Process Modeling of ABCDE Primary Survey in Trauma Resuscitations

A Crucial First Step for Agent-Based Simulation Modeling of Complex Team-Based Clinical Processes

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Introduction: Trauma teams are ad hoc, multidisciplinary teams that perform complex patient care and medical decision making under dynamic conditions. The ability to measure and thus understand trauma team processes is still limited. Agent-based simulation modeling (ABSM) can be used to investigate complex relationships and performance within a trauma team. However, the foundational work to support such efforts is lacking. The goal of this work is to develop a comprehensive process model for the primary survey in trauma that can support ABSM.
Methods: A process model for the primary survey of patients with blunt traumatic injuries was developed using Advanced Trauma Life Support guidelines and peer-reviewed publications. This model was then validated using video recordings of 25 trauma resuscitations in a level 1 trauma center. The assessment and treatment pathway followed in each video were mapped against the defined pathway in the process model. Deviations were noted when resuscitations performance did not follow the defined pathway.
Results: Overall the process model contains 106 tasks and 78 decision points across all domains, with the largest number appearing in the circulation domain, followed by airway and breathing. A total of 34 deviations were observed across all 25 videos, and a maximum of 3 deviations were observed per video.
Conclusions: Overall, our data offered validity support for the blunt trauma primary survey process model. This process model was an important first step for the use of ABSM for the support of trauma care operations and team-based processes.
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Key Words: Agent-based simulation modeling, teamwork, trauma resuscitation, process modeling.

Computer simulation modeling provides an important mechanism to understand healthcare processes, variation in care, and response to interventions. While mannequin-based simulation provides a mechanism to study team processes and performance, such studies can be costly, time-consuming, and resource intensive. These challenges limit our ability to evaluate a large number of different interventions and assess the impact of multiple variables. In this context, computer simulation modeling arises as a useful tool, as it can be used to investigate the impact of such interventions on team effectiveness and patient care.

Computer simulation models can broadly be categorized into 4 classes: Monte Carlo, system dynamics, discrete event, and agent based.[1–7] Of these 4 types of modeling approaches, agent-based simulation modeling (ABSM) offers the most potential to study team processes for trauma resuscitations, as it allows for the modeling of individual behaviors of team members (ie, agents) as well as their interactions.[8–10] Agent-based simulation modeling has been used in a number of healthcare applications.[11,12] In emergency medicine,[5,13–27] ABSM mainly focuses on the modeling of prehospital settings as well as operational issues within the emergency department (ED) such as retriage, patient flow, surge protocols, and system design and does not address bedside patient care.

Agent-based simulation modeling provides a powerful mechanism to study trauma resuscitation team processes. Healthcare team performance depends on processes, such as information collection, processing and sharing, as well as decision making at the individual and team level.[28,29] Healthcare team members are usually heterogeneous both in terms of their roles and responsibilities within the team and their individual skills, goals, situational awareness, interactive behavior patterns, and decision-making tendencies. Agent-based simulation modeling's ability to represent each team member as an autonomous agent with its own characteristics, behaviors, and goals provides a suitable framework to model and analyze team processes. Although ABSM has been used to study team processes in nonhealthcare contexts,[30–33] to our knowledge, ABSM has not been used to investigate team processes for trauma resuscitations.

A crucial first step toward the use of ABSM for the investigation of trauma care teams is the development of a detailed process model that captures the underlying team-based clinical processes. Advanced Trauma Life Support (ATLS)[34,35] guidelines that describe the clinical processes for trauma

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resuscitations are widely accepted and used. Although this information is helpful, ATLS pathways do not completely reflect information inputs and complex team member decision making. Moreover, re-entrant processes, in which earlier actions and decisions are revisited because of changes in patient condition, are not well explicated.[36,37] In this application, re-entrant processes reflect the constant reassessments occurring during resuscitations and the need to go back to earlier domains (eg, airway) when patient status indicates patient instability (eg, severe hypoxia). Ultimately, ATLS guidelines do not provide a model that reflects the complexity of teamwork within a trauma team. Hence, to move ABSM forward within healthcare team science, there is a need to develop an adequately detailed process model for trauma resuscitations that can be used for ABSM.

