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Using epistemic network analysis to identify targets for educational interventions in trauma team communication

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ABSTRACT

Background. Epistemic Network Analysis (ENA) is a technique for modeling and comparing the structure of connections between elements in coded data. We hypothesized that connections among team discourse elements as modeled by ENA would predict the quality of team performance in trauma simulation.
Methods. The Modified Non-technical Skills Scale for Trauma (T-NOTECHS) was used to score a simulation-based trauma team resuscitation. Sixteen teams of 5 trainees participated. Dialogue was coded using Verbal Response Modes (VRM), a speech classification system. ENA was used to model the connections between VRM codes. ENA models of teams with lesser T-NOTECHS scores ($n = 9$, mean = 16.98, standard deviation [SD] = 1.45) were compared with models of teams with greater T-NOTECHS scores ($n = 7$, mean = 21.02, SD = 1.09).
Results. Teams had different patterns of connections among VRM speech form codes with regard to connections among questions and edifications (meanHIGH = 0.115, meanLOW = –0.089; $t = 2.21$; $P = .046$, Cohen d = 1.021). Greater-scoring groups had stronger connections between stating information and providing acknowledgments, confirmation, or advising. Lesser-scoring groups had a stronger connection between asking questions and stating information. Discourse data suggest that this pattern reflected increased uncertainty. Lesser-scoring groups also had stronger connections from edifications to disclosures (revealing thoughts, feelings, and intentions) and interpretations (explaining, judging, and evaluating the behavior of others).
Conclusion. ENA is a novel and valid method to assess communication among trauma teams. Differences in communication among higher- and lower-performing teams appear to result from the ways teams use questions. ENA allowed us to identify targets for improvement related to the use of questions and stating information by team members.

Trauma centers see 30 million trauma patients a year with injury being the leading cause of death in patients 1 to 44 years old. Studies estimate that 10% of trauma deaths are related to preventable errors.[1] Most of these errors occur during the trauma initial assessment.[1,2] Because of the complex, time-critical, and high-risk nature of the trauma initial assessment, errors of nontechnical skill, including decision making, communication, teamwork, and stress management, predominate over errors of technical skill.[2] Development of these nontechnical skills during trauma education is essential to improve trauma outcomes.

Global rating scales, such as the Modified Nontechnical Skills Scale for Trauma (T-NOTECHS),[3] are used currently to provide broad, subjective assessments of overall performance of nontechnical skills. T-NOTECHS evaluates globally the ability of the trauma team to use nontechnical skills, such as leadership, cooperation,

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and decision making, to complete tasks necessary for patient care. Improved T-NOTECHS scores have been found to correlate with clinical performance in both actual and simulated trauma resuscitations[4], however, there is no clear and objective way to identify the components of good or bad performance with these scales, which makes it challenging to use this approach alone to develop focused targets for improvement. Examples are often used to anchor scores, but these anchors are often too broad. For instance, asking a team to “clearly define a team leader” is not as simple as the team announcing a leader at the start because many different elements of team interaction affect leadership. A richer, quantifiable description of team performance is necessary to develop educational interventions for team trauma performance.

This gap can be addressed through the aspect of distributed cognition theory and speech acts theory. Distributed cognition theory suggests that cognition and knowledge are not confined to an individual but rather are distributed among individuals and tools in the environment.[5] The cognition of the team is, therefore reflected in their communication. One way of understanding team communication is by looking at the speech acts performed by group members. Speech acts theory evaluates the performative functions of utterances – the actions we perform by what we say.[6]

Verbal Response Modes (VRM) is a descriptive speech acts taxonomy that categorizes utterances based on the relationship created by what is said between the speaker and another who is the target of the speech act.[7] There are 8 categories in the VRM taxonomy: disclosure, edification, advisement, confirmation, question, acknowledgement, interpretation, and reflection (Table 1). In addition, each utterance is coded twice: once for the form (literal meaning), and once for the intent (pragmatic meaning). For instance, “Would you do the math?” has a question form and advisement intent. Overall, VRM describes how the speaker can be related to the other within each utterance. These “microrelationships” can then be combined to depict the relationships between team members and link observable speech with general psychologic principles.

