iSENS: An Integrated Approach to Combining Epistemic and Social Network Analyses

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ABSTRACT

Collaborative problem solving is defined as having cognitive and social dimensions. While network analytic techniques such as epistemic network analysis (ENA) and social network analysis (SNA) have been successfully used to investigate the patterns of cognitive and social connections that describe CPS, few attempts have been made to combine the two approaches. Building on prior work that used ENA and SNA metrics as independent predictors of collaborative learning, we propose and test the integrated social-epistemic network signature (iSENS), an approach that affords the simultaneous investigation of cognitive and social connections. We tested iSENS on data collected from military teams participating in training scenarios. Our results suggest that (1) these teams are defined by specific patterns of cognitive and social connections, (2) iSENS networks are able to capture these patterns, and (3) iSENS is a better predictor of team outcomes compared to ENA alone, SNA alone, and a non-integrated SENS approach.

CCS CONCEPTS

• **Applied computing → Collaborative learning**.

KEYWORDS

Collaborative problem solving, epistemic network analysis, social network analysis

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1 INTRODUCTION

The complex problems we face today often require the coordinated efforts of multiple individuals. As a result, collaborative problem solving (CPS) has become a critical 21st century skill to study, teach, and assess [10]. CPS is defined as having both a cognitive dimension—for example, representing problems—and a social dimension—for example, negotiating meaning with others. While network analytic techniques such as epistemic network analysis (ENA) [22] and social network analysis (SNA) [9] have been successfully used to investigate the patterns of cognitive and social connections that describe CPS, few attempts have been made to combine the two approaches.

In this paper, we build on prior work that investigated collaborative processes by combining ENA and SNA—social-epistemic network signature (SENS) [8]. Although this work accounted for patterns of cognitive and social connections within the same analysis, the patterns were treated as independent predictors and it did not produce a network representation that captured both kinds of patterns. Here, we propose and test an integrated SENS approach (iSENS) that allows researchers to simultaneously investigate cognitive and social connections.

To test iSENS, we investigated the cognitive and social patterns that defined the CPS processes of military teams in training. We modeled these patterns using ENA, SNA, and iSENS. After comparing the interpretative value of the resulting networks, we statistically compared iSENS to ENA, SNA, and SENS in terms of their ability to predict team outcomes.

2 THEORY

2.1 Collaborative Problem Solving

While many definitions of CPS exist in the literature, it is typically defined as having both a cognitive and a social dimension: framing, investigating, and solving problems collaboratively requires information sharing, negotiation of meaning, and more broadly, attempts to establish and maintain a shared conception of the task [17][20]. For example, in their work developing the PISA 2015 assessment, the Organization for Economic Cooperation and Development [18] defined CPS as the combination of four cognitive competencies (exploring the problem space, representing the problem, planning and executing solutions, and monitoring and reflecting on progress) and three social competencies (maintaining a shared understanding of the problem, taking collaborative actions, and maintaining team organization).

Several learning analytic techniques have been used to investigate the cognitive and social dimensions of CPS including automated discourse analysis [6], pattern mining [19], and lag sequential analysis [14]. In addition to these techniques, network analyses are

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a powerful approach for understanding the cognitive and social connections that characterize CPS.

2.2 Modeling Cognitive Connections

Although it is still common to model the cognitive aspects of CPS by coding and quantifying meaningful elements of discourse as if they occur in isolation [3], work in the learning sciences suggests that the *connections* that people make between these elements are more representative of complex thinking [21]. For example, in the military context we investigate in this paper, teams are training to identify hostile aircraft at sea. In this situation, it is less important to know specific facts about the aircraft, such as speed, location, and weapons, than to know how these facts relate to potentially threatening behavior and the defense of their own ship.

During CPS, these connections are particularly important because when individuals collaborate they respond to and build upon the prior discourse moves of others to form a common ground [2]. Collaborative interactions and the common ground they produce suggest that the discourse moves of individuals during CPS are interdependent, and thus inherently connected.

