Shared Beliefs in Operative Teams: A Social Network Analysis

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Abstract

The constructs of shared mental models and situation awareness are highlighted as influential for team processes and team outcomes. In interdependent teams collaborating to solve tasks, social dynamics are likely involved in such processes. The aim of the current analysis was to explore whether there is a relationship between social dynamics and shared beliefs in emergency response teams, using the approach of social network analysis. Data on communication and reliance dynamics in 11 teams was gathered from scenario training sessions. The data was graphed as networks displaying communication and reliance patterns. Communication and reliance, measured both on individual and team level was assessed as predictors of variance for the measured outcome variables of situation awareness and shared mental models. Further, the applicability of social network analysis for investigating social dynamics related to team functions in our sample was evaluated. The analysis revealed strong associations between network density and degree of shared beliefs, on a team level, but did not display significant covariance between communication or reliance networks and shared beliefs on the individual level.

Keywords: Social network analysis, shared mental models, situation awareness, team dynamics, operative teams.

Sammendrag

Delte mentale modeller og situasjonsbevissthet er sentrale elementer i teamprosesser og har implikasjoner for målbare utfall av teams funksjoner. I team hvor arbeidsmåten preges av gjensidig avhengighet og tett samarbeid, kan underliggende sosial dynamikk trolig påvirke slike prosesser. Denne studien hadde til hensikt å utforske hvorvidt sosial nettverksanalyse kan brukes til å avdekke eventuelle sammenhenger mellom teammedlemmers sosiale samhandling og grad av delte oppfatninger om den aktuelle arbeidssituasjonen. Selvrapporterte mål på kommunikasjon og tillit ble hentet fra scenariobaserte treningsøvelser hos 11 beredskapsteam. Målene ble brukt til å danne grafiske nettverk som avbildet sosial dynamikk på de målte parametrene, for hvert team. Kommunikasjon og tillit ble kartlagt både på individ- og teamnivå. Målene ble brukt som prediktorer for varians i utfallsvariablene delte mentale modeller og situasjonsbevissthet. Videre ble sosial nettverksanalyse evaluert som tilnærming for å kartlegge sosial samhandling knyttet til teamfunksjoner i den gjeldende settingen. Analysen avdekket sammenhenger mellom nettverk med høy tetthet av kommunikasjon og tillit, og delte mentale modeller og situasjonsbevissthet, på teamnivå. Tilsvarende sammenhenger ble ikke funnet på individnivå.

Nøkkelord: Sosial nettverksanalyse, delte mentale modeller, situasjonsbevissthet, teamdynamikk, operative team.

Acknowledgements

This thesis is a result of what we came to think of as uncharted terrain. The more we read about the approach of social network analysis and its potential for application, the more we were baffled to learn that it had rarely been used for exploring social dynamics in interdependent teams. A research project using this approach would be relatively exploratory in nature, but still seemed to be tied to established theoretical and empirical evidence describing team functions, which we found enticing and motivating.

We collaborated on this thesis across the division of master's programmes at the University of Bergen, one enrolled in the Work and Organizational Psychology program, the other in Psychological Science. The process and result has been a fruitful merging of our respective fields and a successful learning experience for us both.

We would like to thank our advisor, Bjørn Sætrevik for sharing his ideas and data, and for introducing us to the methodology of social network analysis. His commitment to transparency in research design as well as his sincere interest in and guidance of our work process has been inspiring and educative. We would also like to express our gratitude to Sascha Wolter, whose mathematical aid was of great importance for understanding, developing and expressing the measures used in the current analysis.

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Working life is increasingly implementing sociotechnical systems, where humans interact with machines in highly complex environments that require skilled collaboration for monitoring and distributing information and tasks. Therefore, teamwork is becoming the norm in most industries (Cross, Rebele, & Grant, 2016). A team consists of two or more people who have defined roles and show some level of interdependence to accomplish a shared goal (Salas, Dickinson, Converse & Tannenbaum, 1992). Further typical characteristics of teams are coordination among team members, roles with own responsibilities and pronounced communication (Salas, Sims & Burke, 2005). Errors in sociotechnical processes, whether human or systemic, may lead to catastrophic consequences. Therefore, determining factors that can contribute to prevention of errors and optimitimizing team functions is vital. A main goal of the current analysis was to explore social dynamics within teams, and whether patterns emerging from such networks can predict team functions.

In the field of human factors (HF), researchers aim to identify and understand physical and cognitive features of individuals or groups that influence processes in sociotechnical systems. High reliability organizations (HROs) are characterized by successfully and perpetually avoiding accidents and errors under circumstances where there is a possibility for loss of lives or considerable resources. Increasingly, organizations commit to using powerful, costly and dangerous technical systems, creating a need for low-risk performance in hazardous environments, to attain the associated benefits. Teams working under such conditions, like emergency response teams (ERTs) in the hydrocarbon industry, are expected to manage complex and hazardous work tasks, and simultaneously maintaining the capacity for high peak demand and productivity (La Porte, 1996).

According to Weick and Sutcliffe (2007), HROs have five common denominators in how they implement preventive measures to their infrastructures; they continually focus on a) tracking small errors, b) resisting oversimplification, c) maintaining sensitivity to the operative tasks, d) reinforcing capabilities for resilience, and e) using shifting locations of expertise to their advantage. Thus, to maintain high reliability and at the same time, high production, rigorous explorations of all aspects of the operative workplace is a prerequisite. This includes insight into social and cognitive processes that contribute to the establishment of shared conceptions (Van Den Bossche, Gijselaers, Segers, Woltjer and Kirschner, 2011).

Social network theory is one approach to explore social aspects that may influence team functions. This methodology is designed to investigate interaction patterns between social actors by graphing dyadic relationships between relevant individuals, groups or institutions (Borgatti & Foster, 2003). In an extensive review on the use of social network theory in team research, Henttonen (2010) described how such studies have mainly focused on individuals (i.e. egocentric networks) or groups within the organization (i.e. bounded networks), as the units of analysis (see also Cummings & Cross, 2003). Both Henttonen (2010) and Balkundi & Harrison (2006) underline that intrateam network analyses is underused in team research, although highly relevant. The current analysis is an attempt to explore this approach. The following provides an introduction to our outcome variables and their relevance in team functions.

Shared Mental Models

Mental models are structures of organized, declarative knowledge that enable us to interact with the environment. They are used to understand the behavior of the world around us by recognizing and remembering relationships between components in our surroundings. Mental models facilitate processes in which we identify, explain, predict, and draw inferences about events, actively constructing the overall understanding of elements in the world around us (Mathieu, Goodwin, Heffner, Salas, Cannon-Bowers, 2000). The content and degree of complexity of a mental model is highly subjective, as it is a product of the individual's personal experiences and knowledge. When discussing mental models in the context of teams in a HRO, it is implied that the mental models in question are task-specific and highly influenced by the level of expertise among these individuals. The increasingly complex sociotechnical systems with which these teams interact, calls for synchronization and coordination of information from all team members.

In operative teams, team members are required to adapt to rapid changes while under considerable pressure. Such teams often have individual team members perform specialized functions while the team as a whole has overarching, common tasks and goals. To achieve such goals, and to efficiently perform the tasks at hand, team members draw on what is referred to as shared mental models (SMM). Mathieu et al. (2000) defines SMM as "the usage of one's own organized knowledge to understand other team members' tasks, resources and challenges, and thereby making informed decisions in line with the team's goals".

Endsley (1995) describes the quality of SMM as an indicator of team coordination and efficiency.

In an impactful empirical study, Bolstad & Endsley (1999) found that providing team members with tools and information that contribute to building SMM of each other's current work status, enhanced efficient team performance. The authors described that boosting teams' SMM could be accomplished through instructions, training or provision of sociotechnical systems specifically designed for that purpose (e.g. shared monitors displaying relevant information).

Cannon-Bowers, Salas and Converse (1993) identified four types of SMM, organized into the following categories: a) equipment, b) task at hand, c) team interaction, and d) type of team. To solve a problem, team members frequently merge information from the various categories of SMM. In an interdependent team, shared knowledge about the sociotechnical system (e.g. computer screen, operator desk) combined with shared understandings of when each member's workload increases and how to support and communicate with each other when it does, is clearly advantageous. According to Espevik, Johnsen, Eid, and Thayer (2006), another important aspect of SMM is that they facilitate effective information exchange without the receiver asking for it. This likely reduces cognitive interference and distractions from essential tasks. Such implicit coordination is considered highly valuable.The impact of SMM on team collaboration, learning, communication, performance and efficiency is widely documented (see Cannon-Bowers et al., 1993; Cannon-Bowers & Salas, 1992; Cannon-Bowers, Salas & Milanovich, 1999; Espevik, et al., 2006, Mathieu et al., 2000; Rouse, Santos, Uitdewilligen & Passos, 2015, among others). In conclusion, the quality and accuracy of mental models are highly influential for achieving necessary states of knowledge and evaluation in complex environments. Thus, they make out the underpinnings of what is referred to as *situation awareness* (SA).

Situation Awareness

Complex, dynamic environments present an ever-evolving composition of factors in which small shifts in the context might have big implications for where the situation is headed. To accommodate the demands of a complex and changing environment that calls for continuous analysis and decision making, SA becomes the binding factor enabling operators to "become and remain coupled to the dynamics of their environment" (Stanton et al., 2017, p. 451).