The connections between VRM codes can then be analyzed with Epistemic Network Analysis (ENA). ENA software was designed to describe and compare epistemic frames which are the connections between the different domain-specific skills and knowledge used by professionals in problem solving.[8] ENA identifies connections among elements of interest in segments of discourse data and models the weighted structure of these connections. ENA software can be used to create communication networks that similarly depict team communication as the connections between different communicative elements. We hypothesized that comparing communication networks of speech acts performed by trauma teams to other markers of team performance can help to describe how higher-performing teams communicate compared with lower-performing teams.

Methods

Participants and setting

This study was determined to be exempt by the Institutional Review Board of the University of Wisconsin, but informed consent for the use of data was still obtained from participants. Sixteen teams of 5 participated in interdisciplinary trauma team training simulations. Each team consisted of a trauma chief resident, surgery resident, emergency medicine resident, and 2 emergency medicine nurses. All resident physicians were certified in Advanced Trauma Life Support (ATLS). In keeping with their usual roles, trauma chief residents were always the trauma team leader. The surgery resident and emergency medicine resident performed the primary survey, secondary survey, and adjuncts. The emergency medicine nurses alternated among their usual roles in the trauma initial assessment. There was 1 circulating nurse and 1 nurse scribe. Although some trauma trainees participated in more than 1 session throughout the year, they never repeated the same scenario.

The simulations were performed in a simulated trauma resuscitation room equipped with a high-fidelity manikin (Laerdal, SimMan 3G, Wappinger Falls, NY), advanced audiovisual streaming, capture and playback systems, and 1-way mirrors for direct observation. Each team was randomly assigned 1 of 8 standardized trauma scenarios randomly (Table 2). Three faculty members (trauma surgery, emergency medicine, and emergency medicine nursing) participated in the educational elements of the program and facilitated the simulation scenario. The sessions were audio- and video-recorded.

Data collection and coding

After completion of each scenario, the T-NOTECHS scale was used to evaluate the overall simulation performance of the trainee team. The T-NOTECHS scale consists of 5 behavior domains that were identified by an expert panel of trauma practitioners based on scoring instruments for the existing teamwork and nontechnical skills: (1) Leadership, (2) Cooperation and Resource Management, (3) Communication and Interaction, (4) Assessment and Decision Making, and (5) Situation Awareness/Coping with Stress. Each domain is scored on a 5-point Likert scale. Each of the faculty facilitators scored the performances individually. The intraclass correlation among the 3 raters was 0.73. T-NOTECHS scores were averaged among the 3 raters for an overall score for each simulation performance. The mean overall T-NOTECHS score was 18.8. Based on the position of their T-NOTECHS scores to the mean overall T-NOTECHS score, the teams were divided into high- ($n = 7$, mean = 21.02 ± 1.09) and low-performing groups ($n = 9$, mean = 16.98 ± 1.45). This was an acceptable division of groups for our analysis, because the average T-NOTECHS behavioral domain scores were approximately 3 for lower-performing teams and 4 for higher-performing teams. Using the scoring guidelines of the instrument, this incremental difference in performance represents teams missing some critical

Table 1
Verbal Response Modes (VRM) classifications.

VRM code	Form	Intention
Disclosure	I, we; first person, declarative	Reveals thoughts, feelings, perceptions, intentions
Advisement	Second person with a verb of permission, imperative	Attempts to guide behavior, suggestions, commands
Edification	He, she, it; third person, declarative	States objective information
Confirmation	We; first person plural	Agreement, disagreement, shared experience or belief
Question	Interrogative; ?	Requests information or guidance
Interpretation	You; second person, verb implies an attribute or ability of the other	Explains or labels the other, judgments or evaluations of behavior
Reflection	Second person, verb implies internal experience	Repetition, restatements, puts other’s experience into words
Acknowledgment	Terms of address or salutation	Conveys receipt of communication

Table 2
Standardized trauma scenarios.

