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Examining Emergency Department Treatment Processes in Severe Pediatric Traumatic Brain Injury

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Abstract

Background—In the treatment of pediatric traumatic brain injury (TBI), timely treatment of patients can impact the outcome. Our objectives were to examine the treatment process of acute pediatric TBI and the impact of non-value added time (NVAT) on patient outcomes.

Methods—Data for 136 pediatric trauma patients (age<18 years) with severe TBI from two trauma centers in the US were collected. A process flow and value stream map identified NVATs and their sources in the treatment process. Cluster and regression analysis were used to examine the relationship between NVAT, as a percentage of the patient's length of stay (LOS), and the patient outcome, measured by their corresponding Glasgow outcome scale (GOS).

Results—There were 14 distinct sources of NVAT identified. A regression analysis showed that increased NVAT was associated with less favorable outcomes (RR=1.015, C.I=[1.002, 1.029]). Specifically, 1% increase in the NVAT-to-LOS ratio was associated with a 1.5% increase in the chance of a less favorable outcome (i.e. death or vegetative state).

Conclusion—NVAT has a significant impact on the outcome of pediatric TBI and every minute spent on performing non-value added processes can lead to an increase in the likelihood of less favorable outcomes.

Keywords

TBI; regression analysis; pediatrics; non-value added time; healthcare

Introduction

Pediatric traumatic brain injury (TBI) is a traumatic insult or blow to the head, occurring in childhood (Backhaus, 2011). In treating patients with severe TBI, it is important to have timely access to quality care (Langlois et al., 2006; Sharma, 2013; Tepas et al., 2009). Lean principles have been applied to enhance healthcare delivery systems and overall quality of care (Dickson et al, 2009; Venkateswarana, Nahmensa, and Ikumaa 2013). Quality in lean thinking is often defined in terms of added value from the patients' perspective (Young &

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McClean, 2008) and has been used effectively in reducing waste and enhancing performance in emergency departments (EDs) (Moody, 2012). The underlying assumption associated with lean principles is that increasing wait time has a direct and negative impact on patient outcome. In this context, patient's wait time is closely associated with non-value added processes. The focus of this study was two-fold: (i) to identify sources of non-value added processes in the system and (ii) to examine the effect of non-value added time on pediatric TBI outcome.

Methods

All institutional review board (IRB) approvals were met for this study. An observational cohort study that included 40 patients at two level I pediatric trauma centers (20 each) was collected for this study. The two centers included Harborview Medical Center at the University of Washington, WA (Center 1), and Nationwide Children's Hospital, OH (Center 2). The data at Center 1 were prospectively collected by trained medical students staffed in the ED during rotations of 12 hour-shifts for a 3 month period. At Center 2, data from video recordings were used. At both centers, an iPad application was designed to collect real time stamped data (Ries et al., 2013). This application recorded the timing and sequence of each patient's interaction with the hospital's staff/resources from the time of ED admission until the time s/he was transferred out of the ED. Patients were children under 18 years of age with severe TBI.

A five-step methodology was developed to examine the treatment process with all analyses conducted using the R statistical software package.

Step 1: Defining Non-value Added Time (NVAT)

In healthcare, NVAT can be considered wasted time that is consumed with rework and delay that could have been avoided if the process worked ideally (Storfjell et al., 2009). Others have considered NVAT as the non-operational times in a treatment process that is spent dealing with defects, errors, and waiting (James & Bayley, 2008). From the patient's perspective, NVAT is "the time(s) during which no medical intervention, diagnostic procedure or treatments were being administered" after patient arrival to the ED. These times include waiting for personnel to transport the patient to CT scanner or waiting for the results of laboratory tests or imaging studies.

Step 2: Identifying NVAT

A dataset for each center was created based on information collected from the iPad application. We refer to this dataset as the developmental dataset. In each center, a unique value stream map (VSM) was developed for each patient in order to identify NVAT (a total of 20 VSMs were developed in each center). Figure 1 shows a part of the VSM created for a patient in Center 2. Each VSM was then used to create a Gantt chart (Wilson, 2003). This is a type of bar chart that shows the sequence of activities performed within a given time window. NVAT was identified as those times that the patient had no interaction with the hospital staff or resources, and no intervention or diagnostic tests were performed.