While first forays into the construct of SA were undertaken in first world wars aviation, today the notion of having a correct mental representation of the situation is deemed important in several different areas. Research on SA has been conducted in a diversity of fields, like general aviation (Taylor, 1990), military air combat (Carretta, Perry & Ree, 1996), naval navigation simulation (Saus, Johnsen, Eid & Thayer, 2012), air traffic control (Endsley & Rodgers, 1994), driving (Ma & Kaber, 2005), process industry (Nazir, Colombo & Manca, 2012) and command and control (Artman, 2000). Research interest in the construct of SA has risen drastically since its emergence as a topic under academic scrutiny in the late eighties. Endsley's two influential articles in 1995 generated a sharp increase in this interest (Patrick & Morgan, 2010). SA has since become one of the most studied phenomenons in the HF literature (Stanton, Salmon, Walker & Jenkins, 2010).

A unified definition of SA has not been agreed upon (Sarter & Woods, 1991; Stanton et al., 2017). This may in part result from SA being the object of study for several disciplines. Engineering, psychology and system ergonomics, among others, have taken a hold of SA as a research interest, each with their own focus on the matter (Stanton et al., 2010).

Another reason for lack of agreement is the fundamental differences between two distinct SA research traditions. As has been pointed out by Durso and Gronlund (1999), the division between process- and product-definitions is common in conceptualizations of SA and a likely source of confusion when comparing SA research that does not clearly distinguish between those two - though both approaches may be appropriate when suitable methods are applied (Durso & Sethumadhavan, 2008; Stanton et al., 2017).

Among the definitions that prevail in the human factor litterature one of the most prominent is Endsley's (1988b), in which SA is defined 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". This definition describes SA as a form of "activated knowledge about a situation in which one is currently involved" (Saner, Bolstad, Gonzalez & Cuevas, 2009). The definition, like the model that builds upon it (Endsley, 1995b), uses a cognitive approach to SA and follows an information-processing tradition that generally places the achievement of SA internally within the individual operator, where perception, comprehension and projection each contribute to a knowledge state about situational cues "within a volume of time and space". Endsley's model (1995b) is comprised of three hierarchical levels of knowledge about the situation, perception (level 1 SA), comprehension (level 2 SA) and projection of future states (level 3 SA), that result in states of knowledge about the crucial task factors in the surroundings (Salmon et al. 2008). The three levels of Endsley's model build on each other, and the operator going through all of them is favorable for achieving the most accurate understanding of his surroundings. While this sounds like the model implies a linear approach, attainment of SA can be heavily driven by top-down processing (Endsley, 2015, Endsley, 1995b; Stanton et al., 2017). Such processes can be described as mental structures built from training and experience guiding both perception and comprehension through a priori expectations.

This contrasts approaches where SA is modelled directly after the processes involved in achieving SA, e.g. in the definition of Gorman, Cooke and Winner (2006), who define SA as a "continuous perception-action process in which ongoing activity plays an integral role in what there is to be perceived" (p. 1314), where the emphasis lies on how the responses to the developing situation partly form the perception and selection of relevant elements. Taking a different stance, Sarter and Woods (1995) even make SA out to be "a variety of cognitive processing activities" (p.16), seemingly not assigning SA the idiosyncratic status among concepts of human cognitive function that other theoretical approaches may seem to imply.

Patrick and Morgan (2010) however, make it clear that the distinction between process and product approaches, while useful on a theoretical level (Endsley, 2015), may be difficult to realize in practical applications of SA (which includes the act of measuring the construct). This is because the cognitive mechanisms and functions used in the description of process definitions of SA are not easily distinguished from the resulting knowledge states, where "a person's SA will in turn have an effect on what information is searched out and attended to, with product affecting process in a circular fashion" (Endsley et al., 2003, p. 25). All the aforementioned definitions are part of a individual focused rendition of SA. Stanton and colleagues (2017) make this (a) individual level out to be one of three distinct types of SA models with different theoretical underpinnings - the others being the (b) team and (c) system model type.

Modern information technology and organizational design have made many industries' `day to day' operations quite complex. Many work tasks today require the effort of a team to be able to be carried out in a timely and accurate manner. In this regard not only the SA of an individual operator but the SA of the whole team is of concern. The situation awareness at the team level, hereafter called TSA, has been a research interest for quite some time (Salas, Prince, Baker, & Shrestha, 1995), and also in this case, different approaches for definition of the concept exists (Stanton et al., 2017). The definition proposed by Endsley (1995) frames TSA as "the degree to which every team member possesses the situation awareness required for his or her responsibilities" (p.39). This definition highlights the individual's need for information in order to contribute to the overall team effort, and thus, TSA. When the tasks carried out by team members have common ground for their respective SA requirements, SA may be shared (Jones and Endsley (1996). This implicates that while some SA requirements may be relevant to several team members, and sharing of related information may be beneficial for raised TSA, other requirements may only be important for one individual's task completion. Salas and colleagues' (1995) TSA model features a combination of individual SA and various team processes. They emphasize the critical importance of information exchange for the attainment of TSA. Salas and colleagues argue that distribution of task relevant information may affect perception of SA elements to a larger degree than information exchange. This is meant in the sense that distribution of information accelerates effects of information exchange, that are relevant for task completion, team competency and clarifications of individual responsibilities and roles (Salas et al., 2005).

The theoretical work for SA presented so far is heavily influenced by a psychological perspective and with an emphasis on individual cognition, even when treated at the team level. In recent years, models for SA have been proposed that provide alternative ways for conceptualizing SA, namely *distributed SA* (DSA) (Salmon et al., 2006; Stanton et al, 2006; Stanton et al., 2010), the third group of models proposed by Stanton et al. (2017).

Distributed SA, which is related to the concept of distributed cognition (Hutchins, 1995), places the emergence of SA in the collaborative system, where SA is held by different agents (Stanton et al., 2006). The main divergence from 'classic' SA models is the assumption that SA may reside also in other parts of the non-human system, like displays and tools, which would be classified as artifacts by cognitive theories (Endsley, 2015). While DSA is seen as complementary to earlier models of SA (Salmon et al., 2008) and not a general critique of how those earlier models conceptualize SA, other researchers have challenged earlier approaches to SA, like Endsley's three level model (Dekker & Hollnagel, 2004; Dekker, Hummerdal & Smith, 2010; Rousseau et al, 2010; Salmon et al., 2008; Stanton et al., 2010; Van Winsen & Dekker, 2015).

Despite the contention around conceptualizations of SA, and which definition to adopt, SA is widely regarded as a crucial element in safety-critical work environments, where technological and situational complexity are main factors (Byrne, 2015; Wickens, 2008; Parasuraman, Sheridan & Wickens, 2008; Saner et al., 2009).

Measurement of Situation Awareness

Various definitions and research disciplines involved in examining SA has led to several different conceptualizations, which leads to direct implications for how one is to go about to operationalize the construct, and to measure it further along the line (Salmon et al., 2008). Measurements of which environmental cues are available to the operator's attention often involves the praxis of establishing a "ground truth" for what information is available to the individual operator in a given scenario. The operator's assessments are compared against this measure of optimal information attainment, to assess the individual's accumulated comprehension of information. A scoring system of what an operator could and should be aware of at a specific point in time is often established by use of subject matter experts (SMEs) who develop a rating scale (Salmon et al., 2006). Since every situation is thought to have different challenges, this enables tailoring the scoring system to the specific SA requirements of the scenario in question. Endsley's commonly used situation awareness global assessment technique (SAGAT; 1995a), employs a variant of this approach.

The notion of normative performance standards to which individual operator responses can be compared against, makes a challenging proposition. Establishing these standards requires considerable resources. It also confines SA measurement to settings which can be sufficiently controlled, which hinders applicability in real-life incidents and complex training scenarios (Sætrevik & Eid, 2014). Further, there may exist situations where the objective standard cannot be established (Stanton et al., 2017). To accommodate situations like these, it has been proposed that rather than measuring responses against a 'ground truth', measures should assess to which degree operators' responses to relevant questions are shared (Sætrevik & Eid, 2014; Sætrevik, 2015).

Bolstad, Cuevas, Gonzalez, and Schneider (2005) state that SA attainment is primarily affected by three distinct components, the operators abilities, their interaction with the environment and their interaction with other operators. The last component will be the focus of this analysis. Measures derived from two separate networks graphing each teams' patterns of interaction regarding communication and reliance, will be used to assess whether shared beliefs can be predicted by social networks. The current analysis uses the approach of measuring SA by comparing team members' responses, based on the notion that the team member who can be assumed to have the most extensive understanding of the situation should be used as a reference for assessing other team members' responses. Bigger overlap in responses is thus taken to be an indicator of a higher degree of shared SA. A similar assessment of the degree to which responses were shared, was used by Saner and colleagues (2009), though the study focused on dyads, and employed a traditional 'ground truth' approach to make judgements on response accuracy.