Scenario	Content
Motor vehicle collision: Hypothermia, pelvic fracture, liver laceration, hemopneumothorax	A 38-year-old man who presents after a motor vehicle collision. Found in a snow bank several feet away from a car struck into a light pole. Initially unresponsive, but now following commands. Complaining of chest and abdominal pain. VS: HR 55, BP 90/50, RR 23, Spo_2 91%
Motor vehicle collision: Pelvic fracture, splenic laceration, right femur fracture	30-year-old woman who presents after a motor vehicle collision. Restrained driver of the vehicle, which struck the highway median. Complaining of abdominal and right lower extremity pain. VS: HR 110, BP 145/70, RR 20, Spo_2 94%
Gunshot wounds: Left rib fractures with hemopneumothorax, right leg vascular injury	A 25-year-old man who presents after gunshot wounds to the left chest and right leg. Complaining of left chest and right leg pain. VS: HR 115, BP 90/60, RR 25, Spo_2 89%
Fall: Cervical spine fracture with acute traumatic spinal cord injury, traumatic brain injury	A 70-year-old woman who presents after a fall down stairs. Found by EMS not moving. Awake but confused. VS: HR 50, BP 100/50, RR 26, Spo_2 91%
Fall: Basilar skull fracture, cerebral edema, aortic rupture, left rib fractures, left femur fracture*	A 23-year-old man who presents after a fall from 35 feet from a scaffolding at work. Found unconscious. Responding to painful stimuli only. Left thigh deformity and left chest wall bruising. VS: HR 100, BP 95/60, RR 24, Spo_2 94%
Fall/electrical injury: Left rib fractures with pneumothorax, electrical burn, cardiac dysrhythmia, rhabdomyolysis, splenic laceration*	A 42-year-old man who presents after making contact with a high-tension electrical wire and falling from the electrical pole. Complaining of shortness of breath, left chest and arm pain. VS: HR 120, BP 90/60, RR 26, Spo_2 90%
Motorcycle collision: Left rib fractures, left diaphragm rupture, left kidney laceration, bilateral mandibular fractures, right depressed skull fracture*	A 35-year-old woman who presents after a motorcycle collision. Ejected after she struck a stopped car. Initially found unresponsive. Now responding to voice, but in respiratory distress. VS: HR 130, BP 80/40, RR 40, Spo_2 90%
Fall: Right rib fractures and pneumothorax, intracranial hemorrhage, right femur fracture*	A 21-year-old man who presents after a fall from a third floor balcony. Initially alert but became unresponsive shortly before arriving. Was complaining of right thigh pain and shortness of breath. VS: HR 110, BP 100/60, RR 24, Spo_2 89%

BP, blood pressure; *HR,* heart rate; *RR,* respiratory rate; *VS,* vital signs.
* Adapted from ATLS initial assessment scenarios.[23]

behaviors versus teams demonstrating these behaviors consistently. Thus, the division of groups in this way captured clinically meaningful differences in performance.

