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Modeling Shared Situation Awareness

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ABSTRACT: *This study presents an initial computational model of shared situation awareness (SA) based upon data collected from a simulated training exercise, designed to mimic real life events in a military personnel recovery center. Situation awareness was measured during the exercise using the Situation Awareness Global Assessment Technique (SAGAT). Our initial model examined how well five factors (social network distance, physical distance, rank similarity, branch similarity, and experience similarity) predicted shared SA. Overall, regression analyses highlighted the significant influence of geographical distribution (physical distance) on the development of shared SA and frequency of communications amongst team members. The discussion centers on the need for developing useful technological tools and techniques for supporting communication and collaboration among distributed teams.*

1. Introduction

Within the military domain, distributed teams are quickly becoming the predominant organizational structure for command and control operations, and serve as the foundation for the Army's Future Force (U.S. Army, 2001). As the military's organizational structure undergoes significant changes to include smaller, more deployable dispersed forces, the need to find new methods to analyze and assess distributed team performance has increased significantly. This need is especially apparent in future asymmetric warfare operations where soldiers will need to capitalize on their strengths and be aware of their own team's abilities and limitations. Further, in this new modernized military, if soldiers are to function effectively in a distributed fashion, they will need to develop a high degree of shared situation awareness (SA). To address these issues, we integrated theories in cognition and situation awareness with state-of-the-art techniques in cognitive modeling and Social Network Analysis in an attempt to develop and validate an initial computational model of shared SA.

1.1 Situation Awareness

In order to measure or model SA, one first needs to have a thorough understanding of the SA construct. Endsley (1995b) formally defines SA as "…the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning and the projection of their status in the near future " (p. 36). Building upon this definition, *shared* SA is a reflection of how similarly team members view a given situation. Thus, if a team has a high degree of shared SA, we can assume they are perceiving, comprehending, and interpreting the situation's information requirements in a similar manner. We felt that shared SA provides the clearest indication of a team's overall functioning and, therefore, focused our initial efforts here.

Our approach rests upon the belief that SA is not a simple construct that can be attributed to a single predictor variable, such as a team's communications. Rather SA entails a complex process, in which multiple factors need to be considered. The complexity arises from having to take into account not only the factors that contribute to a given person's *individual* situation awareness, but also the factors that contribute to any two team members' *shared* SA. We have identified three main components that affect SA formation: individual team member abilities, their interactions with other team members, and the environment in which they work. Within each of these components are multiple factors that affect SA formation and maintenance such as geographical distribution, leadership, collaborative tool usage, network proximity, similar background experiences and familiarity. To accurately model SA, we must first understand how these factors and processes affect the establishment and maintenance of SA in military teams.

Our first step towards developing a computational model of SA was to adopt a theoretical conceptual model of SA formation based on Endsley's work (1995a) (see Figure 1.1). This model was used to determine not only what variables to include in our model, but also the potential relationships between these variables. Our theoretical model shows that each factor can seriously challenge the ability of the warfighter to develop and maintain a high level of SA, and each can affect decision-making and action performance.

We emphasize that SA comprises an iterative and dynamic process, as indicated by the arrows in the model. Accordingly, in this research, we examine several factors, which may potentially have a significant influence on the development of a team's shared SA.

1.2 Social Network Analysis

The modeling efforts for this research are based on the domain of Social Network Analysis (SNA), described as a method designed to focus analysis on a network-based view of the relationships between people and organizations (Dekker, 2002). SNA allows for the quantification of dyadic links that exist among team members. In any organization or team, people influence each other, the ideas being exchanged, and the flow of information (Borgatti, 2002). Thus, a social network is not just a description of who is in the team, but how they are put together and how they interact with one another (Borgatti, 2002). In addition, SNA allows for values to be attached to these relationships to represent strength of the relationships, information capacity, rates or flow of traffic, distance between nodes, and probabilities of information being passed (Borgatti, 2002).