The objective of this article is to describe a method for developing a process model of a complex interdisciplinary team interaction that can facilitate the utilization of ABSM. We use blunt injury trauma patient resuscitations as an exemplar of dynamic, parallel, stochastic clinical events.[38,39] In addition, this work serves as a first step towards understanding, capturing, and developing representations for the highly interdependent processes associated with team-based decision making during trauma resuscitations.

BACKGROUND

Characteristics of Trauma Teams and Trauma Resuscitations

The care of trauma patients is delivered by ad hoc, multidisciplinary action teams that perform complex patient care and medical decision making under dynamic and time pressured conditions. Trauma resuscitation task work is largely guided by Advanced Trauma Life Support (ATLS) guidelines.[34,35] The ATLS describes two major components: a primary survey and secondary survey. The purpose of the primary survey is to identify life-threatening injuries and initiate resuscitation in five domains (airway, breathing, circulation, disability, exposure [ABCDE]), whereas the purpose of the secondary survey is to examine each body region of the patient systematically to avoid missing an injury.

Although ATLS guidelines are helpful in directing treatment, they do not always reflect the fact that trauma resuscitations are stochastic (ie, uncertain), dynamic, patient specific, and resource dependent. More importantly, in most situations, trauma resuscitation is a parallel and re-entrant process.[40] The ABCDE assessments are conducted simultaneously and in parallel by different members of the trauma team under the oversight and coordination of the team leader. Any change in the patient's status may necessitate the rerouting and reentry of the process to another domain of the primary survey or immediate procedural intervention. The highly variable nature of all aspects of resuscitation (ie, patient, team, ED environment, hospital resources) poses a considerable challenge to any ABSM effort.

Agent-Based Simulation Modeling for Team Process Optimization

A system can be described by designating the relationships and interactions among stakeholders (agents), activities (tasks or decisions), and information.[41] Process modeling is a critical component of any system optimization effort.[42] Because a team can be interpreted as a system, process modeling of team-based processes serves as a critical first step for the use of computer simulation approaches for the optimization of team performance. As process modeling is an important tool for the study of any system, a number of methodologies exist in different fields (eg, software engineering and business process management).[43] A careful examination of these methodologies reveals that the types of relationships accounted for can be categorized into 3 main groups, namely, hierarchical (ie, the hierarchical ordering of ABCDE domain), sequential (ie, the sequential ordering of activities, varying from simple to complex tasks and decisions for each assessment), and informational requirements (ie, the information needed for decisions). A process model that can support ABSM has to incorporate all these 3 types of relationships. This is especially true for trauma resuscitations, where a comprehensive process model of primary survey must capture sequential relationships between tasks and decisions as well as informational relationships between tasks and decisions.

METHODS

Overview

This technical report describes the development of a comprehensive representation for the primary survey component in blunt trauma resuscitations. Model validity evidence was established using a video library of actual blunt trauma resuscitations. This work was approved by the University of Florida Institutional Review Board.

Data Source

We used a video database of actual trauma resuscitations recorded at the University of Washington Harborview Medical Center, a level 1 trauma center that admits more than 5000 trauma patients per year from a 5-state region. Data were collected from June 2016 to November 2018. Videos contained the first 30 minutes of the ED resuscitation or up until the patient left the ED, whichever occurred first. Initial inclusion criteria are described in a prior publication.[29] A subset of the database was selected for preliminary process model refinement and validation (n = 25). Inclusion criteria for the validation process were blunt trauma as primary mechanism of injury and 1 or more of the following:

- Hemodynamic instability (systolic blood pressure less than 90 mm Hg) at any time in the field or ED
- Glasgow Coma Scale less than 9
- Difficult or unsecured airway in the ED