Social Network Analysis

While there is no single social network theory (Kilduff & Tsai, 2003), a common denominator of theories for social network analysis (SNA) postulates that individuals are embedded in relational structures that are multilevel in nature (Monge & Contractor, 2003; Newman, 2010, Streeter & Gillespie, 1992). Social networks can be said to have *structure* and *content* (Balkundi & Harrison, 2006). *Structure* include the number of social parties (often referred to as a 'node') in the network, the number of connections between them ('ties'), and the distance between specific nodes, describing the layout of a given network. Structural characteristics involve three levels of analysis, namely the whole network, subgroup level and individual level. For each of these three levels, the analysis provides detailed information about the networks' compositions. *Content*, on the other hand, describe the nature of the relations between nodes in a network. This includes the frequency and importance of the connections between nodes, but also more subtle characteristics, like the flow and distribution of information, resources and influence.

While research with sociological or anthropological background has often concentrated on networks in larger populations, like communities, states or nations (Borgatti, Mehra, Brass, & Labianca, 2009), appliance of SNA has been successfully extended to smaller scale, with modelling network level effects at the organizational (Contractor, Wasserman & Faust, 2006) or team level of analysis (Balkundi & Harrison, 2006). When applied at the team level, SNA highlights the importance of specific patterns of network relationships which makes investigating the effects of group-level peer interactions possible. As opposed to many methodologies commonly used in the social sciences, SNA investigates dyadic attributes, rather than focusing on individual or unidirectional characteristics like gender, age, income or competence. This means that SNA's focal point is the nature of two nodes interconnection and how that relationship may be defined further by its content, e.g. in terms of affective, cognitive and social states, with a common polarization in *expressive* and *instrumental* content (Lincoln & Miller, 1979). Instrumental content is often seen as transfer of information and advice necessary for task completion, while expressive content encompasses the affective ties, like social support given in friendships (Ibarra, 1993). Nodes may consist of a single person or represent an extended group of people, or even institutions.

The dyadic ties commonly investigated in SNA is thought to reveal information about the network as a whole by quantifying and graphing interactions (e.g. communication), affiliations (e.g. friendships), similarities (e.g. group membership) or flow of resources (e.g. information) (Wölfer, Faber & Hewstone, 2015). The method is ideal for uncovering underlying and systematic social patterns that govern who has contact with whom (McCulloh, 2013). Furthermore, it may reveal interdependencies, collaborations and transitional processes that are likely to describe social actors' behavior above and beyond the level of individual characteristics (Borgatti & Halgin, 2011). Social positioning and accumulation of relations are some of the relational terms that often is defined mathematically and graphed by means of a SNA. SNA may uncover hierarchies or social groupings that exist outside of the organization's formal positioning system. Relevant structural properties can be defined mathematically, enabling researchers to operationalize and use them as predictors in further statistical analysis. This facilitates the researcher's endeavour to use a network's structure and content to make inferences about team functioning, in excess of individual factors. SNA may thus be advantageous in describing important social systems' and structures' effect on team outcomes that are difficult to define without using relational terms. A number of network features may be uncovered through SNA. For an extensive introduction to the various network property measures commonly used in SNA, see Wölfer et al. (2015). In the current analysis we have focused on the concepts *centrality*, *centralization* and *density*, which are described in more detail below.

Centrality, centralization and density.

As has been stated above, SNA offers access points for analysis at several levels (Streeter & Gillespie, 1992). One way to look at social structure in a team's network is by examining the characteristics of the nodes that constitute it. The distribution of ties in a network may reveal central nodes that display higher degrees of connectedness and influence on other nodes, both in terms of the frequency with which they interact with other nodes, and their importance in the network. Centrality can be measured by self-reported or observed frequency of participation in a network interaction setting (Sauer & Kauffeld, 2013).

A node's access to social resources is said to be a function of the node's position in the social network. Being in a central position is thus highly advantageous because it increases the chance of getting benefits, such as information or control thereof (Burt, 1992). Likewise, with its high degree of connectedness in the network, a central node is also in a position to convey information to other nodes, i.e. team members in our context, via fewer ties. Shorter, stronger pathways to other nodes are considered to give central nodes greater relational impact than other nodes. A common aggregation of these aspects is a node's *centrality*, indicating where a node is positioned in a network relative to others. Centrality has been associated with various outcomes, like individual performance (Baldwin, Bedell, and Johnson, 1997), group performance (Mehra, Dixon, Brass & Robertson, 2006), and diverse favorable team outcomes in a series of 1950's MIT studies on communication in small groups. Bavelas (1950), Leavitt (1951), Shaw (1954), and Goldberg (1955) collectively demonstrated that a common denominator for problem solving efficiency, speed, activity, leadership and satisfaction was that they were characteristics of central members of the teams (Freeman, 1977), findings which were both analogically and empirically supported in later studies (Balkundi & Harrison, 2006; Katz et al., 2004; Cummings & Cross, 2003).

Figure 1. Examples of teams with high and low centralization

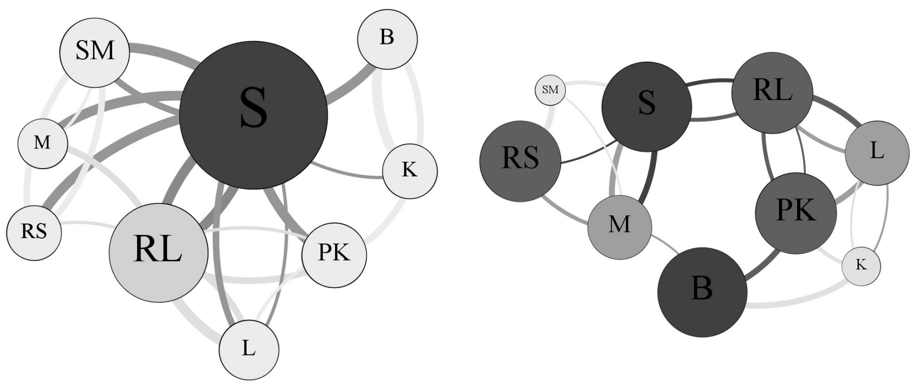

Figure 1. (left) High centralization in team 9's reliance network, (right) low centralization in team 2's communication network; node size scaled to members weighted in-degree centrality.

Networks where one or a few nodes are central and others are more peripheral in comparison, are considered to be high in *centralization*, as opposed to networks where all nodes partake in a more equal manner. In a network with maximal centralization a graphed interaction pattern would take the form of a star-like structure, where the dominant node is positioned in the center and the peripheral nodes are distributed around it, connected by ties to the central node but not (necessarily) to each other. In real-world data, like the examined ERTs in this study, networks with high or low centralization show the difference of centrality scores between nodes, but in continuing degrees, see Figure 1. In the highly centralized network most of the ties in the network are connected to the chief of staff ('S'), while other members receive less direct social interaction. The example from team 2 shows a network of team members with relatively equal distribution of ties, resulting in less difference in individual centrality scores.

Cummings and Cross (1993) showed that groups with markedly disparate core-peripheral and hierarchical structures, i.e. signs of high centralization, displayed lower performance than groups with less distance in their members' centrality. In the same line, Sparrowe, Liden, Wayne, and Kraimer (2001) investigated 38 work groups in five organizations, with groups handling relatively complex work tasks. The field study showed that teams with decentralized communication structures were more efficient in solving complex tasks, receiving higher performance scores and made fewer errors. Lipman-Blumen and Leavitt (2001) also attributed decentralized communication patterns as being favorable for effective teamwork. This aligns with earlier, seminal research where work units or teams characterized by high centralization have been linked to lower performance and efficiency in complex tasks, than work groups where the distribution of ties is not as concentrated around few members (Leavitt, 1951; Shaw, 1954, 1964, 1971). The main thought is that relying on fewer members (i.e. the highly central ones compared to the rest of the team) to convey important social resources, e.g. information and support, raises the chance for performance loss, when the transfer is not successful. Taking information as an example, this could result in an uneven picture of the situation at hand in different parts of the team network. Team members having the same requirements for their SA to carry out their responsibilities, but receiving different information, might hamper the overall TSA. On the same note, limited access to the network transmitted resources could severely intervene with the development of SMM, for instance when the team needs to change their model for the workings of the situation, but is not able to because of disparate information or because important task work that a function relies on has not been executed.

Amidst the vast amount of team-level network variables available to researchers (see McCulloh, 2013; Hanneman & Riddle, 2005; Monge & Contractor, 2003; Newman, 2010) density is commonly seen as highly applicable to the inherent multilevel structure of a team, the communicational and relational patterns, and different team outcomes, e.g. performance (Balkundi & Harrison, 2006). In general, density denotes the extent to which nodes in a network are interconnected (Hanneman & Riddle, 2005). Denser networks are thus realized when interconnectivity between nodes increases (Scott, 2000; Newman, 2010). Applying this to the team level of analysis, a team's density increases when connections between team members are established (Balkundi & Harrison, 2006). So while centralization is indicating a difference in centrality scores between team members, density rises the more team members are interconnected. As can be seen in Figure 2 the high density in team 11's communication network has many of its members tied to each other, resulting in a lot of possible pathways for transfer of social resources. This network also exemplifies that centralization and density are independent measures. Team 11 had a below average centralization score that is very similar to team 5's centralization - while being one of the densest networks in the sample. The low density in team 5's reliance network has some of the team members almost excluded from the rest of the teams interactions, while others have interconnections with their adjacent nodes, but not with many others.