Epistemic network analysis (ENA) is a technique applied to coded data that measures the connections collaborating individuals make between relevant aspects of their discourse. In ENA, network nodes correspond to codes and weighted connections represent the frequency with which codes co-occurred in the discourse. These networks are visualized in a metric space that allows comparisons between individuals and teams in terms of the cognitive connections they made.

ENA accounts for the temporal variation in these connections, while also accounting for the interdependence between individuals. In particular, it measures the connections that individuals make between discourse moves within a recent window of moves, whether those connections are to their own moves or the moves of others. This makes it possible to extract information about the contributions of each individual within the context of their team [23]. ENA has been used to successfully study the cognitive dimension of CPS in contexts such as engineering education [1], military training [27], and medical decision-making [25].

ENA is useful for understanding connections between elements of discourse; however, it does not represent the structure of the social interactions that produce those connections. In other words, it can measure what individuals in collaborative situations are doing and how they thinking, but not the social patterns that give rise to these phenomena.

2.3 Modeling Social Connections

When individuals collaborate, they interact with one another to form patterns of social interactions. Social network analysis (SNA) is one technique for modeling these interactions. In contrast to ENA, which focuses on the connections between meaningful aspects of discourse, SNA focuses on the connections between the individuals that produced the discourse. Specifically, the nodes of social networks correspond to individuals and weighted connections represent the frequency with which individuals interacted.

SNA can provide information about how social networks are interlinked (density), the extent to which the network depends on certain individuals (centrality), whether individuals have similar functions in the network (structural equivalence), and other structural features [9]. SNA is a commonly applied technique within learning analytics [5], and has been used to investigate phenomena such as roles [15] and the relationship between social patterns and academic performance [13].

Although SNA provides insight into the social connections that characterize CPS, it is limited because it does not account for the content of those connections. Content is important because it influences the dynamics of the social network. For example, on teams with individuals in different roles, such as leaders and followers, information passed by the followers may prompt leaders to interact with the team, perhaps giving instructions or guidance. Moreover, the content of the connections can be quite different depending on who is interacting: leaders may interact about planning, followers may interact about implementing instructions. A content neutral technique such as SNA ignores the influence that content has on connections and treats all connections equally.

The discussion above suggests that network techniques such as ENA and SNA are powerful tools for studying the cognitive and social dimensions of CPS. However, each technique is limited by its focus on only one dimension. The complimentary nature of the techniques suggests that combining them is a potentially useful approach.

2.4 Social-Epistemic Network Signature

While prior work has separately used ENA and SNA to investigate CPS, there have been few attempts to combine networks analyses such as these to model the cognitive and social dimensions of CPS within the same analysis. A notable exception is the social-epistemic network signature (SENS), which combines SNA and ENA to model both the structure and content of connections in collaborative settings.

Gašević and colleagues [8] developed and used SENS to investigate the cognitive and social aspects of collaboration in the context of a MOOC. Specifically, they found that (a) ENA was able to predict the structure of social connections at the group and individual level, (b) SNA was able to predict differences in the content of students' discourse, and (c) a SENS model predicted student outcomes better than models using ENA or SNA metrics alone. In other words, this work found evidence for the relationship between the cognitive and social dimensions of CPS using ENA and SNA and that a combined ENA/SNA approach could outperform either approach alone.

While SENS is an important step toward combining network analyses to study CPS, the previous approach used ENA and SNA-based metrics as independent predictors of performance. However, as their study illustrated, and as theory on CPS suggests, the cognitive and social dimensions of are related. Moreover, the previous approach did not produce a network representation that captured both cognitive and social connections. Such a representation could provide researchers a more complete understanding of CPS processes.

2.5 Integrated Social-Epistemic Network Signature

In this paper, we extend the SENS approach in three ways. First, the prior study analyzed student data collected from the discussion forums of a MOOC. In contrast, we apply the technique to data collected from a military context in which professional teams trained using a high-fidelity simulation of air defense warfare (ADW). Thus, the present study applies the technique in a potentially more authentic and more collaborative context.

Second, the prior study combined ENA and SNA, but treated them independently. Here, we propose and test an integrated version of SENS—*iSENS*. This approach uses ENA to position individual team members in a space defined by the cognitive connections they made, calculates a metric that represents the position of the teams in this space, and weights this metric using information about the social networks of teams. The outcome is a unified metric that captures the relationship between cognitive and social connections. In other words, it captures both of who interacted with whom and what they interacted about.