Using both transcriptions and review of audio-video recordings, the discourse of each trauma team was coded with the VRM speech acts taxonomy. The 3 principles of classification used by the VRM taxonomy are understood by describing the source of experience and the viewpoint of an utterance. First, the utterance is classified by whether it concerns the experience of the speaker or another person. For example, in “I like math,” the speaker is the source of experience, whereas in “Do you like math?” the other is the source of experience. Second, the utterance is classified by whether the speaker needs to make a presumption about the other’s experience. When stating “Do you like math?” the speaker does not need to presume the thoughts, feelings, perceptions, or intentions of the other. The presumption about experience is, therefore the speaker. In contrast, by saying “Do math” the speaker imposes an experience (intent to perform math) on the other and has a presumption about the experience of the other. Finally, the utterance is classified by whether it is stated from the personal viewpoint of the speaker or a shared or common viewpoint. “I like math,” “Do you like math?” and “Do math” are from the viewpoint of the speaker, whereas “You want to do math” is from the frame of reference of the other person. Using this taxonomy, discourse can be categorized into 1 of 8 categories of speech as described in Table 1. Each utterance was coded twice: once for the form (literal meaning) and once for the intent (pragmatic meaning). Initially, 2 investigators coded 210 utterances individually to determine interrater reliability. Interrater reliability was established using Cohen κ, with $\kappa = 0.70$. The remainder of the discourse was coded by individual investigators.

Data analysis

Coded data were then analyzed with ENA software. The process of creating epistemic network models has been explained in detail elsewhere.[9] Co-occurrences of concepts in a given segment of discourse data are a good indicator of cognitive connections, particularly when the co-occurrences are frequent. To analyze these co-occurrences with ENA, a symmetric adjacency matrix is created that represents this frequency of association within a selected segment of data, or stanza, with codes existing as columns and rows. Co-occurrence of codes is indicated with a binary classification. Codes that occur within the same stanza receive a 1, and elements that do not co-occur in the same stanza receive a 0. Because each stanza is represented as an adjacency matrix, these matrices can be summed, resulting in a symmetric cumulative adjacency matrix. These cumulative adjacency matrices are represented as discourse networks with each node in the network corresponding to a VRM code. The cumulative adjacency matrices are represented as vectors in a high-dimensional space. ENA performs a dimensional rotation using singular value decomposition to produce a lower-ordered representation that captures the maximum variance in the data. The center position, or centroid, of the network graph is positioned in a low-dimensional space. This is done in a manner such that positions of nodes in the network representations can be used to interpret the dimensions, similarly to Principal Components Analysis.[10-15] In this study, co-occurrences are indicative of the connections among speech acts that serve to distribute the thoughts and actions of the team. Therefore, ENA was used to model the data by creating adjacency matrices that quantified the co-occurrence of VRM codes in the teams’ dialogue. This analysis was performed separately with both VRM form and intent categories.

The speech acts exhibited by individuals working within teams will often be in connection to things that their collaborators say and do. This was accounted for by using a sliding window analysis.[16,17] Each turn of talk was analyzed in the context of a window that contained the preceding turns of talk. The size of this window has been identified previously as 3 or 4 turns of talk.[18,19] A window of 3 turns of talk was selected for this study. Sliding window analysis was used to produce an adjacency matrix for each turn of talk separately, accounting for the connections made by each individual within the context of group communication.

A dimensional reduction was performed, and the nodes of the networks representing the VRM categories were placed in the space using an optimization algorithm, such that the centroid of each communication network of each trauma team corresponded to the location of the network in the dimensional reduction. Two coordinated representations were then obtained: (1) the location of each network in a projected metric space in which all units included in the model are located, and (2) weighted network graphs for each network, which explain why the network is positioned where it is.

ENA software was used to identify the epistemic network locations of communication of the higher-performing and lower-performing trauma teams during simulation. We obtained the mean locations of the 2 groups with confidence intervals as well as independent samples *t* tests. Because the graphs of the network of each individual team are coordinated in the projected metric space, ENA was then used to create mean network graphs for both higher- and lower-performing trauma groups by computing the average value for each edge weight. Then, to see the differences in the relative strengths of connections between the 2 network graphs, ENA was used to obtain difference graphs that subtract the edge weights of one network from another, indicating which connections are stronger in each network.