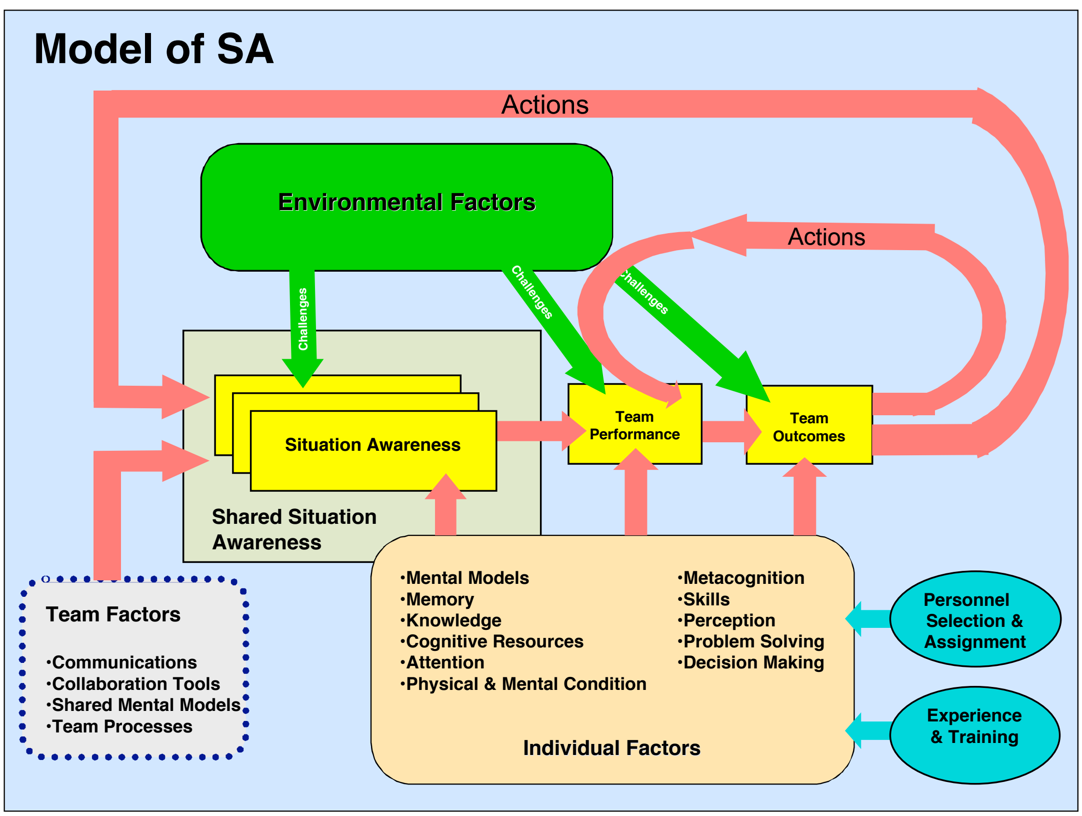

Figure 1.1 Theoretical Model of SA Formation

It is these values that allow SNA to quantify the relationship, thus, presenting a means for mathematically testing the network. The SNA methodology begins by first forming an initial model; additional measures can then be included in subsequent iterations of the model, such as workload, experience, and other factors deemed as potential predictors of the variables of interest. Given that distributed teams must coordinate their efforts across both time and space, relying primarily upon technology-mediated communication channels to accomplish their goals, it is hypothesized that the strength of social network relationships for distributed teams will be weaker than for traditional co-located teams.

1.3 Present Study

Our empirical approach for modeling SA involves: first, determining the critical variables underlying the formation of SA; next, identifying possible relationships between these variables; and finally, using these variables to predict shared SA using a computational model. The primary goal for the research effort reported in this paper was to determine what factors significantly contribute to the development of shared SA.