Table 1 summarizes resuscitation characteristics. To facilitate development of a process model that could capture unexpected patient decompensation, the authors included videos that involved at least 1 nonroutine event, defined as new hypotension (2 consecutive systolic blood pressures less than 90 without prehospital hypotension), new hypoxia (oxygen saturation less than 90% for more than 1 minute without prehospital hypoxia), absence of a secured, stable airway, critical equipment failure, and unexpected medical emergency (eg, acute myocardial infarction). Videos were limited to the above criteria to allow the authors to focus on blunt trauma pathways used for critically ill patients. Although we reflect aspects of

TABLE 1. Characteristics of Blunt Trauma Resuscitations (N = 25)

Patient sex	
Male, n (% total)	17 (68)
Patient age,	
Years, median (IQR)*	52 (32–59)
Patient race, n (%)	
White	18 (72)
Black	4 (16)
Asian	2 (5)
Pacific Islander/Native Hawaiian	0 (0)
Native American	0 (0)
Other or not identified	1 (4)
Patient ethnicity, n (%)	
Hispanic	0 (0)
Non-Hispanic	23 (92)
Not reported	2 (8)
Injury Severity Score	
Mean (SD)†,‡	27 (14)
Nonroutine event type§	
New hypotension, n (%)	12 (48)
Positive FAST, n (%)	8 (32)
Loss of airway, n (%)	2 (8)
New hypoxia, n (%)	2 (8)
Loss of only vascular access, n (%)	2 (8)
Acute medical condition identified, n (%)	1 (4)
Other change in clinical condition, n (%)	4 (16)
Video duration,	
Median (IQR), minutes	29 (21–30)‖

*Interquartile range (IQR) reported as (25th percentile to 75th percentile).
†Baker et al.[46]
‡N = 24, 1 event had no injury severity score reported.
§Several nonroutine events per video possible; hence, cumulative percentage exceeds 100%.
‖Videos ended when the patient left the ED or 30 minutes, whichever occurred first.

penetrating trauma in our process model, these were not refined nor tested within the present work.

Four-Step Process Model Development

Step 1: Basic Model Development

We used a standard systems engineering approach to process modeling.[42] A rectangle represents a task, whereas a diamond represents a decision. Arcs capture the sequential relationships among activities. A task is associated with a single outgoing arc, whereas a decision is associated with 2 or more outgoing arcs. We enhanced this standard representation 2-fold: first, we included the information needed to make every decision. In addition, we explicitly captured the re-entrant nature of the trauma resuscitation work.

The interdisciplinary research team worked with the scaffolding of ATLS guidelines to identify the tasks, decisions, and sequential relationships required for each domain of the primary survey (ABCDE). Using existing literature as well as the emergency medicine expertise within the team, information needed for a decision was identified and noted on the process model next to the corresponding decision nodes. Figure 1 provides a snapshot of a sample process model that was developed for demonstration purposes. Table 2 lists the number of task and decision nodes as well as arcs for each domain, and the complete process model is in the online supplement (see Figure, Supplemental Digital Content 1a–f, process model, http://links.lww.com/SIH/A753).

Step 2: Incorporation of Re-entrant Processes

During trauma resuscitations, critical indicator data (eg, blood pressure, oxygen saturation, and level of consciousness) are continuously monitored and interpreted to assess patient condition on an ongoing basis. As the ATLS guidelines note, critical changes in patient status (eg, hemodynamic instability or loss of airway) need to be assessed using the critical indicator data (eg, blood pressure and blood oxygenation level). A significant change in patient status prompts a return to the appropriate activity of the primary survey to reassess the patient and treat as needed. Consequently, components of the primary survey need to be repeated as necessary. From a modeling perspective, this means trauma resuscitations have dynamic and stochastic re-entrant process flows that are impossible to capture using the standard process modeling tools. To this end, we created a nonstandard element, an icon, that represents critical indicator data tracked throughout the entire resuscitation, for example, oxygen saturation. Figure 2 illustrates the oxygen saturation icon. In this example, if during any part of the trauma resuscitation, the blood oxygen saturation level decreases below 90%, there is a "re-evaluation" that begins again with airway and re-establishes the priority of managing airway and breathing to troubleshoot the new hypoxia noted by the indicators. In a setting with larger resuscitation teams, such as those in a level 1 trauma center, it is expected that the team can divide its task work to attend to the new oxygen issue by revisiting airway while continuing evaluation and management of breathing and circulation. Table 3 identifies the icons and provides brief descriptions. Table 4 lists the number of task and decision nodes as well as arcs for each icon subroutine. Detailed subroutines for icons are provided online (see Figure, Supplemental Digital Content 1g, icon subroutines, http://links.lww.com/SIH/A753).

