff and equipment will not be able to meet the needs of all patients in a timely manner. These findings are in line with previous research that showed a relationship between arrival rate and LOS or wait time.^{25–27} The emergency department at this center has three CT scanners, but only two can function at the same time; one is always available for trauma imaging as soon as patients are deemed hemodynamically stable for transport to the scanner. Hence, the existing scenario was modeled with two operational CT scanners. That said, the optimum configuration was not one with three CT scanners.

The arrangement of the resuscitation rooms (bed allocation strategies) has a significant impact on ED LOS. The lowest LOS occurs with a layout that includes two CT scan machines and a resuscitation team of eight physicians/nurses. Bed allocation policy B2 was optimal because it provided the shortest mean travel time to the areas attended to by a TBI patient. This model demonstrates that even a small change in the bed allocation policy can positively enhance the overall efficiency of the ED treatment. The result is consistent with other studies that show that the layout of an ED is associated with overall ED capacity.^{28–29}

An increase in length of stay (LOS) will directly impact the wait time for all patients, and the overall healthcare quality for children with TBI. The study outcome should be generalizable for children with severe TBI who also have other injuries since the data included patients with TBI who may or may not have other injuries. We did not exclude patients with polytrauma because many patients at this center with severe TBI also have other coexisting injuries. Hence, model assumptions reflect priorities of care for the spectrum of patients with severe TBI. In TBI, as with other injuries, circulation, airway and breathing are part of the primary survey and occur early in the resuscitation process.

CONCLUSION

The major contributions of this study are: (i) creation of a simulation model of the ED treatment care process for pediatric TBI patients that includes patient and staff movement throughout the ED and verified with real-world data from a level I trauma center, (ii) identification of a bed allocation policy that could reduce the overall ED LOS while also

accounting for staffing, equipment, and movement in the ED process, and (iii) identification of the optimal number of CT scans and optimal resuscitation team number to meet the needs of the current severe pediatric TBI ED arrival rate of 1 to 10 patients per week at a high volume adult and pediatric trauma center. Computer simulation allowed us to evaluate multiple scenarios in the complex setting of a trauma center ED. Future studies should validate our findings with other trauma centers that include different organizational structure and ED treatment processes. It would also be interesting to know whether the reduction in ED LOS in children with TBI will impact hospital stay and long-term recovery.

IMPLICATIONS

Timely treatment is very important in the care of children with TBI and can have a significant impact on patient outcomes.²¹ The study provides a step in understanding how ED length of stay can be minimized in a more systematic way. A computer simulation model is used to examine various scenarios in a cost-effective way to enhance the overall ED treatment process for the care of severe pediatric TBI.

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Figure 1.
Value stream map of the emergency department (ED) treatment process.

Figure 2. Screenshot of the 2-D simulation model. The arrows show the movement pattern of patients and staff throughout the ED for the allowed directions of travel.

Figure 3. Histograms for ED level of service (LOS) as predicted from the simulation model (right) and from actual data (left). Note: the density (y-axis) depicts the relative count (e.g., 0.04 out of 1000 simulated patients translates to 4 patients).

Figure 4.
The simulated mean ED LOS as arrival rate for pediatric TBI patients increase.

Table 1

Mean ED LOS of 100 simulated patients for each simulated scenario. The best combination (minimum LOS) for each layout is denoted by asterisk (*).

Bed Allocation	No of Staff	No. of CT scan machines				
		1	2	3*	4	5
B1	1	433.12	397.21	380.41	387.21	367.73
	2	393.21	302.78	212.56	185.06	195.98
	3	253.73	245.29	205.74	212.45	204.91
	4	200.12	192.58	176.32	159.69	179.66
	5	151.43	152.56	144.30	139.87	162.86
	6	103.92	198.74	186.96	95.43	112.93
	7	88.34	82.34	79.32	76.38	90.54
	8	88.87	91.09	79.52	71.43	81.06
	9	78.01	84.63	69.54	68.92	80.54
	10*	72.06	72.43	62.04*	66.07	78.68
B2	1	296.18	278.05	494.53	425.93	330.96
	2	314.57	272.50	233.82	129.54	254.77
	3	202.98	220.76	246.89	212.45	163.93
	4	240.14	154.06	211.59	143.72	215.59
	5	121.14	198.33	173.16	181.84	130.29
	6	124.70	178.96	168.26	104.97	79.05
	7	70.67	98.81	95.18	84.56	81.49
	8*	68.76	57.43*	63.62	68.43	97.27
	9	72.12	67.65	69.54	62.03	104.70
	10	59.65	86.92	80.65	66.07	94.41
B3	1	465.43	350.63	457.47	424.57	367.34
	2	393.21	294.64	241.19	167.30	242.38
	3	228.36	236.03	238.31	219.45	204.42

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Bed Allocation	No of Staff	No. of CT scan machines				
		1	2	3*	4	5
4	4	240.14	179.32	212.95	162.71	202.62
5	5	136.29	179.44	165.73	170.85	156.57
6	6	83.14	189.90	191.61	110.20	99.99
7	7	70.67	107.57	102.25	100.47	88.01
8	8	67.10	73.26	78.57	70.93	95.17
9*	9*	70.21	61.57*	79.54	84.47	98.62
10	10	72.06	82.67	81.35	78.07	91.54