Third, the prior study did not develop a network representation of SENS that could be used to simultaneously investigate cognitive and social connections. The iSENS approach incorporates such a representation, allowing researchers to view cognitive and social connections in relation to one another.

Here, we argue that the iSENS approach is significant because it has the potential to streamline the analysis of CPS while also providing a more complete representation of CPS processes.

To test iSENS, we address the following research questions using data from ADW teams:

(1) What patterns of cognitive and social connections are salient for these teams?
(2) What do ENA, SNA, and iSENS networks reveal about these teams?
(3) Does iSENS predict team outcomes better than ENA alone, SNA alone, or SENS?

To address these questions, we conducted a qualitative analysis, network analyses, and a comparison of predictive models of team performance that used statistics from ENA, SNA, SENS, and iSENS. Prior qualitative analyses and ENA have been conducted on this ADW dataset [27][26], and we draw on the methods and results of those studies below.

3 METHODS

3.1 Data

16 teams participated in four training scenarios to test the impact of a decision-support system and teamwork training in an ADW context [11]. During the scenarios, teams used a *watch-station* that provided information about the identification and behavior of ships and aircraft (referred to as *tracks*) in the vicinity of their warship. Teams needed to detect and identify multiple tracks, assess whether they were threats, and decide how to respond.

Each team consisted of up to six participants assigned to roles. Command roles included the Commanding Officer (CO) and the Tactical Action Officer (TAO), who were primarily responsible for making tactical decisions. Supporting roles included the Electronic Warfare Supervisor (EWS), the Air Defense Warfare Coordinator (ADWC), the Tactical Information Coordinator (TIC), and the Identification Supervisor (IDS), who were primarily responsible for managing radar contacts and passing information to the commanders. Team members talked over an open radio channel and could also communicate with training personnel. The teams were divided into two conditions with eight teams in each. Control teams had access to standard watch-stations; experimental teams received teamwork training and had access to watch-stations augmented by a decision-support system that highlighted track information and actions taken by the team.

The dataset consists of transcripts and teamwork scores for each combination of team and scenario (*team-scenario*) for a total of 63 team-scenarios. The transcripts are segmented by turn of talk for a total of 12,027 lines. Teamwork was assessed using the Air Defense Warfare Team Observation Measure (ATOM), an externally validated measure of team performance that summarizes four dimensions of CPS—supporting behavior, leadership, information exchange, and communication—into a score from 1 (worst) to 55 (best) [12].

3.2 Qualitative Analysis

To address our first research question, we conducted a qualitative analysis using an automated coding scheme developed and validated during a prior study of the same data [27]. These codes reflect the processes teams used to make decisions regarding potentially hostile tracks. For each code, all pairwise combinations of raters (humans and automated classifier) achieved acceptable values of Cohen's kappa ($\kappa > 0.80$) and Shaffer's rho [7] ($\rho\ (0.65) < 0.05$). We applied the automated coding scheme to the transcripts such that each turn of talk was coded for the presence or absence of the codes in Table 1.

3.3 Network Analyses

To address our second research question, we conducted ENA and SNA on the data using the rENA package for R [16]. We conducted the iSENS analysis by integrating statistics derived from ENA and SNA as described below.

3.3.1 *Epistemic Network Analysis.*

ENA uses a moving window to construct an undirected network for each turn of talk in the data. Connections in the network are defined as the co-occurrence between codes in the current turn of talk and codes within the window, defined as a specific number of prior turns. For this analysis, the window included each turn plus the previous four turns (a window size of 5). This window size was determined through our qualitative analysis of the data.

To create networks for individuals in the different team-scenarios, ENA aggregates the networks associated with their turns of talk, normalizes the collection of these networks to account for variation in amount of talk, and performs a dimensional reduction on this data via singular value decomposition.

Networks were visualized using two coordinated representations: (1) an *ENA score* for each individual, which represents the location of their network in the ENA space produced by the dimensional reduction, and (2) a *weighted network graph* for each individual in which the nodes correspond to codes, and the edges are proportional

Table 1: Codes, definitions, and examples.