Figure 2. Examples of ERTs with high and low density

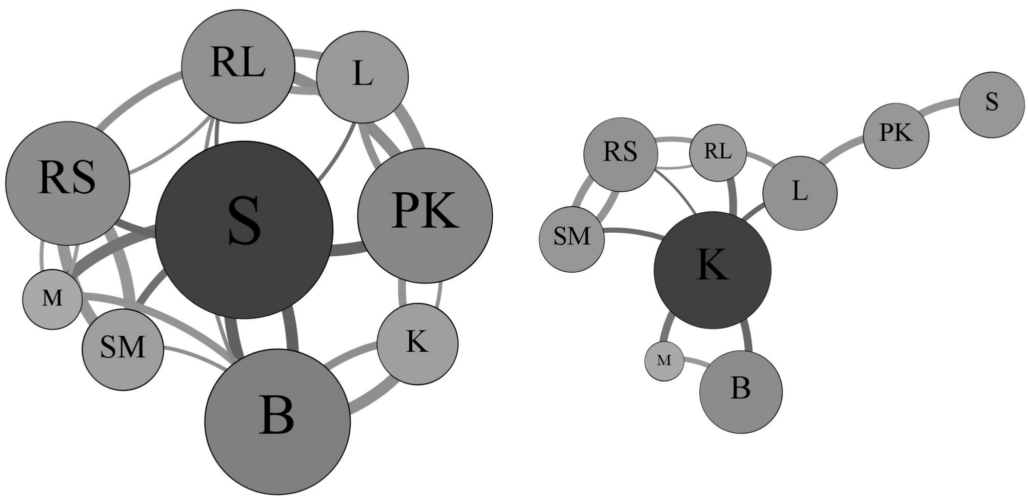

Figure 2. (left) High density in team 11's communication network, (right) Low density in team 5's reliance network; node size scaled to members weighted in-degree centrality

Characterizations of denser teams are often reported in form of increased information exchange, collaboration, and general interaction between team members (Sparrowe et al., 2001; Wölfer, Faber & Hewstone, 2015).

SNA has increasingly been selected as the method of choice for scholars interested in inter- and intra-team dynamics in the last decade, this is especially true for organizational research (Borgatti & Foster, 2003; Burt, Kilduff & Tasselli, 2013). However, both Wölfer et al. (2015) and Henttonen (2010) states that SNA is still underused in relevant areas of research, possibly on account of lack of knowledge about the analytical possibilities inherent to this approach. The authors strongly encourage the use of SNA to shed light on what they deem to be "open research questions within the science of groups" (Wölfer et al., 2015, p. 47), underlining that social dynamics are salient predictors for team functions. In a methodological assessment of SNA's usability in field settings of command and control, Houghton et al. (2006) encourages further use of the approach for investigating such teams. In the current analysis, we hope to expand the knowledge about ERTs' intra-group communication and reliance dynamics in relation to shared beliefs, on both individual and team level.

Research Setting

The current analysis was performed using data previously gathered from a Norwegian hydrocarbon industry company, considered a HRO. Specifically, 11 second-line emergency preparedness teams responded to questionnaires during scenario based training sessions. The subjected teams are mustered when an alarm sounds at any of the company's offshore installations. Potential incidents include detection of gas leakages, fires, vessels on collision course, or personnel injury (Sætrevik, 2015). The teams assist the tactical first-line emergency management in making decisions on how to mitigate the ongoing situation. Functions performed by the ERTs include collecting and distributing relevant information between involved parties, and organizing resources like sea- or airborne vessels. The team is also responsible for continually keeping the strategic third-line officials on corporate level updated, and converting managerial decisions into practice, for instance by establishing and operating an information hotline for next of kin or initiating and organizing evacuation or production shut-down. Each team consists of about 10 individuals. Every team member's competence is specified in accordance with their respective area of responsibility, and all teams include the following roles: chief of staff (emergency commander), personnel coordinator, medical advisor, air transport officer, maritime resource officer, maritime communications officer, government liaison, communications officer, and strategic line leader. Some scenarios put particular team functions under a relatively high workload, and by corporate routine, these functions may therefore be reinforced with an extra operator in some scenarios (see the Methods and results section for adjustments). All team members have other office jobs in the company, and are mustered if an alarm is detected, in which case they are expected to be present in the preparedness center within one hour. A total of six teams work on a rotating schedule, five weeks off, one week on 'call'. Usually, each team starts their week on call duty with a simulated training scenario. The data used for the current analysis was gathered in an actual training session (Experiment 1), and in a scripted training scenario, closely resembling a regular training simulation session (Experiment 2). The training sessions were intermittently 'frozen', during which time the team members would fill out a questionnaire asking about their understanding of the ongoing events. At the end of each session, they also rated which of the other team members they communicated most with, and who they had relied most upon to complete their own tasks, during the training session.

Chief of staff's role.

The chief of staff has a prominent role in the investigated teams, functioning as an information hub, gathering and distributing information among the other team members. In ongoing emergency events, the chief of staff arranges brief (2-3 minutes) status update meetings every 20-30 minutes. When initiating meetings, the chief of staff takes a position in front of the rest of the team, using screen displays and a writing board to visualize relevant updates. The other team members are seated at desks forming a V-shape surrounding the chief of staff. Each team member is seated in a specific location, the proximity to other team members predetermined by their individual roles. The chief of staff performs an executive function in the team, merging the detailed descriptions of the situation from every team member's area of expertise to formulate strategies aimed at resolving the ongoing incident. This includes intel from the corporate strategic (third line) level (although the strategic line leader is responsible for the direct contact between third and second line teams). The team members are typically communicating with external sources, like the first line offshore crew or other relevant personnel. The chief of staff is thus expected to be the best informed team member. This is not a new notion, and a recent example that reinforces it is Vogus and Rerup (2017), who describe how HRO team leaders systematically identify and re-configure resources to achieve superior team performance, thus underlining the inherent importance of leaders in HRO team.

Sætrevik (2015) found that ERT members' degree of shared beliefs, measured as SMM and SA, was affected by which team they belonged to, but not the specific function they performed in the team. Sætrevik thus attributed the variation in shared beliefs to team specific characteristics. He hypothesized that variance in leadership characteristics, the team's shared experience and communication patterns may contribute to variance in shared beliefs. We will explore the possibility of patterns in the teams' social networks being a predictor for shared beliefs, using the same data as Sætrevik (2015) and Sætrevik & Eid (2014). Any findings of explained variance in shared beliefs could be beneficial in terms of understanding the underlying dynamics of team efficiency, as it is widely accepted that accurate shared beliefs facilitate team cooperation and thus, team performance (see Cannon-Bowers & Salas, 2001; Espevik et al. 2006; and Sætrevik & Eid, 2014, among others).

Hypotheses

Based on the discussion above we propose that SNA may be a useful method for shedding light on social dynamics involved in ERTs' functions. The predictions comprises assumptions about relationships that to some extent have already been established in previous publications, e.g. that intra-team communication is vital for the establishment of SMM (Stout, Cannon-Bowers, Salas & Milanovich, 1999). In extension to this, we wanted to explore whether a SNA, and concepts commonly used in network analyses, such as centrality, centralization and density, would be applicable to these types of data. In line with Henttonen's recommendation (2010), our study aims to widen the scope of team types investigated by SNA. The following section will detail the hypotheses formed to explore the applicability of SNA to the ERTs, and the emergence of possible associations between the patterns of their social relations and their shared beliefs.

Predictions for the individual team member's centrality in the network.

Information is transferred through communication between team members, and the degree to which a team member has similar information as other members determines the individual's SMM. It is therefore expected that team members' centrality in the communication networks will be positively associated individual SMM (measured by comparing individual team members' responses to the teams' mean responses) (H1a). Further, in interdependent teams, closely monitoring and supporting of each others tasks are key for team functioning. Team members that are evaluated as highly reliable therefore likely share other members' mental models of the tasks at hand. Thus, it is expected that centrality in the reliance networks will be positively associated with individual SMM (H1b). Further, information regarding all aspects of the ongoing situation may be crucial for making evaluations, decisions and projections in an ERT. As the flow of information is distributed through communication, it is expected that team members' centrality in the communication networks will be positively associated with individual SA (H1c). Being alert to and mindful of the team's overarching tasks and goals requires insight into the complex nature of the workplace, including other team members' roles. Team members that are skilled in providing support and foreseeing when this is needed is likely regarded as reliable. It is therefore expected that team members' centrality in the reliance networks will be positively associated with individual SA (H1d).

Predictions for the teams' overall network centralization.

Equal distribution of information in teams is regarded as a vital element of the establishment of SMM. Centralization is an expression of the degree to which individual centrality is concentrated on one or a few individuals (nodes) in a network. It is therefore expected that higher degrees of centralization in the ERTs' communication networks will be negatively associated with TSMM (H2a). Following a line of reasoning, where reliance is an expression of team members' backing and monitoring each other, it is likely that equal distribution of reliance between team members facilitate SMM. It is therefore expected that higher degrees of centralization in ERTs' reliance networks will be negatively associated with TSMM (H2b). Following Salas and colleagues (1995), TSA is likely highly influenced by equal distribution of communication. Higher levels of TSA are expected to be achieved only when all team functions have sufficient information to support individual SA requirements (Endsley, 1995b). It is therefore expected that higher degrees of centralization in ERTs' communication networks will be negatively associated with team SA (H2c). The degree to which team members rely upon each other equally likely expresses its accelerated capacity for perceiving, evaluating and projecting internal and external events. It is therefore expected that higher degrees of centralization in ERTs' reliance networks will be negatively associated with team SA (H2d).