Results

The centroids of the VRM code communication network of the high- and low-performing trauma teams were obtained for both form and intent codes. Fig 1 shows the network centroids of the groups of lower- and higher-performing teams (green and purple respectively) for the analysis of the form codes. The means are represented by the corresponding squares, and the boxes around each mean indicate the 95% confidence interval on each dimension. Teams with different T-NOTECHS performance scores had different patterns of connections among VRM form codes along dimension 1 (meanHIGH = 0.115, meanLOW = –0.089; t = 2.21; P = .046, Cohen d = 1.021) but not dimension 2 (meanHIGH = –0.019, meanLOW = 0.015; t = –0.449; P = .661, Cohen d = –0.242). The same analysis was performed on the intent codes. These patterns were not different in VRM intent code connections along dimension 1 (meanHIGH = 0.079, meanLOW = –0.061; t = 1.362; P = .196, Cohen d = 0.732) or dimension 2 (meanHIGH = –0.005, meanLOW = 0.004; t = –0.092, P = .929, Cohen d = –0.053).

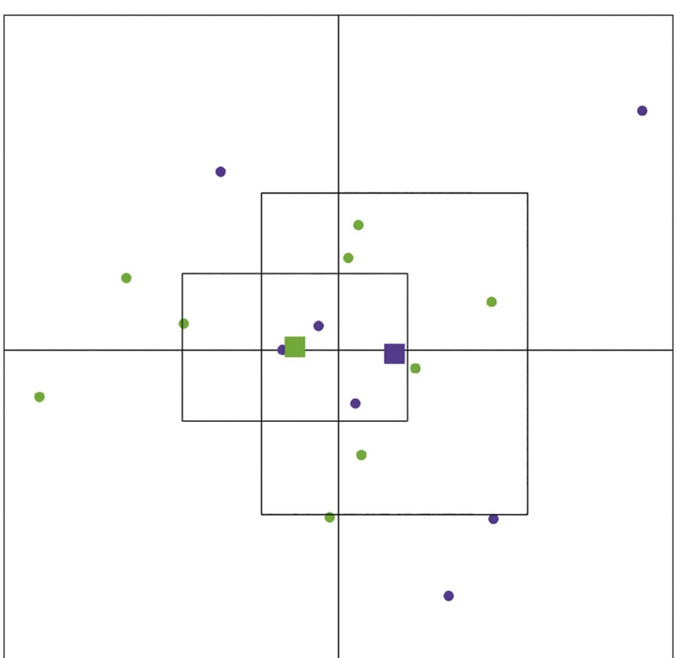

Fig. 1. VRM form coded communication network centroids of higher- (purple) and lower-performing (green) trauma teams were obtained with corresponding means (colored squares) and confidence intervals (boxes).

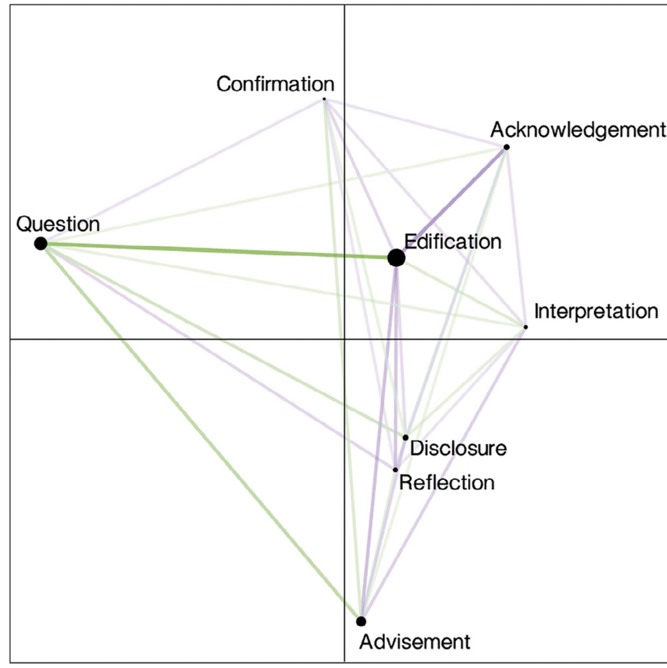

Fig. 2. Subtracted mean network graphs comparing the mean network graphs of higher-performing teams (purple) to lower-performing teams (green) for VRM form coded communication. Thicker lines indicate proportionally stronger connections.