Code	Definition	Example
Detection	Talk about radar detection of a track or the identification of a track, (e.g., vessel type).	IR/EW NEW BEARING, BEARING 078 APQ120 CORRELATES TRACK 7036 POSSIBLE F-4
Track Behavior	Talk about kinematic data about a track or a track's location	AIR/IDS TRACK NUMBER 7021 DROP IN ALTITUDE TO 18 THOUSAND FEET
Assessment	Talk about whether a track is friendly or hostile, the threat level of a track, or indicating tracks of interest	TRACKS OF INTEREST 7013 LEVEL 5 7037 LEVEL 5 7007 LEVEL 4 TRACK 7020 LEVEL 5 AND 7036 LEVEL 5
Status Updates	Talk about procedural information, e.g., track responses, or talk about tactical actions taken by the team	TAO ID, STILL NO RESPONSE FROM TRACK 37, POSSIBLE PUMA HELO
Seeking Information	Asking questions regarding track behavior, identification, or status.	TAO CO, WE'VE UPGRADED THEM TO LEVEL 7 RIGHT?
Recommendation	Recommending or requesting tactical actions	AIR/TIC RECOMMEND LEVEL THREE ON TRACK 7016 7022
Deterrent Orders	Giving orders meant to warn or deter tracks.	TIC AIR, CONDUCT LEVEL 2 WARNING ON 7037
Defensive Orders	Giving orders to prepare defenses or engage hostile tracks	TAO/CO COVER 7016 WITH BIRDS

to the relative frequency of connection between codes. In these graphs, thicker edges indicate relatively more frequent connections.

The positions of the network graph nodes are fixed across all networks using an optimization routine. These graphs can be used to interpret the dimensions of the space, and thus the positions of the ENA scores: the dimensions distinguish individuals in terms of connections between codes whose network nodes are located at the extremes of the space. For example, individuals with ENA scores on the left side of the space will tend to have stronger connections between codes on the left side. Similarly, those with ENA scores on the right side will tend to have stronger connections between codes on the right. To create network graphs for each team-scenario, we averaged the individual networks by team-scenario and plotted the results.

3.3.2 Social Network Analysis. The SNA algorithm included in rENA uses a moving window to construct an undirected network for each turn of talk in the data. Connections in the network are defined as the co-occurrence between the speaker of the current turn and the speakers within the window, again defined as 5 total turns of talk. In other words, these connections represent the social network created by each turn of talk.

To create networks for each individual team member, the algorithm aggregates the networks associated with their turns of talk. Similarly, to create networks for each team-scenario, the algorithm aggregates the networks associated with the individuals in the team-scenario. The results of this processes can be plotted as a weighted network graph for each team-scenario in which the nodes correspond to individual team members, and the edges correspond to the frequency with which individuals communicated. Thicker edges indicate more frequent communication.

3.3.3 Integrated Social-Epistemic Network Signature. To conduct the iSENS analysis, we integrated the outputs of ENA and SNA to create a representation of each team-scenario's social network in ENA space. Specifically, we created weighted network graphs for each team-scenario whose nodes corresponded to individuals, and whose edges corresponded to the frequency with which individuals communicated. However, rather than an arbitrary placement of the nodes calculated using SNA, the nodes in these diagrams correspond to the locations of the individuals in the ENA space—that is, their ENA scores. This node placement means that iSENS networks reflect both the social structure of team connections, via the edges, *and* the cognitive structure of team connections, via the locations of the nodes in the space.

3.4 Predictive Model Comparison

To address our third research question, we first calculated summary statistics for each team-scenario that could be used to compare ENA, SNA, SENS, and iSENS.

For the ENA statistic, we calculated the *centroid* of each team-scenario's ENA scores—that is, for each team-scenario, we calculated the mean location of the ENA scores corresponding to the individuals in the team-scenario. This statistic summarized the structure of cognitive connections made by each team-scenario. For the SNA statistic, we calculated the *weighted density* [4] of each team-scenario's network: the sum of the weighted connections in the network, divided by the number of possible connections in the network. This statistic summarized the structure of the social connections made by each team-scenario. And for the iSENS statistic, we calculated a *weighted centroid* for each team-scenario's iSENS network: the average position of the network nodes weighted by

Table 2: Team Excerpt.