Step 3: Using Cluster Analysis to Find Patient Commonality

The IRB protocol for the emergency department did not allow the collection of patients' personal or clinical characteristics for the developmental dataset. Hence, a validation dataset was used to examine the overall impact of NVAT on patient outcome. The validation dataset did not include time-related information on treatment process, but was developed and used in the Pediatric Guideline Adherence and Outcomes Study (Vavilala et al., 2014). The dataset contained data on 56 and 40 additional patients for Centers 1 and 2, including age, clinical indicators, and discharge outcomes. The inclusion criteria and the treatment process for these patients were exactly the same as those in the validation dataset.

The NVAT information from the developmental dataset was linked to the baseline/clinical data in the validation dataset. Cluster analysis was then used to find common attributes in the developmental dataset and was validated using patients in the validation dataset. Examples of cluster analysis used in healthcare can be found in (Berkhin, 2006; Newcomer et al., 2011).

The four common indicators in both dataset included: (1) hypoxia (i.e. arterial oxygen saturation $[SaO_2] < 90\%$), (2) hypotension (i.e. systolic blood pressure $[SBP] < 70$ mmHg + $2 \times (\text{age in years})$), (3) low end-tidal carbon dioxide (i.e. $ETCO_2 < 30$ mmHg), and (4) time to perform head computed tomography (CT) scan. Each indicator was classified as absent/present. The first three binary indicators were used to cluster the datasets and the fourth was used for validation.

Step 4: Estimating NVAT for the Validation Dataset

The mean NVAT from the developmental dataset was used as an estimate for the validation dataset based on the observed clusters. More specifically, patients in each corresponding cluster were assumed to have the same NVAT. The accuracy of this assumption was validated based on a test dataset.

Since actual NVAT was not available for all variables in the validation dataset, the accuracy of the estimation procedure was validated using the time to perform head CT scan, a variable available in both datasets. Accordingly, the time from head CT scan ordered to results received was the value used for the validation phase. The clustered data in the developmental dataset were used to estimate the head CT scan time for the corresponding clusters in validation dataset. The estimated and the actual results were then compared to each other to give an accuracy measure for the estimation procedure.

Step 5: Determining the Association between NVAT and Patient Outcomes

The impact of NVAT on patient outcomes was examined using a regression model with binary outcomes. The outcome of interest was based on a binary recoding of the Glasgow outcome scale (GOS). The outcome was coded as 1 for "less favorable outcome" if the GOS value was 1 (death) or 2 (vegetative state) and coded 0 for "more favorable outcome" if the GOS values was 3 (major impairment), 4 (minor impairment), or 5 (baseline state). The GOS score of 3 was included in the more favorable group as the majority of surviving

patients in Center 1 had major impairment (i.e., only 3 patients had GOS scores of 4 or 5) (See Table A).

The binary outcomes were analyzed using a log-binomial regression model to obtain odds ratios (OR). More specifically, when the outcome event is common (i.e. incidence of 10% or more) as in this study, it may be more appropriate to estimate a relative risk or risk ratio (RR) instead of an OR (Greenland, 2004; McNutt et al., 2003). One drawback of using log-binomial models to obtain RR is that they produce narrower than expected confidence intervals. Moreover, there can be convergence problems when using such models (McNutt et al., 2003; Zou, 2004). To overcome these issues, Zou (2004) suggests using a "modified Poisson" with robust error variances and this is applied in the forthcoming analysis.

Three separate regression models were developed to investigate the impact of NVAT on patient outcome as the percentage of ED LOS. The first two models examined factors within each center (Center 1; N=56 and Center 2; N=40). The third model used a combined dataset to examine differences between centers (N=96).

Results

NVAT and Its Sources

The histograms of NVAT for Centers 1 and 2 are shown in Figure 2. The mean NVAT was 70.99 minutes (SD=12.21) in Center 1 and 61.23 (SD=10.14) minutes in Center 2. NVAT as the percentage of the patient's length of stay (LOS) were 37.21% and 33.41% in Center 1 and 2, respectively. The skewness observed in the histogram for Center 1 was due to the lack of available beds in the ICU at the time patients were ready to be admitted to ICU, hence increasing their wait time in the ED.

The total NVAT over each patient's length of stay (LOS) in the ED was based on the sum of the NVAT at each treatment process. Given that each NVAT might be due to sources outside of the treatment process, each source of NVAT were compared between centers.