To understand the differences between higher- and lower-performing groups of teams, we constructed a difference graph of the VRM form networks (Fig 2) to compare the mean network graphs. As Fig 2 shows, in lower-performing teams (green) the strongest connections (those influencing the position of the centroid the most) were from questions to edification, disclosure, and interpretation. In high-performing teams (purple), the strongest connections were from edification to acknowledgement, advisement, and confirmation. Although the difference between the centroids of the networks graphs was not statistically significant, for exploratory purposes, the same graph was produced for VRM intent networks. Notably, the strength of connections in lower-performing teams between question and edification persisted, and the strength of connections in higher-performing teams between edification and acknowledgement persisted. The correlation between the centroids and the projected points in the model had good model fit for both VRM form (dimension 1: Pearson r = 0.997, Spearman ρ = 0.996; dimension 2: Pearson r = 0.976, Spearman ρ = 0.972) and VRM intent (dimension 1: Pearson r = 0.994, Spearman ρ = 0.991; dimension 2: Pearson r = 0.98, Spearman ρ = 0.98) networks.

Discussion

In this study, communication networks of the trauma teams were compared with the teams' overall nontechnical skills performance using speech acts coding and ENA. Examination of network graphs for VRM form codes had significant differences along dimension 1. This difference resulted from the ways in which teams were using questions. In low-performing teams, the strongest connections between VRM form codes were from questions to edification, disclosure, and interpretation. In high-performing teams, there were stronger connections from edification to acknowledgement, advisement, and confirmation.

Review of the coded transcripts suggested that the connection between question and edification for lower-performing teams was a reflection of increased uncertainty. These teams appeared to engage

Table 3
Examples of connections between codes.

Participant	Turn of talk	VRM form code
Example of question-edification connection related to prompting for information		
Resident 2	Did we have breath sounds?	Question
Resident 1	Yeah, she had breath sounds.	Edification
Leader	How about femoral pulses?	Question
Example of question-edification connections related to increased uncertainty		
Leader	I'm sorry, what is our blood pressure?	Question
Resident 2	I've got good pulses.	Edification
Leader	Do we have a blood pressure?	Question
Nurse	It's on.	Edification
Nurse	Can we cycle?	Question
Example of edification-interpretation connection		
Nurse	Second 18-gauge in the left.	Edification
Resident 1	Alright.	Interpretation
Nurse	Labs are drawn and sent.	Edification
Example of edification-acknowledgment connection		
Resident 2	So pupils, uh, equal, round, reactive.	Edification
Resident 1	Yeah.	Acknowledgment

in more use of questions to prompt the giving of information by team members. The connections from edification to disclosure and interpretation may reflect attempts to mitigate poor performance. These groups seemed to do this by trying to disclose next steps for proceeding with treatment or offering interpretations in the form of judgments and evaluations to clarify what information was still needed by the team.

In comparison, higher-performing teams more often communicated information to other team members without prompting. In the model, this type of communication resulted in more connections from edification to acknowledgement, advisement, and interpretation. Because essential information was being shared by the team members who were in charge of gathering and conveying that information, the team was then able to devote more of their cognitive resources to performing tasks, giving directives, and making judgments based on shared information. Several examples of dialogue and associated VRM codes for both higher- and lower-performing teams are included in Table 3.

Although VRM intent models did not have a statistically significant difference along the different dimensions, the strength of connections in lower-performing teams between question and edification persisted and the strength of connections in higher-performing teams between edification and acknowledgement persisted. The impact of form and intent discordance of communication in trauma teams is not yet well described. In other words, according to the VRM theory of speech acts, differences in the form and intent of speech may affect the effectiveness of communication.[7] Thus, models of communication of form and intent for trauma teams were analyzed individually, however, although not statistically compared with each other in our analysis, the network models of both VRM form and intent appear similar with minor differences. Although this must be confirmed, the overall similarities may suggest that future studies would be able to limit analysis to VRM form data.