Line	Speaker	Utterance
1	EWS	TIC,TAO/EW HOLD PRIMUS 40 RADAR BEARING 165 CORRELATES A SUPERPUMA HELO ORIGIN FARSEE ISLAND
2	TIC	TRACK NUMBER
3	EWS	TRACK NUMBER CORRELATION 7037
4	TAO	CO/TAO WOULD LIKE TO CONDUCT LEVEL ONE QUERY ON 7037 ITS HEADING FOR US
5	TIC	IDS/TIC INTERROGATE 7023 BEARING 024
6	IDS	INTERROGATE TRACK 7023 ID AYE
7	CO	TAO/CO CONDUCT LEVEL ONE TRACK 7037
8	TAO	TIC/TAO CONDUCT LEVEL ONE ON TRACK 7037
9	TAO	CO/TAO WOULD LIKE TO CONDUCT LEVEL TWO WARNING ON TRACK 7013 LEVEL ONE IS A NEGATIVE RESPONSE
10	CO	AYE TAO/CO CONDUCT LEVEL TWO WARNING AND COVER TRACK 7013

the edge values of the network. Effectively, this statistic weights the centroid (the ENA statistic) by the density of the social network (the SNA statistic), summarizing the structure of the cognitive and social connections of each team-scenario.

We compared ENA, SNA, SENS, and iSENS by incorporating these statistics into four hierarchical linear models (HLMs). HLM is a regression technique for data with a nested-structure [24]. In this case, team-scenarios (level-one) were nested into teams (level-two). Each model included the team variable as a random effect and the team-scenario ATOM scores as the outcome variable. The models differed with respect to their explanatory variables. The ENA-HLM used the centroid locations on the first two dimensions of the ENA space, while the SNA-HLM used weighted density. Following Gašević and colleagues (2018), the SENS-HLM used ENA and SNA statistics as independent variables. Specifically, it included the centroid locations from ENA and the weighted density from SNA. Finally, the iSENS-HLM used the weighted centroid locations on the first two dimensions of the ENA space.

We compared these modeling approaches in two ways. First, we compared them in terms of the presence of statistically significant explanatory variables. Second, we used bootstrapping to compare the performance of models that had statistically significant explanatory variables. This second procedure is similar to common methods for comparing the performance of machine learning models [28].

To conduct the bootstrapping procedure, we generated 100 bootstrap samples of the transcript data. For each bootstrap sample, we randomly selected (with replacement) from the list of 63 team-scenarios 63 times, adding all lines of the transcript for the selected team-scenarios to the sample. For the approaches with significant explanatory variables, we created HLMs for each bootstrap sample and calculated the sum of the squared errors (SSE) between the predicted ATOM scores of each model and the true scores. This resulted in a distributions of SSEs for each approach. To test for differences between the approaches, we constructed 95% confidence intervals around the differences between their mean SSEs.

4 RESULTS

4.1 RQ1

To illustrate the patterns of cognitive and social connections our qualitative analysis revealed, we present an excerpt from one high-performing team-scenario.

The task that these teams performed involved the radar detection of tracks (identified by a *track number*), decisions regarding their threat level, and decisions regarding deterrent or defensive actions. Actions included "interrogating" or "querying" tracks to gain information about their intentions, sending warnings to tracks that strayed too close to the warship, and defensive actions such as "covering" tracks with guns. During the scenarios, teams had to manage several tracks simultaneously at different stages of this process. For example, new tracks could be detected while the team was waiting on the responses of other tracks to warnings. These conditions made for a complex and quickly evolving context.

In the excerpt shown in Table 2, this team makes a radar detection of a track while they are in midst of sending queries and warnings to previously detected tracks. Team members held particular roles, such as the commanding officer (CO) or tactical action officer (TAO), and often began their communications by stating who they were addressing and who was speaking. For example, in the transcript "CO/TAO" indicates that the TAO was directing their communication to the CO. However, team members communicated via an open-channel, meaning that when one team member spoke, all others received the communication.