To address this objective, data was collected from a training exercise at the Joint Personnel Recovery Agency (JPRA), a subordinate activity of U.S. Joint Forces Command. As the Department of Defense (DoD) executive agent for personnel recovery, JPRA is responsible for the shaping, planning, preparation, execution, and repatriation of personnel recovery, such as POWs (prisoners of war). Military personnel from all the different service branches staff recovery centers all over the world.

For this exercise, data was collected at the Personnel Recovery Education and Training Center (PRETC), where servicemen are trained to staff the recovery centers. The servicemen, comprised of both enlisted and officers of the Navy, Army, Marines, and Air Force, attend a two-week training program followed by a one-week simulated exercise designed to mimic real life events in a recovery center.

2. Method

2.1 Participants

Sixteen active servicemen and 3 DoD contractors (mean age = 33.85) participated in this study. Four individuals had some prior experience working at a military recovery center. The DoD contractors were being trained to teach the recovery center training program.

2.2 Design

Participants were assigned to one of four teams: Navy, Army, Special Operations, or Joint Service. Each player was rotated though the various positions and teams such that everyone had a chance to be a member in each team.

2.3 Background Data

A background questionnaire was distributed to all participants, soliciting information regarding age, rank, specialty area, and recovery center experience.

2.4 SAGAT – Situation Awareness Measure

The Situation Awareness Global Assessment Technique (SAGAT) is an objective measure of situation awareness designed to elicit information from all three levels of SA – perception, comprehension, and projection (Endsley, 1995a). Utilizing a concurrent memory probe technique, SAGAT involves: first, temporarily stopping operator activity at randomly selected times and removing task information sources; next, administering a set of queries that target individuals' dynamic information needs (SA requirements) with respect to the domain of interest; and, then, resuming the exercise (Endsley, 2000). For this study, five SAGAT queries were created based on the fidelity of the exercise and the criticality of certain information requirements, as identified by the PRETC instructors (see Table 2.4).

SAGAT Query
1. How many isolated incidents are you aware of?
2. How many of these isolated incidents have been verified and validated as actual incidents?
3. Who is the SMC (SAR Mission Coordinator) for each incident?
4. Indicate the number and status of isolated personnel (IP) for each incident *(OK, slightly injured, severely injured).*
5. What is the current tactical situation around the IPs for each incident *(high threat, medium threat or low threat)*?

Table 2.4 SAGAT Queries

2.5 Scenarios and Questionnaire Administration

The exercise consisted of five different scenarios over a three-day period. All four teams participated simultaneously in the scenarios. In each scenario, participants encountered a varying number of recovery incidents, ranging from 3 to 12. During the simulated exercise, the scenarios were randomly stopped three times to collect SAGAT and communication data, for a total of 15 stops. In order to obtain independent assessments of the measures, no communication was allowed between the participants during questionnaire administration.

2.6 Social Network Data

Social network data was gathered by asking participants to report the people with whom they had communicated in the time since the previous questionnaire and then rank order these individuals based upon by their *frequency* of communication with them during the session. A rank of "1" was given to the person with whom they communicated most frequently, "2" to the person with whom they communicated second most frequently, and so on, up to the *n*th person, where *n* represents the total number of people with whom they communicated during the last test session.

2.7. Procedure

Before the exercise began, participants completed the background data questionnaire and were then handed a sample test booklet that contained the SAGAT and communication (i.e., social network data) questionnaires. Participants were given the opportunity to review the material and ask the researcher any questions about the materials.

At the start of the first scenario, participants were randomly assigned to one of four teams (Navy, Army, Special Operations, or Joint Service). During the 3-day exercise, participants rotated through the teams. The SAGAT and communication questionnaires were administered at three random times throughout each of the five scenarios, as previously described.

3. Results

Predictor variables for our computational model were drawn from participants' responses to the background data and communication questionnaires and their team assignments during the exercise. The dependent variable for shared SA was derived from participants' responses to the SAGAT queries.

"Similarity" scores, as will be described next, were calculated for both the predictor and dependent variables. Note that these values were computed for <u>each</u> possible pairing of participants in the sample and this data was calculated for each of the 15 stops, that is, three stops per scenario. Means and standard deviations and intercorrelations for all predictor and dependent variables are presented in Table 3. An alpha level of .05 was used for all statistical analyses.