For each patient, a unique code was assigned to each NVAT according to its cause to distinguish between different sources of NVAT in the system (Table 1). "Unidentified gaps" was noted for idle times between consecutive processes. Figure 3 illustrates such gaps between processes for one patient. Upon further investigation, there were three categories of NVAT observed in both centers: (1) waiting for test results (e.g. head CT scan, blood work, etc.); (2) waiting for hospital resources (e.g. surgery/neurosurgery consultant, waiting for nurse to transfer the patient, etc.); and (3) unidentified idle times between consecutive processes. The NVAT for each patient could be categorized into one, two or all three categories (Table 1).

On average, 52.94% of the patient's total NVAT was due to category 1. Categories 2 and 3 accounted for 8.04% and 39.02% of patient's NVAT, respectively. For center 1, the percent of NVAT for categories 1, 2, and 3 was 57.57%, 5.78%, and 36.65%, respectively. In Center 2, NVAT encompassed 46.43%, 11.04%, and 42.36% for categories 1, 2, and 3; respectively. Clearly, category 1 (waiting for test results) was a major source of NVAT in both centers.

Waiting for the head CT accounted for 83.4% (42.7 minutes) and 79.21% (37.7 minutes) of NVAT in this category in Center 1 and 2, respectively.

Cluster Analysis Results

In Center 1, the patients in each dataset (developmental and validation) were categorized into three clusters: Cluster 1 (no hypoxia, hypotension, or low ETCO₂) which contained 55% and 63% of sample size in the developmental and validation dataset, respectively; Cluster 2 (at least two out of the three indicators were detected) with 30% and 21% of sample size; and Cluster 3 (all three indicators were detected) with 15% and 16% of sample size.

In Center 2, the patients were also categorized into three clusters: Cluster 1 (no hypoxia, hypotension, or low ETCO₂) with 65% and 63% of sample size in the developmental and validation dataset, respectively; Cluster 2 (hypotension detected) with 23% and 26% of sample size; and Cluster 3 (low ETCO₂ detected) which contained 12% and 11% of sample size.

Validation Results

Time from ordering head CT scan to the patient receiving the result was used to validate the NVAT obtained for the validation dataset as previously described. The actual times for Clusters 1, 2 and 3 in Center 1 were 48, 55, and 59; respectively, and the predicted values were 43, 49, and 50 minutes, respectively. The difference between the actual and predicted CT times ranged from 5–12%, indicating that the estimation process that was applied in this study was reasonable for estimating NVAT. Analysis of variance also revealed that there was no statistically significant difference between the estimated and the actual head CT time values ($p > 0.05$) in either centers.

Effect of NVAT on Patient Outcome

The response variable for all three regression models was the binary-coded discharge GOS score. There were several predictor variables considered including NVAT (numerical), ED LOS (numerical), age (numerical, in years), gender (categorical), maximum head Abbreviated Injury Score (AIS) (numerical), and Injury Severity Index (ISS) (numerical). Because NVAT and LOS are highly correlated ($\rho = 0.81$), a modified predictor variable defined as NVAT divided by ED LOS (percent) was used. We used head AIS and ISS to adjust for injury severity in our model.

In the combined center model, a sixth predictor, namely Center (categorical with 2 levels: 1 and 2), was added to account for the potential differences in centers. Statistical significance was defined as $\alpha = 0.05$. The clinical characteristics of the patients used in the regression model are shown in the supplementary Table A.

Table 2 shows the result of regression analysis for Center 1, 2, and the combined dataset. Goodness of fit for each model was assessed using the log likelihood (LL) method. The results of the three models were quite similar and the slight differences could be explained by differences in organization and patient population. The result in all centers showed that

NVAT had a significant impact on discharge GOS. More specifically, the higher the NVAT, the worse was the patient outcome. The results of the combined dataset showed that NVAT, as the percentage of patient's LOS at the ED, was significantly associated with the likelihood of a less favorable outcome ($p = 0.021$, $RR = 1.015$, $C.I = [1.002, 1.029]$). That is, one unit increase in the percentage of NVAT-to-LOS ratio will increase the relative risk of a less favorable outcome by 1.5%. Head AIS ($p = 0.007$) and age ($p = 0.034$) were also significant predictors. More specifically, younger age was associated with a less favorable outcome. If we define π as the odds of a less favorable outcome and remove the insignificant variables, the estimated model is shown in equation (1) and for each coefficient β_j we have $RR_j = \exp(\beta_j)$.