Step 3: Model Review and Refinement

We performed an initial testing on the preliminary version of the process model by reviewing 2 blunt trauma resuscitation videos. We chose 2 videos to represent 2 different mechanisms of injury (motor vehicle collision and fall) with different teams on different dates. All authors viewed videos with the process model to allow for a critical review of the model. Authors discussed areas where the model did not accurately reflect activities performed by the trauma team, and consensus was reached to determine effective representation of performance. Where necessary, the process model was revised and additional activities and sequential relationships were included.

Step 4: Testing and Validity Evidence

We applied the process model to the library of 25 trauma resuscitation videos. Our approach to coding and characterizing process deviations are discussed hereinafter.

Coding

Each resuscitation video was independently coded by two of the authors (T.L., R.F.) using the process model to indicate the pathway followed by the trauma resuscitation team. After individual coding, coders met to review coding and discuss any disagreements. When needed, a third coder (E.A.) reviewed resuscitations to resolve any remaining disagreements. Data collection during coding occurred as follows: if a task is completed, then the outgoing arc is coded as "1." If the task

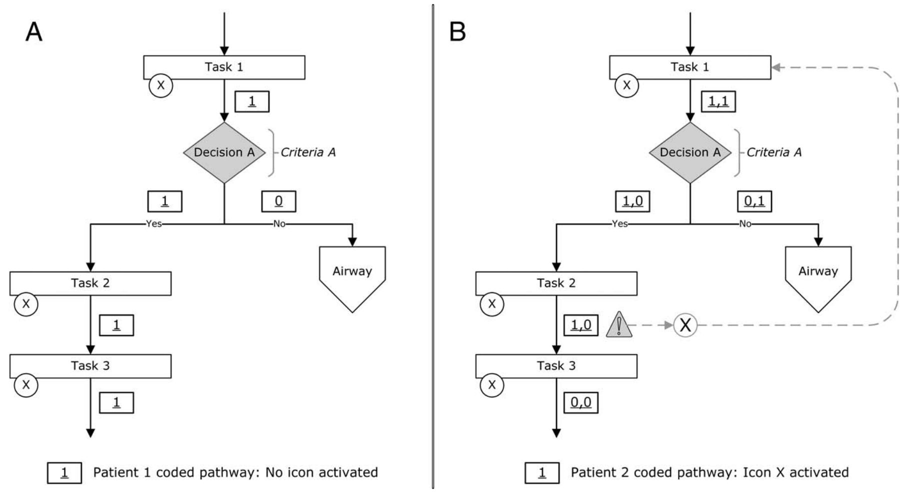

Figure 1. Example of a process model coded with 2 sample patients. Figure 1 demonstrates our process model logic, including the implementation of a re-entry icon. It also shows the coding of 2 sample patients' paths: Tasks (eg, "Task 1") are represented as large rectangles, whereas a diamond represents a decision (eg, "Decision A"). Each decision has its decision criteria (eg, "Criteria A") listed next to it and its outgoing arcs describe the possible outcomes/alternatives of the decision. The pentagon is an off-page connector, connecting the various domains of the process model, in this case linking to the beginning of the airway domain. The ⊗ represents a sample icon. The presence of the (warning sign/⊗ next to the outgoing arc/dashed arc) monitored data indicates the activation of an icon, instead of immediately continuing with the next activity or decision. An icon is called activated if its criteria are met. For example, the blood oxygen saturation level decreasing less than 90%. The small rectangles containing the numbers 0 and/or 1 demonstrate the coded path for sample patient 1 in Figure 1A and patient 2 in Figure 1B. If an activity is completed, its (outgoing arc) is coded as "1." In the case of an icon activation, each arc has 2 codes (of zeros or ones), with the first entry referring to the path independent of the icon activation and the second entry referring to the path followed due to the icon activation. For patient 1, icon ⊗ is never activated and does not require reentry. The team performs task 1, chooses the "Yes" arc of decision A, then performs tasks 2 as well as 3. For patient 2, there is an activation of icon ⊗. The team performs task 1, then chooses the "Yes" arc of decision 1 and performs task 2. After performing task 2 the evaluation of criteria X relating to icon ⊗ is positive and the re-entrant process requires the team to move back to task 1 (demonstrated by curved arrows). This time, after performing task 1 again, Criteria A is not met, resulting in sending the patient to the operating room.