3.1 Operationalization of Predictor Variables

Five predictor variables were examined in our initial computational model: social network distance, physical distance, rank similarity, branch similarity, and JSRC experience similarity. The operationalization for each of these predictor variables will be described next.

Variable	Mean (SD)	1	2	3	4	5	6
Sum SAGAT Similarity	1.75 (1.17)	__	-.156**	-.232**	.022	-.036*	-.026
Social Network Distance	2.23 (1.04)		__	.603**	-.005	-.009	.005
Physical Distance	1.79 (0.41)			__	.059**	-.006	.041**
Rank Similarity	4.35 (3.09)				__	-.008	-.032*
Branch Similarity	0.47 (0.50)				__	__	.056**
JSRC Experience Similarity	0.69 (0.46)						__

Table 3 Means, Standard Deviations, and Intercorrelations for Shared Situation Awareness Measure and All Predictor Variables[a]

[a] *N* = 3394 for Social Network Distance. *N* = 4080 for all other variables.
* $p < .05$ (two-tailed). ** $p < .01$ (two-tailed).

Social Network Distance refers to the distance between each pair of participants in the social network, based upon the communication distance they reported (see **2.6 Social Network Data**). Smaller values represent closer distance or greater communication frequency; larger values represent farther distance or less frequent communication. An undirected social network was used. This value changed at each stop.

Physical Distance was based upon whether participant pairs were co-located or distributed. Note that each team was placed in a separate room. Thus, participant pairs in the same team were co-located and closer together physically, and were assigned a distance of "1." Participant pairs comprised of members in different teams were distributed and thus, assigned a distance of "2." This value changed with each scenario.

Rank Similarity was determined by assigning each participant a numeric value corresponding to their rank (as reported in the background data questionnaire). The Rank Similarity score for each participant pair was then computed by taking the absolute value of the difference between their ranks. For example, if one participant in a pair had a rank of 14 (Lieutenant Commander) and the other had a rank of 5 (Staff Sergeant), the Rank Similarity score for that participant pair would be "9," the absolute value of the difference between their ranks (14 – 5).

Branch Similarity was determined by assigning each participant to one of three branches (Aviation, Operations, or Intelligence) based upon their specialty area (as reported in the background data questionnaire). Participant pairs where both participants reported the same specialty area (i.e., branch) were assigned a Branch Similarity score of "1" and participant pairs reporting different specialty areas were assigned a score of "0."

Similarly, *JSRC Experience Similarity* was determined by comparing participants' self-reported experience in JSRC operations (as reported in the background data questionnaire). Participant pairs were assigned a JSRC Experience Similarity score of either "1" or "0," depending upon whether their self-reported experience was either the same or different, respectively.

3.2 Operationalization of Dependent Variable

Shared SA amongst team members, the dependent variable for our computational model, was operationalized by assessing the similarity of participants' responses to the SAGAT queries. Specifically, SAGAT similarity scores were determined for participants' responses to each of the five queries. Participant pairs reporting the same response for a given query were assigned a score of "1" for that query. If their responses were different, participants in the pair were assigned a score of "0" for that query. A *Sum SAGAT Similarity* score was then computed by summing participants' similarity scores across the five individual queries, with values ranging from 0 (no matches on any of the query responses) to 5 (all query responses matched).

3.3 Regression Analysis on Shared SA

A standard multiple regression analysis was performed to determine which of the five independent variables (Physical Distance, Social Network Distance, Rank Similarity, Branch Similarity, and JSRC Experience Similarity) were significant predictors of the dependent variable, shared SA, as indicated by the Sum SAGAT Similarity scores.