The excerpt begins as the EWS detects a new track in line 1 [Detection]. The TIC asks for the identification number for the track in line 2 [Seeking Information], which the EWS provides in the next line [Detection]. In line 4, the TAO suggests that they query the track because it is heading toward the warship [Recommendation, Track Behavior]. Meanwhile, the TIC orders the IDS to interrogate a previously identified track, 7023, in line 5 [Deterrent Orders]. Responding to the previous recommendation from the TAO, the CO orders a query sent to track 7037: "Conduct level one track 7037" in line 7 [Deterrent Orders], and the TAO passes this order to the TIC in the next line. In line 9, the TAO recommends sending a warning to a previously identified track, 7013, that has failed to respond to a query [Recommendation, Status Update]. The CO orders the warning and also orders that they "cover" the track with guns in preparation for combat [Deterrent Orders, Defensive Orders].

This excerpt illustrates a typical pattern for this team-scenario. Specifically, that the EWS provides critical information regarding the detection and identification of tracks (e.g., lines 1 and 3), but that the focus of the team interactions are between the CO, TAO, IDS, and TIC as they process track information and take tactical actions (e.g., lines 4-10).

In alignment with this example, our qualitative analysis found that the social interactions of high-performing team-scenarios were more focused on processing track information and taking tactical actions, such as queries, warnings, and defensive positions. For low-performing team-scenarios, we found that their social interactions were more focused on seeking information about the tactical situation, for example, asking for information about track behavior or identification.

4.2 RQ2

To illustrate our findings for this research question, we present the ENA, SNA, and iSENS networks for the team-scenario described above. We also draw on prior ENA analyses of this dataset.

Figure 1 shows the ENA network for the team-scenario, the ENA scores for individual team members (green points), and the centroid (green-square). The positions of the network nodes and the connections they define can be used to interpret the dimension of this space.

On the left side are connections to codes related to processing tracks: Seeking Information, Deterrent Orders, and so on. On the right side are connections to Detection and Track Behavior. This suggests that the first dimension distinguishes individuals in terms of whether they focused on *Track Processing* versus *Track Information*. Toward the top of the space are connections to Seeking Information. Toward the bottom are connections to Defensive Orders, Deterrent Orders, Status Updates, and Recommendations, which relate to actions taken toward tracks. This suggests that the second dimension distinguishes team-scenarios in terms of whether they focused on *Seeking Information* versus *Tactical Actions*.

The ENA network indicates that this team-scenario made strong connections between many of the codes. The location of all of the ENA scores (save one) and the centroid in the lower left quadrant of the space suggests that this team-scenario focused more on Track Processing and Tactical Actions. The ENA score in the upper right quadrant corresponds to the EWS, whose contributions were more focused on Seeking Information and Track Information. These results align with prior ENA analyses, which found that, on average, high-performing team-scenarios focused more on Tactical Actions, while low-performing team-scenarios focused more on Seeking Information [26]. In turn, the ENA scores and centroids of high-performing team-scenarios tend to fall in the lower half of the space, while those for low-performing team-scenarios tend to fall in the upper half.

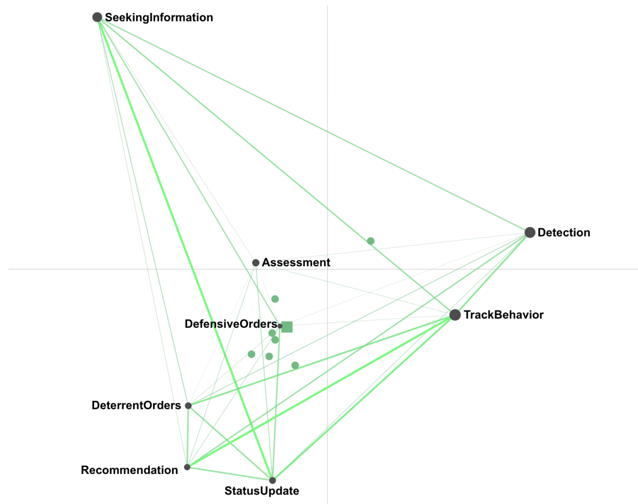

Figure 1: Epistemic network, ENA scores, and centroid for the team-scenario shown in the excerpt.