is not completed or not performed, then the outgoing arc is coded as "0." Recall that a decision node can be associated with multiple outgoing arcs. Hence, the outgoing arc that corresponds to the decision made is coded as "1," whereas all the others are coded as "0." If a task cannot be completed or decision cannot be made because the patient has to be removed from the ED (eg, a positive FAST [focused assessment with sonography in trauma] so patient emergently taken to the operating room and the exposure domain of the process model is not completed), the corresponding arc is coded as "N." If an activity cannot be observed because the video ended prematurely, all remaining activities are also coded as "N." When a critical change in patient status is observed/identified/diagnosed based on the pertinent critical indicator data, the associated icon is coded as "activated" and the associated icon subroutine indicates how the team should continue.

The total number of tasks, decisions, and arcs for each of the domains are presented in Table 2. For each resuscitation, we note whether a particular arc was taken. If no icon is activated, then each arc is coded with a "0" or "1." If an icon is activated, then each arc has 2 codes ([0,0], [0,1], [1,0], [1,1]). The first entry represents whether the arc is included on the pathway for the patient before the icon activation. The second entry represents whether the arc is included (or potentially repeated) because of the icon activation. Arcs and activities within an icon subroutine were coded only if the icon was activated. In our work, we observed that there was at most 1 icon activation per patient. Note that, however, if more icons need to be activated for a patient, then each code for the resuscitation can be expanded accordingly. If a task cannot be completed or a decision cannot be made because the patient has to be removed from the ED, "N" is assigned to an arc pre or post icon activation. Our coding approach and data representation are scalable. Figure 1demonstrates hypothetical coded resuscitations for 2 patients, one without icon activation (patient 1) and one with an icon activation (patient 2).

TABLE 2. Number of Tasks, Decisions, and Arcs for each Domain of the Developed Process Model

	Airway	Breathing	Circulation	Disability	Exposure
Task nodes	34	16	37	13	6
Decision nodes	23	14	31	7	3
Arcs	80	46	100	28	12

Deviations

In several instances, the observed flow in the resuscitation video did not match the process model. Coders discussed each mismatch. When a mismatch did not impact the prioritization of activities according to the ABCDE ATLS guidelines, it was deemed to be within expectations for parallel work. For example, a subset of the team undressing the patient during the assessment of Breathing would not be considered to be a deviation because of the parallel nature of the work as long as it did not interfere with critical interventions such as chest tube placement. However, if a mismatch impeded critical completion of other steps, for example, prioritizing a neurologic examination and limiting the ability to assess the airway, it would be deemed a deviation. Furthermore, when one deviation directly impacted another one, for example, early chest tube