The overall model was significant with an $R^2 = .063$, $F(5,3388) = 45.344$, $p < .0005$. Together, these variables explained about 6% of the variance in shared SA. Of the five variables entered, however, only Physical Distance made a significant unique contribution to the prediction of shared SA, uniquely explaining just under 4% of variance ($sr^2 = .0355$, $t = -11.326$, $p < .0005$, two-tailed). Although the semi-partial correlations for Rank Similarity ($sr^2 = .0017$, $t = 2.494$, $p = .013$, two-tailed) and Branch Similarity ($sr^2 = .0013$, $t = -2.133$, $p = .033$, two-tailed) were also significant, their unique contributions were each less than 1%. Neither Social Network Distance nor JSRC Experience Similarity was a significant predictor.

Thus, of the five variables entered into the model, it appears that Physical Distance (i.e., co-location) may be the best predictor of shared SA. Note that the direction of this relationship was inverse ($r(4080) = -.232$, $p < .0005$, two-tailed). Specifically, the greater the Physical Distance between the participant pairs (i.e., participants were distributed), the lesser the likelihood that their responses to the SAGAT queries would be the same (i.e., lower Sum SAGAT Similarity scores).

3.4 Regression Analysis on Social Network Distance

Further analysis was performed to determine if Physical Distance also had an influence on the frequency of communications amongst participants, as measured by Social Network Distance. Specifically, a standard multiple regression analysis was performed with Social Network Distance as the dependent variable and Physical Distance, Rank Similarity, Branch Similarity, and JSRC Experience Similarity as the independent variables.

The overall model was significant with an $R^2 = .366$, $F(4,3389) = 488.034$, $p < .0005$. Together, these variables explained about 37% of the variance in Social Network Distance. Of the four variables entered, however, only

Physical Distance made a significant unique contribution to the prediction of Social Network Distance, uniquely explaining almost all (36.5%) of the variance (sr^2 = .3653), t = 44.175, p < .0005, two-tailed). Although the semi-partial correlation for Rank Similarity (sr^2 =.0014, t = -2.770, p = .006, two-tailed) was also significant, its unique contribution was less than 1%. Neither Branch Similarity nor JSRC Experience Similarity was a significant predictor.

Thus, these results again highlight the significance of Physical Distance. In this case, the relationship between Physical Distance and Social Network Distance was positive (r (3394) = .603, p < .0005, two-tailed), suggesting that the greater the Physical Distance between the participant pairs (i.e., participants distributed in different teams), the farther the distance in their Social Network. In other words, co-located participant pairs communicated more frequently and distributed participant pairs communicated less frequently.

4. Discussion

The results of this study draw attention to the potentially negative impact that distribution may have on team performance. Physical Distance uniquely contributed over half (3.6%) of the 6.3% of the variance in shared situation awareness accounted for by the predictor variables entered into our initial computational model, revealing an inverse relationship between Physical Distance and shared situation awareness. Further, Physical Distance also uniquely accounted for almost all (36.5% out of 36.6%) of the variance in Social Network Distance, revealing a direct relationship between co-location and frequency of communications. In general, distributed participants were less likely to demonstrate shared situation awareness and communicated less frequently with each other.

These findings point to the need for garnering a better understanding of distributed team performance and for developing useful technological tools and techniques to support communication and collaboration among distributed teams. The technology-mediated interactions inherent in distributed environments may negatively impact the development and maintenance of shared situation awareness among team members (Bolstad & Endsley, 2003). The development of shared SA is critically dependent upon the effective use of shared SA devices (i.e., verbal and nonverbal communications, shared displays, and a shared environment) (Endsley, Bolte, & Jones, 2003). Yet, with distributed teams, shared SA devices are limited in that members lack access to nonverbal communication and a shared environment, resulting in an over-reliance on verbal communication and shared displays (Endsley et al., 2003).