A pre-registration of the current analysis was submitted to Open Science Framework (osf.org) prior to accessing the data and conducting the analysis. The pre-registration provides an extensive account of all variables and predictions, including details on data transformation, exclusion criteria, alpha levels, and Bonferroni adjusted alpha levels. See appendix 1 for a disclosure of the preregistration in its entirety.

Methods

Sample

We used data from two separate experiments, conducted in the same setting and within the same organization. The following account of data recording in Experiment 1 and Experiment 2 is adapted from Sætrevik (2015). All possible respondents were invited to partake in the scenario training sessions performed in Experiment 1 and Experiment 2. This means all members of the ERTs that make up the second line of our industry partner's emergency organization. Some teams and team members will have been measured twice in our sample. In Experiment 1, data was gathered during the ERTs' routine scenario training sessions, with durations of 2-3 hours. All the six ERTs participated in the data collection. Each team consisted of one chief of staff and between 9 and 11 team members, yielding a total of 58 participants. The participants in Experiment 2 were the same individuals as in Experiment 1, but the team constellations were rotated in accordance with staff availability and compliance to participate in the study. Some of the staff were unable to attend the experiment, resulting in the recording of five, rather than six teams, each consisting of one chief of staff and eight team members, yielding a total of 45 participants in Experiment 2.

Procedure

Scenario training sessions take place in the emergency room, with team members interact with the same personnel and equipment that would be involved in an actual event. Experiment 1 made no restrictions on the scenario design. The chief of staff announced status meetings 4-6 times during each training session. After the meetings were announced but before they commenced, team members were issued with a pen-and-paper survey booklet, comprising of eight probe questions. The first five probes queried for information about individuals' understanding of the ongoing incident by asking about the incident location and type, status of personnel involved in the incident, and by asking participants to make statements about the team's prioritized tasks and predictions on the outcome of the incident. The responses to each probe question (also referred to as "domain of knowledge", in Sætrevik & Eid, 2014, and Sætrevik, 2015) were used to calculate a similarity index for SMM, and a similarity index for SA. These similarity indices were developed by Sætrevik & Eid (2014) and has previously been applied to the current data to quantify individual SMM and SA.

The format of the recording sessions was altered in experiment 2, with the aim of enhancing experimental control. The researchers developed detailed scripted scenarios for the training sessions. A staff of actors were introduced to perform the scripted roles of the various external personnel with whom the ERT members would communicate during the sessions. The scripts and the actors were introduced as a means to regulate task complexity (Sætrevik, 2015). Furthermore, eight status meetings were planned for the scripted scenario sessions, every 20 minutes minutes after the sessions were initiated. The pen-and-paper questionnaires from Experiment 1 was replaced by questionnaires distributed by email, timed to arrive at each planned freeze point. Participants were required to submit the questionnaires in order to proceed with their tasks. These modifications enabled a stronger temporal resolution and reduced the potential for variability to be caused by the chiefs of staff's decisions on when to initiate status meetings. The electronic format of the questionnaires were meant to enhance compliance and reduce missing responses.

Measures

A network can take many forms and it is up to the the researcher to define a useful ruleset of what should comprise the network structure. The ERTs that were examined in the two conducted sets of experiments were continually probed throughout the emergency scenarios they were participating in. When the scenario was finished they were asked to rank their top three for whom they had communicated most with and a corresponding ranking of which other team members they had relied most upon. This made it possible to attain two networks, one for communication and one for reliance. Since the data collection did not set out to collect all communication and all forms of reliance, but the three most frequented other team members for the individual, the formed networks do not, strictly speaking, display communication and reliance patterns, but rather a network of all respondents' triplet of dyads deemed most important. This being said, interaction with more than three functions occurred rather seldom. Thus, the networks will be treated as representing communication and reliance networks, for ease of discussion. This ranking was used to assign weights to the tie, with a weight of three for the first, two for the second and one for the third rank. Since every team member was asked to point out three functions in the team, the amount of outgoing ties was rather foreseeable, with not answering or answering erroneously being the only way to have less than three outgoing ties. The decision was made to exclude the outgoing ties from a node's own centrality equation, because they would be more or less equal for all participants. Rather, the number of ties a team member would receive was of interest. A node's number of received ties and strength, formed through the amount of assigned weights, lay the basis to calculate a node's tuned, weighted in-degree centrality. Opsahl, Agneessens and Skvoretz (2010) referred to this measure as reflecting the node's "popularity", which is the term we will proceed to use. This measure, apart from being used on its own on the individual, node-level of analysis, will also lay the groundworks for calculations of centralization and density on the team level. The calculations, as well as the expansion of classic centralization and density measures to accommodate information from both ties and weights, will be detailed in the following section.

Calculation of popularity, centralization and density.

In-degree centrality, according to Freeman (1978) is given by

$$k_i^{in} = C_{D-in}(i) = \sum_{j=1}^{n} x_{ji}$$

where i is the focal node, j are all other nodes, n is the total number of nodes and $(x_{ji})$is the adjacency matrix, in which the cell x_{ji} is defined as 1 if node j is connected to node i, and 0 otherwise. Thus, k_i^{in} reflects the amount of ingoing ties a node receives from other nodes in the network. An extension of degree centrality to include networks where the ties are assigned different weights, hereafter called node strength, can be defined as

$$s_i^{in} = C_{D-in}^{w}(i) = \sum_{j=1}^{n} w_{ji}$$

where (w_{ji}) is the weighted adjacency matrix, in which w_{ji} is greater than 0 if the node j is connected to node i, and the value represents the weight of the tie (Barrat et al., 2004; Opsahl et al., 2010). This measure includes weights, but foregoes the information included in the number of ties a node has received.

An alternative approach is given in accordance to Opsahl and colleagues (2010), who postulate a centrality measure that retains information of both tie count and weight assignment. Calculation of the tuned in-degree centrality in a weighted network (popularity), combining traditional in-degree centrality k_i^{in} and node strength s_i^{in}, is given by

$$C_{D-in}^{w\alpha}(i) = k_i^{in} \cdot \left(\frac{s_i^{in}}{k_i^{in}}\right)^{\alpha} = (k_i^{in})^{(1-\alpha)} \cdot (s_i^{in})^{\alpha}$$

where α is a positive tuning parameter which, depending on the value chosen, influences the relative impact of in-degree centrality and node strength. When α is set to either of the benchmarking values of 0 or 1 the equation equals the node's in-degree centrality or strength, respectively. When $\alpha < 1$ the number of contacts over which the strength is distributed increases the value of the measure, when $\alpha > 1$ the number of contacts decreases it (assuming the total node strength is fixed, in both cases, Opsahl et al., 2010). As pointed out before, the way participants were asked to rank other members implies a prominence of the weight aspect of the data and a tuning parameter below one would therefore seem natural. An $\alpha = \frac{1}{2}$ was thus deemed appropriate, with

$$C_{D-in}^{w\alpha}(i) = (k_i^{in} \cdot s_i^{in})^{\frac{1}{2}}$$

giving the final equation of a nodes popularity. This equation bears resemblance to a standard square root function, which is strictly monotone.

General calculation of centralization in a network (NC_X) according to Freeman (1978) is given by

$$NC_X = \frac{\sum_{i=1}^{n} (C_{Xmax} - C_{Xi})}{max \sum_{i=1}^{n} (C_{Xmax} - C_{Xi})}$$

where n is the number of nodes, C_{Xi} represents the individual nodal centrality values, $C_{X\,max}$ is the largest value of C_{Xi} for any node in the network, and max $\sum_{i=1}^{n} (C_{Xmax} - C_{Xi})$ equals the maximum possible sum of differences in nodal centrality for a network of n nodes.

Given the ruleset imposed on the network through the way in which data was collected, participants were able to rank three other members at most, excluding themselves. Thus a member u_i , $i \le n$, ranks up to three other members. In the following a set of networks Φ over a set of n nodes the ranking of a node u_i is given by the assigned weights from other members u_j with

$$w_{j,i} = 3 \text{ for rank 1; 2 for rank 2; 1 for rank 3.}$$

For a network $\phi \in \Phi$ let the factor $\gamma(\phi)$ be defined as

$$\gamma(\phi) := \sum_{i=1}^{n}(C^{w\alpha}_{D-in\,max} - C^{w\alpha}_{D-in}(i))$$

From the networks ruleset follows $\gamma(\phi) \ge 0$. Further let γ_{max} be

$$\gamma_{max} := MAX\,\{\,\gamma(\phi)\ |\ \phi \in \Phi\,\}$$

the maximal $\gamma(\phi)$ for all possible networks $\phi \in \Phi$. Under the assumptions that n is greater than 3, the given ruleset implies $\gamma_{max} > 0$, thus the following is well-defined.