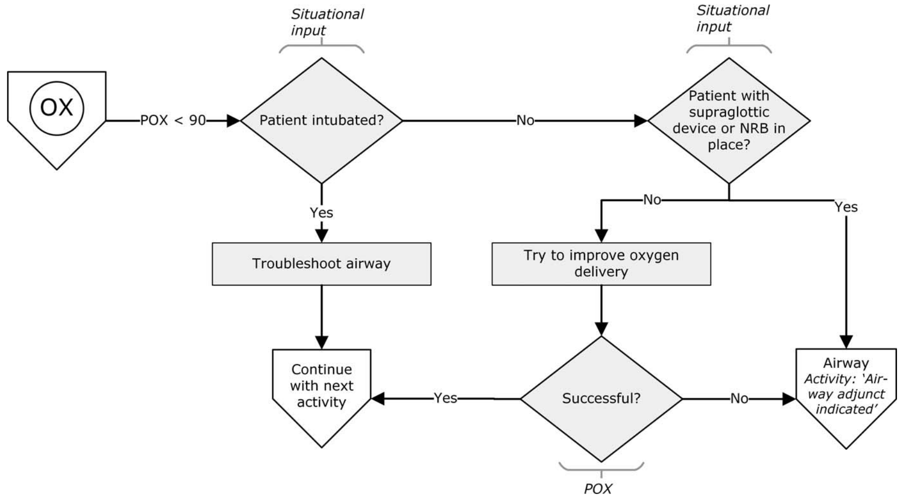

FIGURE 2. Oxygenation icon activation. This figure shows the subroutine of our oxygen saturation icon; if, during any part of the trauma resuscitation, the blood oxygen saturation level decreases below 90%, there is a "re-evaluation" that begins again with airway and re-establishes the priority of managing airway and breathing to troubleshoot the new hypoxia noted by the indicators. NRB, non-rebreather mask; POX, pulse oximeter.

placement delayed both chest x-ray and pelvis x-ray, these were recorded separately but ultimately reported as a single deviation. Observed deviations were classified into 6 categories of (1) addition, (2) omission, (3) sequence, and (4) delay in terms of their relationships to the underlying process model, as well as (5) other for those deviations that could not be assigned to 1 of the 4 categories and (6) data interpretation issues for incidences in which the videos' audio and/or visual limitations did not allow a clear allocation to a specific category (Table 5).

With this method, the coded data can be used to recreate the entire pathway taken by each resuscitation team. That is, given the coded data, it is possible to go through the process model and mark all arcs according to the code, which, in turn, would replicate the process flow in the trauma resuscitation.

RESULTS

Process Model

Table 2 describes the number of tasks, decisions and arcs for each domain (ie, ABCDE) of the developed process model. Not surprisingly, the ABC domains contain more decision nodes than D or E. The most complicated domains seem to be A and C with 23 decision and 34 task nodes, and 31 decision and 37 task nodes, respectively. Whereas B and D are comparable in terms of the number of task nodes involved, B has double the number of decision nodes of D. Among all domains, E is the least complex/complicated one with only 3 decisions and 6 tasks. Tables 6 and 7 provide summary statistics on the number of activities completed by trauma teams for the 25 videos coded.

Deviations

A total of 34 deviations were observed across all 25 videos (Table 8). The distribution of deviations per video was relatively uniform (7 [28%] had 0 deviations, 8 [32%] had 1 deviation, 4 [16%] had 2 deviations, and 6 [24%] had 3 deviations). Thirty deviations were observed in ABC domains (7 [21%] in A, 9 [26%] in B, 14 [41%] in C). More than half of the deviations were categorized as either addition (8 [24%]) or sequence (12 [35%]). Two deviations could not be categorized because of missing information or inability to interpret video.

DISCUSSION

We describe the initial process modeling required for the subsequent development of an ABSM approach that can support the investigation of team-based processes and decision making in trauma teams. We used an existing video library of trauma resuscitations from a level 1 trauma center to collect validity evidence supporting our process model for blunt injury trauma resuscitation. Our method produced a process model that (1) captured trauma resuscitation processes and (2) supported the identification and characterization of trauma team process deviations. While other resources[35,44] describe the basic steps involved in ATLS-guided resuscitations, to our knowledge, this is the first description of a process model capable of supporting ABSM.

Our findings suggest that the circulation domain may be most complex from a decision-making standpoint. We also found that our re-entry nodes, when activated, resulted in

TABLE 3. Description of Icons

Icon	Critical indicator data	Description
BP	Systolic blood pressure	If the patient's systolic blood pressure decreases below 90 (or precipitous drop), the team continues with or returns to circulation.
LC	Level of consciousness	If the level of consciousness decreases, the team moves back to airway.
OX	Oxygen saturation	If the oxygen saturation decreases below 90%, the team moves back to Airway.