Thus, to ensure successful distributed team performance, team members need access to technological tools that support shared SA, providing important information on changes both within the team (e.g., individual member actions) and in the external task environment (e.g., approaching enemy targets) (Cadiz, Fussell, Kraut, Lerch, & Scherlis, 1998; Endsley et al., 2003; Gutwin & Greenberg, 1998). In addition, as discussed earlier, the formation of SA may be affected by numerous factors, including individual team member abilities, their interactions with other team members, and the environment in which they operate (see Figure 5). As such, collaboration tool usage represents only one of many factors that must be considered for a comprehensive computational model of SA.

5. Conclusion

In conclusion, while our initial computational model only accounted for a modest proportion of the variance in shared situation awareness amongst team members, it nevertheless represents an important first step toward objectively quantifying this construct. Future work will expand upon this initial model and explore the influence of other variables on shared SA. Including additional individual (e.g., problem solving and decision making abilities), team (e.g., collaboration tool usage, team processes), and environmental (e.g., workload, interface complexity) factors will lead to the development of a more robust computational model of SA. Our long-term goal, therefore, is to develop a theoretically-based, empirically-validated approach for modeling shared situation awareness across multiple complex domains.

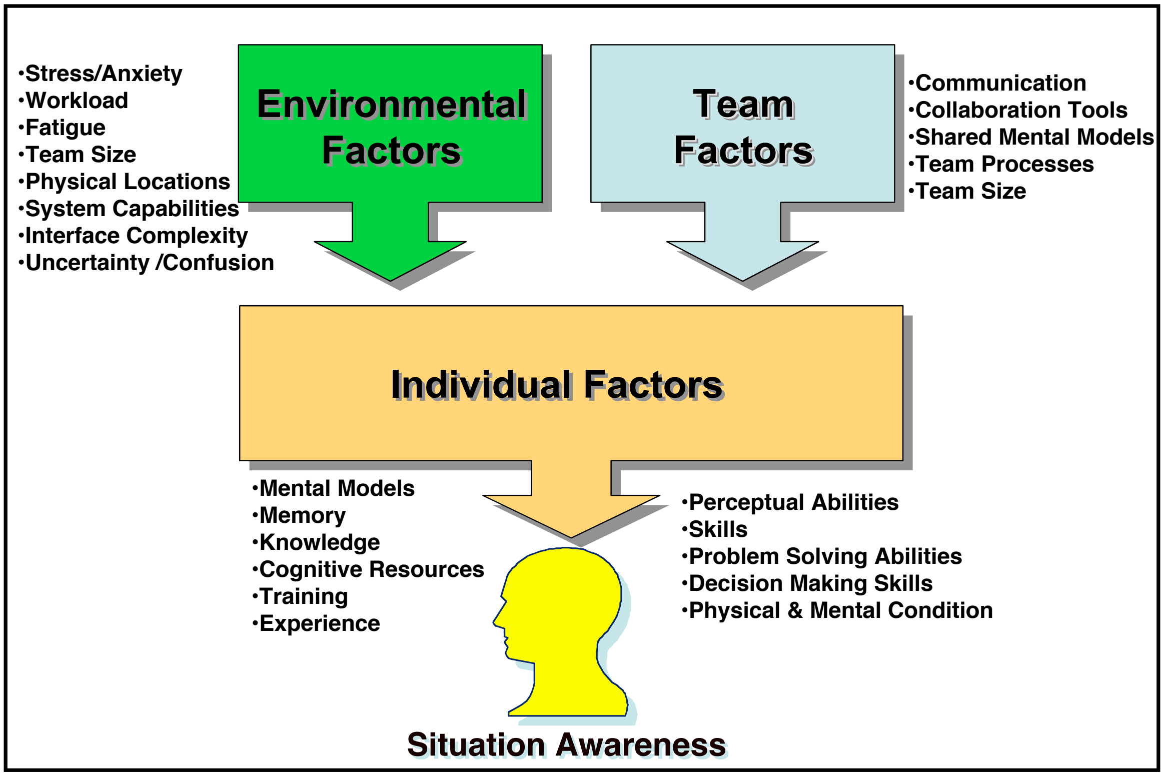

Figure 5 Factors Affecting SA Formation

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