In analogy to Freemans centralization measure it is now possible to define

$$NC^{w\alpha}_{D-in}(\phi) = \frac{\sum_{i=1}^{n}(C^{w\alpha}_{D-in\,max} - C^{w\alpha}_{D-in}(i))}{MAX\,\{\gamma(\phi)\,|\,\phi\in\Phi\}} = \frac{\gamma(\phi)}{\gamma_{max}}\ ;\ \forall\phi \in \Phi$$

with the denominator being the maximum sum of difference for tuned nodal in-degree centrality in a weighted network, with the measure $NC^{w\alpha}_{D-in}(\phi)$ ranging between 0 and 1. Applied, Freeman’s term compares the sum of differences of the actual maximum popularity and all other nodes popularity in a network with the absolute maximal sum of differences that are possible to obtain for a network - constrained by the ruleset given through how data was collected.

For every network $\phi_m \in \Phi$ that holds $\gamma(\phi_m) = \gamma_{max}$ has to contain a node u_k with $C^{w\alpha}_{D-in}(k) = C^{w\alpha}_{D-in\,max}$, maximizing the term $C^{w\alpha}_{D-in\,max} - C^{w\alpha}_{D-in}(i)$ for all $i \neq k$. Such a u_k can be constructed if u_k is ranked first by all other nodes, in terms of popularity:

$$w_{j,k} = 3\ ;\ \forall j \neq k.$$

To simplify we assume k = 1.

To determine how the rest of the weights have to be distributed to obtain a maximum sum of differences we construct γ_{max} by considering

$$\gamma(\phi) = \sum_{i=1}^{n}(C^{w\alpha}_{D-in\,max} - C^{w\alpha}_{D-in}(i))$$

$$= n \cdot C^{w\alpha}_{D-in\,max} - \sum_{i=1}^{n}(C^{w\alpha}_{D-in}(i))$$

$$= n \cdot C^{w\alpha}_{D-in\,max} - \sum_{i=1}^{n} (k_i^{in} \cdot s_i^{in})^{\frac{1}{2}}$$

Since $C^{w\alpha}_{D-in\,max}$ is constant this becomes maximal, when the term

$$\sum_{i=1}^{n} (k_i^{in} \cdot s_i^{in})^{\frac{1}{2}}$$

is minimal. In accordance with the semblance to a common square root function this sum becomes minimal if the remaining weights are concentrated on as few as possible other nodes, i.e. nodes u_2, u_3 and u_4.

Let u_2 be so that

$$w_{1,2} = 3 \text{ and } w_{j,2} = 2\ ;\ \forall j \neq 1, 2.$$

Further let u_3 be so that

$$w_{1,3} = 2,\ w_{2,3} = 2 \text{ and } w_{j,3} = 1\ ;\ \forall j \neq 1, 2, 3.$$

Finally let u_4 be so that

$$w_{j,4} = 1 \text{ for } j = 1,2,3 \text{ and } w_{j,4} = 0 \text{ for } \forall j \geq 4.$$

This way a total of $3 \cdot (n-1) + 3 = 3 \cdot n$ ties and n times first-, second- and third-rank weights are assigned, respectively.

Common team-level density is derived by dividing the sum of tie values by the total number of possible ties for the network (McCulloh, 2013; Hanneman & Riddle, 2005). To retain information of both weights and tie counts for a node, density d in the current networks is calculated by dividing the sum of actual popularity scores for each network by the maximal possible popularity scores for a network of size n. Thus the term becomes

$$d^{w\alpha}_{D-in}(i) = \frac{\sum_{i=1}^{n} C^{w\alpha}_{D-in}(i)}{\sqrt{3n \cdot 6n}} = \frac{\sum_{i=1}^{n} C^{w\alpha}_{D-in}(i)}{3n\sqrt{2}}$$

with a total of $3n$ possible ties and $6n$ possible weights in the network, with the given ruleset for the network.

Shared mental models, situation awareness and team situation awareness.

For the individual and team SMM and SA calculations, the same approach was used as in the previous study (Sætrevik and Eid, 2014). If a team member had not submitted any responses a given freeze point, this freeze point was excluded from the calculation of that member's average score (as he/she may have been unavailable to answer the probes at the time). If a team member had responded to some but not all probe questions at a freeze point, the unanswered probes were scored as "Don't know". If the team leader had not responded to some or all probe questions at one or more freeze points, the team's SA was not calculated for those freeze points.

The SMM index was calculated by comparing all team members' (including chief of staff's) answers to the group mean answer, for all domains of knowledge. The values are subsequently standardized to vary between 0-1, where 1 expresses that the individual's response matches perfectly with the team's average responses, and numbers closer to 0 indicate little overlap between the individual's and the team's average responses.

The SA index was calculated by defining the numerical distance between the individual team member's answer and the chief of staff's answer, for every domain, standardizing it to vary between 0-1. On the SA index, 1 expresses perfect alignment between a team member's and the chief of staff's responses on the probe questions, while numbers closer to 0 indicate increasing discrepancy between such responses. Since the number of status meetings varied between recording sessions, only the first four data points for each team were used for calculating similarity index scores, enabling comparison between the teams. For more details on similarity index calculations, see Sætrevik & Eid (2014).

Analysis Plan

Upon receiving the data, a number of data transformations and adjustments were performed. Subsequently, a t-test was conducted to determine whether the chiefs of staff were more central than the other team members, as expected. Preliminary Pearson product-moment correlations were then performed for both individual and team level in order to determine if the data were suitable for further analyses. Given the directed hypotheses these were one-tailed. The initial alpha level was set to $p = .1$ in the pre-registration, with a Bonferroni correction for eight simultaneous hypotheses tested (four for both the individual and the team level), resulting in a final alpha level of $p = .013$. When initial alpha levels were met, simple linear regression was used for the relevant prediction. After concluding testing of the pre-registered hypotheses, further exploratory analyses were conducted, namely the inclusion of density as a possible predictor of shared beliefs. The same order of statistical tests as for the previous analyses was used here.

Pre-analysis adjustments and data transformations.

Upon data entry of raw data and preparations for social network analysis, we realized that our data (mainly for Experiment 1) contained a number of limitations. To correct for these limitations we made several adjustments, some of which were not anticipated in the pre-registration. Once the limitations were identified, how they were to be handled was decided on and registered (see appendix 2). The adjustments were made during data entry, before social network and statistical analyses were conducted, and before the predictor variables were compared to the outcome variables, in accordance with Kerr's (1998) recommendations to indicate what was known when to enhance research transparency. For a complete account for adjustments, please refer to appendix 3 alongside the preregistration, disclosed in full in appendix 1.

Results

Descriptive tests of the popularity scores were followed by eight Pearson product-moment correlations were used to determine whether regression analysis for the predicted associations for H1a-d and H2a-d were justified. Further, exploratory analyses, investigating density in relation to shared beliefs, were performed. Results from all analyses are presented below.

Descriptive Statistics

It was expected that the chief of staff would, on average, be the most central member in all scenarios, given the team composition with a designated role working as an information hub and the physical layout of the control room, designed to support this mode of operation. An independent t-test indeed showed a significant difference in mean popularity in the communication network for chief of staff (M = 6.9, SD = 3.63) and other team members (M = 3.23, SD = 1.97); t(10.75) = -3.3, p = .007. This mean difference was also present for popularity scores in the reliance network; $t(10.79) = -4.96$, $p < .001$.

Inferential Statistics

Popularity's effect on individual measures of shared mental models and situation awareness.

Preliminary analysis of popularity scores in both networks and individual SMM and SA scores were not significant, apart from popularity's positive association with individual

SMM, which passed the initial alpha level; $r = .14$, $p = .09$. The planned linear regression analyses were not conducted for the individual level analyses, as the results of the preliminary analyses did not justify further analyses. H1b-d did therefore not find any support, while H1a gained partial support.

Since the experiments were conducted in two separate sets, with partly different team compositions, we examined whether results would differ between the two experiments. By dividing popularity variables from each network, and the associated individual SMM and SA scores by experiment 1 and 2, testing the correlations for each experiment set were made possible (see Table 1.).

Table 1. Correlations for communication and reliance popularity and individual SMM and SA, for each experiment set

		SMM			SA		
		com. popularity	rel. popularity	ind. SMM	com. popularity	rel. popularity	ind. SA
Experiment 1	1	-	.81***	.19*	-	.80***	.27*
	2		-	.18*		-	.20*
	3			-			-
Experiment 2	1	-	.91***	-.01	-	.8***	-.11
	2		-	-.07		-	-.09
	3			-			-

Note: * denotes $p < .1$; ** $p < .05$; *** $p < .01$; N = 99 (SMM), N = 88 (SA)

Table 1 shows how the positive associations were significant on the unadjusted alpha level in the first set of experiments, but only with small correlations. Nonetheless, this distinction might be indicative that the differences in the setup of the two sets of experiments might have impacted the respective ERTs in a way that covariation between popularity-values from their networks and individual SMM and SA scores were affected.

Centralization's effect on team shared mental models and team situation awareness.