$$\ln(\pi) = -0.011 \text{ Age} + 0.134 \text{ Gender}_{\text{Female}} + 0.118 \text{ HeadAIS} + 0.015 \text{ NVAT} - 0.947 \quad \text{eq (1)}$$

Discussion

There are three areas typically targeted for improvement in health care: structural items (i.e., environment within which care is delivered), processes of care (i.e., professional activities associated with providing care), and outcomes (i.e., changes in the patient's current and future health status as a result of care) (Donabedian, 1980). This study addressed the latter two by identifying sources of NVAT and the association between pediatric trauma care and patient outcome. The first area (structural items) was indirectly considered using the data collected across the two centers (e.g. differences in CT scan time across centers, differences in facility layout). However, additional data on the structural aspect (e.g., additional centers and facilities) would be useful to identify best global practices for adhering to pediatric TBI guidelines.

Table A summarizes patient characteristics for Centers 1 and 2. Both centers not only have organizational differences in term of process flow (which was accounted for in the unique VSM created each center), but also different patient populations in terms of age, mechanism of injury, discharge disposition and discharge GOS. Center 2 has a significantly younger population (mean age: 7 years), with 33% having abusive TBI, 25% were discharged home, and 23% were deaths. Patients with inflicted TBI were younger and had more deaths.

A total of 14 different sources of NVAT common to both centers were identified, which was associated with 33 to 37% of patient's LOS in the ED. Despite differences in organizational structure (Center 1 is a mixed-model level 1 adult and pediatric trauma care center whereas Center 2 is a purely level 1 pediatric trauma center), NVAT sources identified in both centers were quite similar. This was expected due to similar process flows and the fact that both centers were similarly adherent to the 2003 guidelines for severe pediatric TBI (Adelson et al., 2003). These findings suggest that the underlying workflow and best practice paradigms are more important than official designation.

Waiting for test results (category 1) was the largest source of NVAT, accounting on average for over 52% of the total NVAT in the system. In this category, waiting for the result of the head CT scan was the major cause of NVAT in both centers. Given that the results are key to

determining further treatments for patients, the importance of this factor is expected. The wait time is based on the patient's perspective and defined as the time from head CT ordered to results received. This time also included patient transfer to CT scan bay, delay in neurosurgeon arrival after consult order placed, and patient's transfer to OR/ICU depending on staff and/or bed availability. Waiting for the results of X-ray chest and blood work were the other parts of category 1.

Even in an ideal process, there is still some wait time before receiving laboratory test results. Thus, such NVAT cannot be completely avoided. For example, from the health professional perspective, it is important that the interpretation of the head CT scan be as accurate as possible, which may not necessarily be considered as value added from the patient's perspective. Using more predictive methods can help minimize the need for more time-consuming laboratory tests. For instance, using clinical indicators to predict the outcomes of computed tomography could lead to considerable time saving if appropriately applied (Lotfi-Sadigh & Gholipour, 2015; Smits et al., 2005).

The second biggest source of NVAT was from gaps between consecutive processes (category 3), and accounted for approximately 39% of total NVAT. One possible explanation could be the time it takes for physicians to evaluate and make a decision about the patient condition (e.g. transfer to intensive care unit or operating room, need for additional expertise, etc.). Although this may be considered value-added from the physician's perspective, it is NVAT from the patient's perspective. The gap between processes can be attributed to transition time between locations.

The regression analyses confirmed our hypothesis, as well as the underlying assumption in other studies, that NVAT was significantly associated with worse outcomes ($p = 0.02$). This finding underscores the importance of timely care in the treatment process of pediatric TBI and is consistent with previous studies (Granacher, 2004; Jallo & Loftus, 2011). Results also showed that younger patients are more likely to have less favorable outcome. Head AIS was another significant factor ($p < 0.01$). No significant differences in outcomes were observed for Center 2 but this could be due to other unobserved variables not captured in our model (e.g., staffing, facility layout), which may have had a greater impact on the outcomes for Center 2.