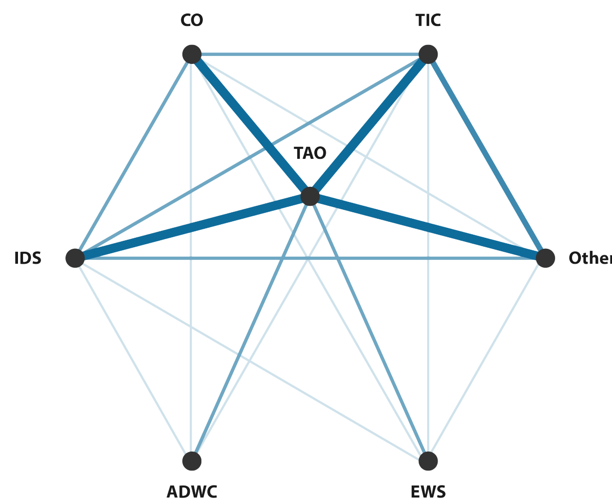

Figure 2: Social network for the team-scenario shown in the excerpt.

Figure 2 shows the SNA network for the team-scenario. While the placement of the nodes are arbitrary, the network shows that most frequent communication occurred between the TAO, TIC, IDS, CO, and Other, as indicated by the thicker and darker connections between these nodes. Here, "Other" refers to training personnel who played the role of external command and tracks during the scenarios.

Figure 3 shows iSENS network for the team-scenario with the dimensional interpretations added. The dimensions of this space correspond to the dimensions of the ENA space shown in Figure 1, the nodes correspond to the ENA scores of the individuals in Figure 1, and the edges correspond to social connections between individuals in Figure 2.

Table 3: Comparison between HLMs.

		ENA		SNA	SENS			iSENS	
Model	Intercept	1	2	WD	1	2	WD	1	2
I ENA-HLM	**37.34* (0.65)**	5.41 (4.20)	-6.67 (3.51)						
II SNA-HLM	**38.84* (3.16)**			-0.06 (0.13)					
III SENS-HLM	**40.93* (3.00)**				5.62 (4.10)	**-7.85* (3.35)**	-0.15 (0.12)		
IV iSENS-HLM	**37.59* (0.65)**							7.37 (4.04)	**-6.97* (3.12)**

() indicates standard error; * indicates $p < 0.05$

Table 4: 95% confidence interval and effect size for differences in mean SSE

Models	Mean SSEs	Difference in Means	95% CI	Cohen's d
(iSENS, SENS)	(649.33, 666.70)	-17.37	**(-32.28, -2.46)***	0.30

* indicates a statistically significant difference

As in Figure 1, the green square is the centroid of the team-scenario, and we can clearly see that EWS made cognitive connections that were very different from the rest of the team. The position of the EWS's ENA score has the effect of moving the centroid toward the upper right of the space. However, as illustrated in the excerpt and shown in the edges of iSENS network, the EWS interacted less with the team compared to others, while the most frequent interactions were between the CO, TAO, TIC, IDS, and Other. This asymmetry in the social network of the team is reflected in the weighted centroid (blue square). The frequent interactions between team members other than the EWS has the effect of moving the centroid toward the bottom left of the space. Put another way, because the EWS interacted less with the team, their talk contributes less to the representation of the team-scenario in the epistemic space using iSENS.

Comparing these two statistics to the excerpt above, the weighted centroid aligns more closely with the qualitative understanding of the data: it describes not only the content of the communication but the individuals who were most involved in those interactions. Moreover, because high-performing team-scenarios tend to fall in the lower half of the space and the weighted centroid places the summary statistic for this team-scenario lower in the space, this suggests that the iSENS statistic is a better predictor of performance. Our next research question addresses whether this is the case more generally for this dataset.