To establish whether there were associations in line with H2a-d, the individual popularity scores were used to calculate centralization scores for each team (i.e. each scenario). The resulting values are presented in Table 2. A Pearson product-moment correlation between centralization variables from both networks and TSMM and TSA, showed small negative associations between reliance centralization and TSMM and TSA, and small positive associations between communication centralization and TSMM and TSA, though neither of the associations were significant. The analysis thus did not find support for H2a-d.

Table 2. Density and centralization values for both networks for each team

	Centralization		Density	
Team	Communication	Reliance	Communication	Reliance
1.	0.30	0.65	0.72	0.70
2.	0.11	0.43	0.75	0.83
3.	0.26	0.51	0.90	0.91
4.	0.36	0.45	0.94	0.93
5.	0.31	0.29	0.59	0.56
6.	0.56	0.45	0.88	0.85
7.	0.49	0.53	0.90	0.88
8.	0.36	0.46	0.88	0.83
9.	0.48	0.73	0.94	0.94
10.	0.64	0.64	0.96	0.87
11.	0.30	0.27	0.96	0.87
M	0.38	0.49	0.86	0.83
SD	0.15	0.14	0.12	0.11

Exploratory Analyses

Density's effect on team shared mental models and team situation awareness.

After testing of the pre-registered hypotheses was concluded, an examination of whether the networks' interconnectedness could serve as a predictor for shared beliefs was conducted. This approach deviates from the pre-registered analysis plan, but follows the same theoretical outline where evenly distributed networks are more likely to have higher TSA and TSMM. As mentioned above, interconnectedness in a network can be assessed through the ratio of a networks actual distribution of connections and maximal possible interconnection for the network. Using density as a means to represent the degree of completeness in all the teams' networks, both communication- and reliance-variants, preliminary analysis showed large, significant positive correlations for both communication and reliance density and TSMM and TSA, see Table 3. The density values were also highly intercorrelated, meaning that teams with more complete communication networks also showed higher interconnectedness in their reliance networks, and vice versa.

Table 3. Correlation for density for both network types and TSMM and TSA

	Com. Density	Rel. Density	TSMM	TSA
1	-	.92***	.60**	.58**
2		-	.64**	.58**
3			-	.87***
4				-

Note: * denotes $p < .1$; ** $p < .05$; *** $p < .01$; one-tailed

Further analysis consisted of simple linear regression to predict both TSMM and TSA scores by communication and reliance density, respectively. The results of the four models are shown in Table 4.

Table 4. Simple linear regression of density for both network types and TSMM and TSA

	TSMM			TSA		
	B	*SE B*	*β*	*B*	*SE B*	*β*
Constant	.78	.04	-	.71	.06	-
Com. density	.10	.04	.60**	.15	.07	.58**
Constant	.77	.04	-	.71	.06	-
Rel. density	.11	.05	.64**	.16	.08	.58**

Note: * denotes $p < .01$; ** $p < .05$; *** $p < .01$; N = 11; one-tailed

A linear regression to predict TSMM based on communication density resulted in a model (F(1,9) = 5.107, p = .025) with an R^2 of .36. Two further linear regression used to predict TSA by communication (F(1,9) = 4.59, p = .031) and reliance density (F(1,9) = 4.494, p = .032) resulted in two models with an R^2 of .34 and .33, respectively. The model found in the prediction of TSMM by reliance density (F(1,9) = 6.317, p = .017) showed an R^2 of .41. While all the models presented showed tendencies for prediction of TSMM and TSA by network density, none of the models reached significance at our Bonferroni-adjusted alpha threshold.

Discussion

The aim of the current analysis was to assess SNA viability as a method to describe ERTs. By deriving measures from the graphed networks we sought to determine whether patterns of relations between team members were associated with measures of SMM and SA.

Analyses confirmed that the chiefs of staff were significantly more central than other team members, for both communication and reliance. The initial individual level analyses (for H1a-d) showed significant positive associations between popularity and individual SA, and popularity and individual SMM for Experiment 1, but not for Experiment 2. The planned tests for team level analyses (H2a-d) did not support the hypothesized relationship between centralization and TSA or TSMM. When proceeding to test the team level hypotheses using density measures, however, analyses yielded large, significant correlations between density in both network types and both measurements of the teams' shared beliefs.

Sætrevik (2015) found that ERT members' degree of shared beliefs were affected by which team they belonged to, but not the specific function they performed in the team. He therefore attributed the variation in shared beliefs to team-specific characteristics, and suggested that leadership, the team's shared experience, and communication patterns could be possible contributing factors to variance in shared beliefs.

The current analysis was intended to further explore Sætrevik's proposed relationship between social dynamics and shared beliefs. We tested whether a SNA of communication and reliance patterns could predict ERTs shared beliefs. This method is commonly used to investigate underlying social or structural elements influencing team functions (Henttonen, 2010; Wölfer et al., 2015). Any explained variance in shared beliefs would be beneficial in terms of understanding underlying influences on team functions, as it is widely accepted that accurate shared beliefs facilitate team cooperation and thus, overall team performance (Bolstad & Endsley, 1999; Mathieu et al., 2000). The results will be interpreted and discussed, organized into individual and team level analyses, followed by a general discussion SNA's suitability as a research method for investigating social dynamics and shared beliefs in ERTs.

Individual Level Analyses

Communication in the emergency response teams.

Initial correlation analyses for popularity in both network types (from both experiments) and SMM and SA measures did not show significant associations, except for a moderate covariance between reliance and SMM. The nature of communication in the ERTs may have influenced these results. Communication in the teams comprising our sample is most commonly brief, concise, task-oriented and to the point. Using closed-loop communication and minimizing the amount of intra-team communication is thought to reduce the possibility for cognitive interference in highly complex work environments, thus optimizing the capacity for performance (Espevik et al., 2006). The networks we investigated might be reflective of this type of communication. The chief of staff's function in the team include perpetually gathering and distributing information between team members to facilitate coordinated team processes. The chief of staff's role therefore inherently imply that they communicate most with all other team members, as indicated by their popularity in the communication networks in the current analysis. This leads to communication between other team members being somewhat limited, and the communication that does take place in other dyads is likely to be of a instrumental and functional nature. The networks emerging from a SNA is meant to express social dynamics. It is possible that the communication networks from the current analysis reflects the highly systematic approach to communication that takes place in our sample. For this reason, communication popularity may provide less predictive value for shared beliefs than reliance popularity in these ERTs.

Intra-team communication likely affects team processes, and especially so for teams that are highly interdependent to fulfil their tasks (Bolstad & Endsley, 2005). According to Henttonen (2010), communication is one of the most prevalent phenomena to be subjected to SNA. Communication in some form takes place in all networks and is thus a natural vantage point for researchers to investigate relationships among social actors, whether connected through virtual platforms or working face-to-face in an ERT. Communication patterns therefore seemed an appropriate subject for investigation in our attempt to uncover relevant social dynamics in ERTs. Whether the networks were influenced by the nature of communication existing in the investigated teams could be the subject for future research in this setting.

Reliance in the emergency response teams.

The networks that emerged from the current analysis displayed which reliance ratings each team member received, enabling us to establish an association between reliance and shared beliefs. In a recent meta-study, De Jong, Dirks & Gillespie (2016) found intrateam trust to be a predictor for team performance across 112 independent studies. Interpersonal trust is defined as “an individual’s willingness to accept vulnerability based on positive expectations of the intentions or behavior of another” (Rousseau, Sitkin, Burt, & Camerer,1998, cited in De Jong et al., 2016, p. 1136). Upon inspecting trust as a covariate in main effects, and as moderator, De Jong and colleagues concluded that the element of trust seems to matter most in teams that are highly interdependent, and where there is a clear leader. This description matches the ERTs in our sample well, reinforcing the assumption that reliance would be a relevant variable for investigating team functions, such as shared beliefs. Although ‘trust’ and ‘reliance’ may not be the same, they are likely closely related in this context.

In ERTs, the members are experts in performing their jobs in a highly efficient and coordinated manner, leaving little room for socialization that is not task-related. Although the question about intra-team reliance used in the current study may have been interpreted in different ways, we believe that the scope of such interpretations was limited due to the questions being asked in the context of scenario training sessions. In that context, it is unlikely that participants interpreted ‘reliance’ as being related to anything but the relatively instrumental supportive functions each team member provides. Thus, asking participants to rate the ones they ‘trusted’ the most would likely yield similar responses as asking about ‘reliance’. The results of our analysis indicated an association between team members’ reliance popularity and shared beliefs, implying support for the validity of such a measure for future use.

In some networks the chief of staff did not have the highest popularity score. A few networks even displayed chiefs of staff with below-average popularity scores and the networks being highly centralized around another team member. This occurred on two occasions, where the communication officer and the line leader, respectively, were most central. Although the chief of staff was the most central team member for most of the networks, the exceptions may be due to some scenarios requiring more of one specific team member’s resources. Each team member in the ERTs has their own area of expertise and a given scenario may engage these skills in varying degrees. If one team member’s expertise was especially relevant in a training session, this may have caused the other members to rank this function/member as the one they relied most upon and communicated most with, instead of the chief of staff. It should be underlined, however, that the chiefs of staff were among the highest ranked team members in all but the two mentioned networks. The remaining four networks displayed a less centralized structure, not indicating a protruding team member. Importantly, since the most popular member was not always the chief of staff, as expected (see Figure 2., for an example of a team network in our study where this was the case), the association between reliance popularity and shared beliefs could be determined to exist beyond the popularity of the chief of staff. Had the chief of staff been the most popular member in all reliance networks, we would have had to take into account the possibility that other unique characteristics of the chief of staffs’ function in the ERTs could have had confounding effects on the covariance.