The lack of NVAT data for the validation dataset was a study limitation. To compensate for this limitation, we clustered patients around similar clinical indicators and validated the accuracy of the estimation procedure in the validation phase. There was also limited sample size at each center. However, this was a preliminary study aimed at developing a framework for examining NVAT in pediatric trauma care and future work will need to validate our approach and findings. It was also not possible to account for the times related to clinical decision making by physicians in the ED in this study, which may be viewed as wait times from the patient perspective.

Conclusions

The study examined health care delivery in patients with critical conditions in two level I trauma centers, and considers NVAT associated with the care of pediatric TBI, and related patient outcomes. Results showed that NVAT adversely affects discharge outcomes and each minute spent on performing non-value added processes increases the likelihood of a less favorable outcome. Therefore, eliminating sources of such processes (delays, interruptions, waiting time, etc.) in the system could help improve system efficiency and pave the way towards a leaner process flow.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Figure 1.
Partial value stream map of the ED processes in Center 2.

Figure 2.
Histogram of NVAT for the two centers.

Figure 3.

Gantt chart of the treatment process. Note: there is no interaction with hospital/staff between the completion time of process 6 and the beginning of process 7 (this is identified as lag time).

Table 1

Summary of NVAT sources; sorted by their frequency (# of cases/total # of cases).

Source of NVAT (wait time)	NVAT Category*	Frequency	Percent of NVAT**
Head CT scan results	1	34.10%	38.00%
Unidentified gaps	3	18.20%	39.02%
X-ray chest results	1	12.10%	7.20%
X-ray abdomen results	1	8.50%	2.20%
X-ray pelvis results	1	5.10%	1.10%
Blood work results	1	4.90%	4.00%
Neurosurgery consultant to arrive	2	4.20%	2.10%
Surgery consultant to arrive	2	3.20%	1.10%
Hand off	2	2.10%	0.28%
Trauma team to arrive	2	1.90%	1.80%
Waiting to be transferred	2	1.90%	2.10%
Ultrasound results	1	1.60%	0.40%
Missing equipment	2	1.20%	0.50%
Available bed	2	1.20%	0.20%

* Categories: (1) waiting for test results; (2) waiting for hospital resources; (3) unidentified idle times.

** The percent of NVAT for each source of NVAT (row) is based on all patients across the two centers (N=40).

Table 2

Regression analyses for (a) Center 1, (b) Center 2, and (c) combined dataset.

Coefficients	RR	Robust SE	p-value	Lower C.I.	Upper C.I.
(a) Center 1 (N=56)					
(Intercept)	0.565	0.259	0.027	0.340	0.939
Age	0.991	0.006	0.177	0.979	1.004
Gender (female) *	1.208	0.083	0.023 *	1.026	1.423
Head AIS *	1.125	0.053	0.027 *	1.013	1.250
ISS	1.000	0.003	0.916	0.995	1.005
NVAT-LOS *	1.147	0.059	0.021 *	1.021	1.288
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<i>LL_φ: 45.340 LL_F:32.765 AIC:40.245</i>					
(b) Center 2 (N=40)					
(Intercept)	0.000	2.947	0.024	0.000	0.231
Age *	0.933	0.031	0.024 *	0.878	0.991
Gender (female)	0.981	0.573	0.974	0.319	3.017
Head AIS	3.139	0.670	0.088	0.844	11.675
ISS	0.971	0.019	0.127	0.935	1.008
NVAT-LOS *	1.141	0.055	0.017 *	1.024	1.272
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<i>LL_φ: 32.211 LL_F:20.510 AIC:54.511</i>					
(c) Combined (N=96)					
(Intercept)	0.388	0.383	0.001	0.223	0.677
Age *	0.989	0.005	0.034 *	0.980	0.999
Gender (female) *	1.143	0.068	0.048 *	1.001	1.305
Center (1)	1.073	0.071	0.324	0.933	1.233
Head AIS *	1.125	0.044	0.007 *	1.032	1.226
ISS	1.001	0.002	0.641	0.997	1.005

Coefficients	RR	Robust SE	p-value	Lower C.I.	Upper C.I.
NVAT-LOS*	1.015	0.007	0.021*	1.002	1.029
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<i>LL₀: 25.374 LL_F: 11.674 AIC: 45.543</i>					

Notes: Statistically significant factors are denoted by asterisk (*).

LL₀ and LL_F denotes the log-likelihood at initial and convergence, respectively; and AIC represents the Akaike information criterion (Akaike, 1973).