TABLE 4. Number of Tasks, Decisions, and Arcs for each Icon Subroutine

	OX	LC	BP
Task nodes	2	0	1
Decision nodes	3	0	1
Arcs	9	1	4

TABLE 5. Categorization and Examples of Deviations

Category	Description	Example
Addition	Activities performed without clear indication in process model for given patient/situation	Transfusing blood products without indication
Omission	Activities that are omitted, despite clear indication to be performed in process model for given patient/situation	Not immobilizing cervical spine in patient that cannot be examined (ie, intubated patient)
Sequence	A mismatch between the indicated sequence in the process model and the resuscitation video, relating to nonparallel, critical interventions	Chest x-ray being delayed for chest tube while patient is intubated
Delay	Activities that are delayed	OR not ready therefore delay in time from positive FAST to OR
Other	Every remaining deviation not belonging to any other category	Patient meeting criteria for intubation not intubated due to DNR/DNI status
Data interpretation issues	Incidences that do not allow a clear allocation to a specific category due to data collection and/or interpretation limitations (audio/video quality issues or video cut off early)	Video inadequate to determine conclusively if airway exam was performed.

DNR/DNI, do not resuscitate/do not intubate.

revisiting the circulation pathway. While it is certainly possible that new issues could arise in airway or breathing domains, new hypotension was more common than new hypoxia. It is possible that a trauma institution where prehospital intubation was less common might demonstrate different results. Considering patient-level factors will continue to be important in model refinement and ABSM design.

Trauma teams are spontaneously formed, highly multidisciplinary teams that have to make decisions expeditiously under rapidly changing conditions to deliver complex care. Successful completion of trauma resuscitation critically relies on efficient coordination and effective adaptation of leader and team member interactions to dynamically changing patient condition. Currently, our ability to model individual information collection, processing, and sharing along with decision-making processes of the leader and team members to investigate how these individual processes influence the collective performance of the team is insufficient. However, ABSM with its inherent capability to model the decision-making processes of each agent (ie, leader and team members) explicitly has the potential to provide a framework to enable a rigorous approach to model and analyze complex domains with multiple agents. Hence, this work serves as a crucial first step for the development of an ABSM approach to study team processes involved in primary survey for blunt trauma care.

Our process model makes a distinction between tasks and decisions required during trauma resuscitation. Some decision and task nodes involve complex task work (eg, chest tube insertion) and could be modeled in further detail to distinguish among the multiple different steps involved. If more detailed representations are needed, future research is warranted to identify and characterize the elemental steps associated with the task work of interest. Moreover, the current process model can be extended to include additional nonroutine resuscitation activities (eg, traumatic cardiac arrest and return of spontaneous circulation) that may require an irregular procedure, re-entrance to a previous activity, or early exit from the ED.

Model deviations provide insight into areas where model revision could be warranted. Deviations could represent areas where clinical decisions or actions are inaccurately or incompletely represented in the model. Alternately, they may represent places where the team's performance did not match evidence-based guidelines. Our deviations were most commonly addition related, that is, added actions not represented in the model, or sequence-related, where the actions of the team did not follow expected order of events. It is possible that the model did not account for the complexity involved in certain aspects of trauma resuscitation decision making. As our sample size for validation is relatively small, more data will help inform if the model requires revision.

The next step toward the development of an ABSM methodology for the modeling and analysis of team processes in trauma care would include (1) the identification of the agent (s) that are needed to complete each task or decision on the process model; (2) information collection, processing, and sharing behaviors for each of these agents that would influence the effective and efficient completion of team processes; (3) the underlying empirical probability distributions that represent the timing and efficacy of the demonstration of these behaviors for each individual on a given team; (4) a stochastic process that represents the evolution of the patient during the delivery of trauma care; (5) the hypothesized/expected/observed impact of these behaviors on the evolution trajectory of the patient. Once an agent-based simulation model has been

TABLE 6. Number of Completed Tasks and Made Decisions During 25 Blunt Trauma Resuscitations