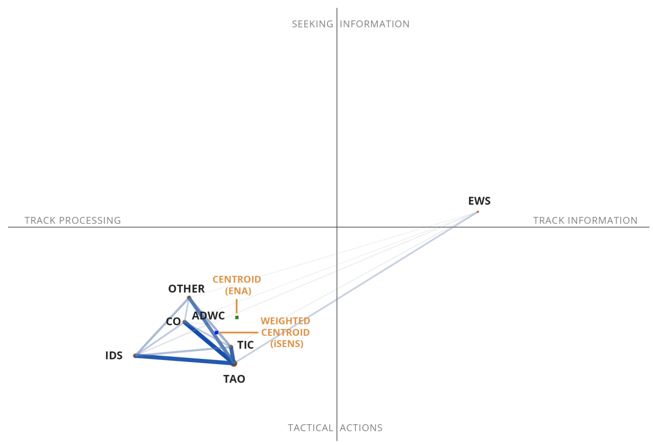

Figure 3: iSENS network for the team-scenario shown in the excerpt.

4.3 RQ3

While the findings above illustrate the interpretive value of iSENS, the model comparisons using HLM tested whether this approach also has statistical advantages. We found that only the SENS-HLM and the iSENS-HLM had at least one statistically significant explanatory variable. The coefficients and standard errors for each model are shown in Table 3.

The SENS-HLM had one statically significant explanatory variable: the position of the (unweighted) centroid on the second dimension of the ENA space. The negative coefficient (-7.85) indicates that team-scenarios with higher teamwork scores focused on Tactical Actions versus Seeking Information.

The iSENS-HLM also had one statistically significant explanatory variable: the position of the weighted centroid on the second dimension of the ENA space. The negative coefficient (-6.97) indicates that team-scenarios with higher scores where characterized by dense social interactions focused on Tactical Actions versus Seeking Information.

While the interpretations of the two significant predictors are similar, the iSENS predictor accounts for both the cognitive and social patterns of connections made by the team-scenarios.

To test for differences between the two modeling approaches with significant predictors, we used the bootstrapping procedure described above. Table 4 shows the 95% confidence interval for the difference in mean SSE between the iSENS and SENS models, as well as effect size of the difference.

This mean comparison shows that the iSENS approach had the lower mean SSE with an effect size of 0.30. The confidence interval around the difference does not include zero, indicating that the performance of the iSENS model was significantly better than the performance of the SENS model.

5 DISCUSSION

Our results suggest that teams in this context are characterized by specific patterns of cognitive and social connections. ENA and SNA were able to capture these patterns separately, but the iSENS approach integrated them into a visual representation and summary statistic that better aligned with our qualitative understanding of the data. Moreover, our statistical results suggest that iSENS can model team outcomes better than ENA alone, SNA alone, and (non-integrated) SENS.

Our results have several limitations. First, this study was meant to illustrate the value of iSENS. As such, we only present results using CPS data from one context. From these results, we cannot conclude that iSENS is a better approach for CPS data more generally. Second, CPS processes occur in sequences that could be important to model. While the approaches we used were sensitive to order due to the use of moving windows, the models did not explicitly represent sequence. However, previous analysis of this dataset has found that a non-sequential model yields results that are statistically better and more interpretable than a sequential model [26]. Finally, our iSENS approach combined relatively simple SNA and ENA metrics. More sophisticated SNA techniques could be used, such finding latent team structures with mutually stronger or more reciprocal ties. Similarly, more sophisticated ENA metrics could be used, such as the deviation of team members' ENA scores from the average score of their role. Here however, we deliberately implemented simpler techniques as a proof of concept. Our future work will continue to test iSENS using data from different contexts, explore the combination of sequential versions of ENA and SNA, and the combination more sophisticated ENA and SNA techniques.

Despite these limitations, this work suggests that iSENS is a potentially powerful technique for modeling CPS. Specifically, iSENS makes two contributions. First, this approach streamlines the analysis of CPS by combining ENA and SNA into a unified technique. This means that researchers who wish to conduct a network analysis of both the cognitive and social dimensions of CPS no longer have to run and coordinate two separate analyses. Second, and more importantly, iSENS affords the simultaneous investigation of the social structure of teams within a space defined by the cognitive connections they made. In other words, this approach can give insights into both the structure and content of collaborative interactions, providing researchers a more complete understanding of CPS.

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