This form-intent similarity is important for future automated coding. Automated modeling of the data may allow for immediate feedback on performance for both teachers and students working to develop nontechnical skills. Automated coding for implied meaning is difficult, and focusing on form rather than intent would increase the ease and scalability of ENA methods in studying trauma communication. There also may be effects of form-intent discordance that have not yet been captured in our sample. In lower-performing groups, there appears to be a concomitant decrease in both the connections between question to edification and advisement to edification. related likely to the use of form- and intent-discordant statements of advisement in lower-performing teams (eg, "Why don't you ask him his history first?"). If this is confirmed in subsequent models as an important marker of higher- versus lower-performing teams, educational interventions can be developed to target this aspect of communication in trauma teams.

Findings from our pilot data align with previous work indicating that teams without shared mental models are more likely to have suboptimal patterns of communication.[20] These results further strengthen the evidence for the importance of communication in nontechnical skills performance for the development of shared mental models, or a shared understanding of knowledge, decisions, tasks, goals, and the unique roles of the individuals required to accomplish the task.[21] The development of teamwork skills, such as situation monitoring and communication, can facilitate the development of shared mental models for improving patient care.[22] These skills are also important factors for distributing the cognition or thinking processes of the team across individual members.[5] Our data from this study allow us to explore how the ways in which things are being said may reflect the development of shared mental models within trauma teams. A natural next step is to add information about what is said and the elements of the context to which team members are attending. This approach will allow us to better understand if certain communication elements are particularly essential at specific times for clear communication and the development of a shared mental model. In addition, moving these methods in situ or into the actual trauma bay will allow us to test whether these models apply in practice and evaluate the predictive validity of our results to determine impacts on our most important metric, patient outcomes. In the meantime, improvements in T-NOTECHS scores have been reported previously to positively correlate with objective measures of trauma team performance and are a useful surrogate in our educational environment.[3]

Despite the efficacy of our analysis methods in revealing meaningful differences between the 2 groups of higher- and lower-performing teams, there are several limitations to this study. First, although VRM does reflect to some degree the content of speech, it is mostly concerned with the structure and relationships within speech. The effect of knowledge on team communication can only be examined indirectly by how it affects how people talk. Second, although T-NOTECHS does evaluate the global ability of the trauma team to complete the objective tasks necessary for patient care, it is not a true marker of patient outcomes. The impact of trauma communication on patient care may be better addressed with task checklists or direct patient outcomes, both of which are subjects of our ongoing studies. Third, our sample sizes remain small, and results may be affected by the different communication patterns of a few team members or teams. Although statistically significant based on the *t* test, the confidence intervals for the networks were overlapping. Thus, these models need to be evaluated with data from additional teams to see if the differences hold. Additionally, we did not address individual factors, such as communication styles and comfort working in the trauma setting, and the impact they may have had on team communication and outcomes. Some participants were involved in both high- and low-performing teams, suggesting that individuals play a complementary rather than dominant role in determining performance in trauma teams. In future studies, we can use ENA to look at the individual contributions of participants across teams and scenarios to investigate this result further. Finally, because the study is limited to the communication between trainees, the findings in our high-performing teams in simulation may be different from findings in high-performing teams in practice.

In conclusion, analyzing types of communication within trauma teams with the VRM taxonomy and epistemic network analysis identified differences in communication between high-and low-performing teams. ENA appears to be a novel, viable, and informative method to assess communication within a trauma team. The models were able to help us identify specific targets for improvement related to the use of questions and stating information by team members, which are essential for establishing a shared mental model. Future studies may uncover further targets for educational interventions.

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