	No. Arcs Coded as Median (IQR)*			
Domain	**[0]/[0,0]**	**[1]/[1,0]/[0,1]**	**[1,1]**	**N**
Airway	67 (64–71)	13 (9–16)	0 (0–0)	0 (0–0)
Breathing	33 (30–36)	13 (10–16)	0 (0–0)	0 (0–0)
Circulation	71 (66–74)	28 (26–32)	0 (0–0)	0 (0–0)
Disability	17 (17–23)	5 (5–11)	0 (0–0)	0 (0–1)
Exposure	3 (1–4)	8 (3–8)	0 (0–0)	0 (0–9)
Total†	192 (180–196)	69 (64–72)	0 (0–0)	0 (0–19)

*Interquartile range (IQR) reported as (25th percentile to 75th percentile).
†Total does not include icon subroutine counts.

TABLE 7. Number of Completed Tasks and Made Decisions During 25 Blunt Trauma Resuscitations for Each Icon Subroutine

	No. Arcs Coded as Median (IQR)*			
Domain	**[0]/[0,0]**	**[1]/[1,0]/[0,1]**	**[1,1]**	**N**
OX	0 (0–0)	0 (0–0)	0 (0–0)	0 (0–0)
LC	0 (0–0)	0 (0–0)	0 (0–0)	0 (0–0)
BP	0 (0–1)	0 (0–3)	0 (0–0)	0 (0–0)

*Interquartile range (IQR) reported as (25th percentile to 75th percentile).

TABLE 8. Overview of Characteristics of Process Model Deviations*

Distribution of deviations per video, n (%)	
0 deviations per video	7 (28)
1 deviation per video	8 (32)
2 deviations per video	4 (16)
3 deviations per video	6 (24)
Deviations per domain, n (%)	
Airway	7 (21)
Breathing	9 (26)
Circulation	14 (41)
Disability	3 (9)
Exposure	1 (3)
Deviation types, n (%)	
Addition	8 (24)
Omission	7 (21)
Sequence	12 (35)
Delay	4 (12)
Other	3 (3)
Data interpretation issue	2 (6)

*If deviations directly impacted one another, for example, an unindicated chest tube placement delayed both the chest and pelvis x-ray, then although they were coded individually, only the initial deviation was counted in the statistics reported.

developed, it has to be verified and validated.[45] The resulting model can then be applied to study the impact of individual, team, and system-level variables on team processes and bedside delivery of patient care. In addition, researchers can perform initial simulations to evaluate how interventions might affect trauma patient care. These initial studies can be used to inform the design and execution of observation and randomized controlled trials.

There were several limitations related to our methodology. First, our process model does not include several categories of injuries (eg, thermal injuries, poisoning) nor a full range of patient types (eg, obstetric patients, pediatric patients) and the testing our process model with a video library was limited to blunt trauma resuscitations. We focused on testing our process model with a video library of blunt trauma resuscitations. This was necessary to strike a balance between complexity/exhaustiveness versus practicality. Second, our process model does not account for critical pieces of equipment needed to complete tasks or make decisions. A third limitation is the source of our video library data. All resuscitations were recorded at a single trauma center. While this is a large institution capturing patients from 5 states, it still reflects care at a single institution. Fourth, we occasionally had challenges with audio and video when a large resuscitation team had significant concurrent verbal communication and activity. In these cases, hearing specific instructions or seeing certain behaviors were limited. Our videos were also limited to a maximum of 30 minutes, and in some cases, part of the diagnostic and treatment pathway for a patient could not be observed. Finally, our coding approach did not incorporate time stamps for decision and task nodes. Time stamps would provide a more accurate representation of the flow of the process, but this initial work focused on refining tasks, decisions, and decision criteria.

CONCLUSIONS

This technical report describes an approach to develop and verify process models for dynamic, stochastic, urgent clinical care delivery by interdisciplinary teams. Our preliminary testing demonstrates that the approach is effective in developing and testing process models for primary survey of trauma resuscitations. Our process model can facilitate the use of ABSM for the investigation of team-based processes and decision making in trauma care. Additional testing and refining focusing on penetrating trauma videos as well as nonroutine events is warranted to further enhance the process model.

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