Popularity and individual shared beliefs.

Team members' SMM of a given task is developed through communication and collaboration with the other team members (Cannon-Bowers et al, 1993; Mathieu et al. 2000; Stout et al., 1999). Relational configurations such as communication and reliance are necessary for collaboration to take place in a team, and individuals that have central roles in these configurations should therefore be better equipped to develop SMM. It is reasonable to assume that having a central position with regards to communication or reliance in an interdependent team enhances insight into other team member's work tasks and operational modes, which in turn facilitates monitoring and supportive behavior associated with SMM (Espevik et al., 20016). Extensive contact with other members, implied by popularity, should in itself lead to greater overlap in mental models between closely knit units, leading us to expect central members to have higher degrees of SMM, measured on the individual level. Results from the planned analysis were not in line with these expectations. However, upon splitting the data between experiments, we found that analyses for the individual level measures of popularity in the reliance and communication networks indicated a positive relationship between reliance popularity and shared beliefs in the networks from Experiment 1, but not for networks from Experiment 2.

The chiefs of staff were expected to be the most central team members, as their function involves constantly acquiring, evaluating and distributing information from all involved personnel. As mentioned above, the prominent position of the chiefs of staff was confirmed by descriptive analysis. While the chief of staff's beliefs about the scenario was included in the SMM calculations, following the approach from Sætrevik & Eid (2014), the chief of staff's replies formed the referent in the SA calculations, and was therefore excluded from the sample. The popularity correlations with SA were likely influenced by how SA was calculated. We acknowledge that removing the most central member from the analyses may have caused some variance between the network variables and individual scores of shared beliefs to be lost. Inclusion of a second measure for SA might be a possible solution to retain the chief of staff in future analysis. For instance, the chief of staff's SA could be calculated by using the second-best informed member's responses as reference values. Several factors may have had an influence on the discrepancy between results from Experiment 1 and Experiment 2, and the following is our account of those deemed most notable.

In Experiment 1, all teams consisted of the actual team members, but in Experiment 2, some team members were replaced by another participant, belonging in another team but performing the same function. Some of the respondents in Experiment 2 also participated in more than one training session. Communication between team members that are used to working together and know each other well may be very different from communication in teams where the members do not know each other (Bolstad & Endsley, 1999, Espevik et al., 2006). In small, interdependent teams, collaboration is largely based on previous experience from working in a specific team constellation, and with specific individuals. It is therefore possible that the communication and reliance ratings would in some way be affected when some participants were placed in an unfamiliar or less familiar team, which was the case in Experiment 2.

This line of thought resonates with previous research on SMM in operative teams. For instance, Espevik and colleagues (2006) found that team familiarity enhanced performance in submarine attack teams, and that SMM contributed more to team performance than operative skills did. Being placed in an unfamiliar team had measurable implications for several different aspects of performance, such as stress reactivity, information exchange and number of hits on target. The authors argue that expert knowledge about and mastery of rules, skills and procedures is not sufficient to establish an optimally functioning team, and that SMM is necessary to succeed in performing such functions. These empirical results are in line with Balkundi and Harrison's (2006) findings, who in an extensive meta-study on social network configuration in teams, identified member familiarity as a moderator in structure-performance connections.

The above exemplifies how team members' familiarity based on personal experiences in working and training together is both empirically and theoretically linked to SMM. The individual's ability to make correct inferences about the behavior and mental states of others in interdependent teams is also likely to influence the individual's SA (Bolstad & Endsley, 2005; Nonose, Kanno, Furuta, 2010; Shu & Furuta, 2005). Thus, implying that experience and intimate knowledge about one's collaborative partners is an advantage in the formation of SA (and TSA). For this reason, keeping the established team constellations intact should be emphasized in future investigations.

Familiarity as a precursor for extended team performance may also explain the difference in correlation in between experiment sets in another way. In their special issue on the state of science regarding high team performance, O'Neill & Salas (in press) presented four key aspects for future research and development in the field. One of these aspects is the dynamic properties of teamwork. Individual and team factors have been investigated extensively, but the authors pointed out that there is an increased need for knowledge on temporal developments of social dynamics and their effect on team functions. Lin, Yang, Arya, Huang, & Li (2005) argued that different predictors for team performance come into play in different stages of group development. In particular, while factors at the individual level were, to a greater extent, predictive of performance in a group's starting phase, group level factors, like network properties, were far more useful in a more matured group where team members knew each other better. As pointed out, even small changes in a team's composition can affect performance. The introduction of team members who do not regularly work on the team may have changed the team dynamic in such a way that it resembled a team in an initial phase, where members have to get to know how to work with each other. It is thus possible that network level factors lost some predictive power in the second set of experiments, where changes like this occured.

The fluctuations in team constellations that occurred in the sample of Experiment 2 was limited to some members' participation in more than one scenario training, and some participants stepping in for another, performing the same function. This was not expected to compromise the results dramatically, but we acknowledge the possibility that it might have skewed the networks and caused some of the discrepancies between the results of the analyses when divided between Experiment 1 and Experiment 2. Another possible consequence of some team members participating in several training sessions is the potential for fatigue and diminished compliance. This may have led to more erroneous or missing responses, although there was no evidence of this in our data. Sætrevik and Eid (2014) measured compliance for the current data and did not report decreased compliance for Experiment 2.

The discussed elements relevant for individual-level analyses identifies that systematic communication, the chief of staffs' inherently central position in the ERTs, and the way SA was calculated, may explain why initial analyses only reached the predetermined significance level for the predicted association between individual reliance popularity and SMM. When analysing the two sets of experiments separately, the experiments conducted with intact teams showed associations in line with our predictions. This may be a consequence of less familiar team members taking part in some training sessions, although this is difficult to establish in hindsight. Taking the aforementioned limitations into account, we consider the results to be promising for future research.

Team Level Analyses

Centralization and shared beliefs.

While popularity, i.e. the application of an individual level network measure, showed some tendencies for an association with individual SMM scores, the main interest in examining the team level was to establish whether teams characterized by especially central members had lower degrees of shared beliefs. Earlier research of SNA in a team context has focused on centralization (Katz et al., 2004), i.e. one or few members having especially high centrality scores compared to the rest of the group working together. Work units or teams characterized by high centralization have already in early studies been linked to lower performance and efficiency in complex tasks than work groups with lower centralization (e.g. Leavitt, 1951; Shaw, 1954, 1964, 1971), and continue to do so in more recent publications (Cummings & Cross, 2003; Henttonen, 2010; Leenders, van Engelen & Kratzer, 2003; Lin et al., 2005; Mehra et al., 2006; Sparrowe et al., 2001). In accordance with Bolstad and Endsley (1999) and Mathieu and colleagues (2000), distribution of communication and collaboration is vital in the formation of objectively accurate mental models and that these are shared between team members. High degrees of centralization in a communication network may inhibit distribution of information on a team level, as the flow of information is concentrated around the most central team member(s). The same assumption can be made about centralization in reliance, as the team's overall shared beliefs may diminish when one or a few individuals are relied the most upon, compared to when reliance is equally distributed between all team members. Such a mechanism may be explained by concentration of ties on one or few team members in a network raising the chance for those team members to act as 'gatekeepers', nodes through which information has to flow to reach from one part of the network to another. Such restrictions on the workflow could potentially act as a 'bottleneck', in particular if the team member representing the node in question does not pass on the social resources sent through them (e.g. information, social support or advice) in an adequate manner.

Analyses testing centralization's predictive quality for shared beliefs did not show any clear tendencies. Overall, the results from the current analysis indicate that for this sample there was no association between centralization and shared beliefs. These results depart from the expected negative association of centralization and team outcomes. Taking up the idea of a 'gatekeeper' as described before, the implied bottleneck first becomes a problem for the team, if the most central team member fails to distribute the social resources channeled through them. The ERTs in question are highly trained and specialized units, with a chief of staff that collects, condenses and disperses resources and function as an information-hub. The chief of staff was also the most central team member in a majority of teams (16 out of 22). If centralization of resource distribution leads to the a bottleneck (in the current setting), a well-adapted and skilled chief of staff may have the exact opposite effect of a bottleneck. This would be a possible explanation for why centralization did not have the predicted associations with shared beliefs in these particular teams. It has been argued (Balkundi & Harrison, 2006) that central positions for leaders in social networks may be of great importance, since leaders are assumed to use their social position in the network, e.g. for task completion. It is thus possible that factors like the organizational and physical layout of the ERT, clear team role and function distinction, and considerable expertise, in combination, were able to offset potential detrimental factors of centralization.

Another factor might be that the aforementioned association between centralization and team outcomes often uses measures of performance or efficiency, e.g. time needed to complete complex tasks as a team (Shaw, 1964), complex project tasks (Sparrowe et al., 2001; Cummings & Cross, 2003) or sales performance (Mehra et al., 2006). Possibly, measures of shared beliefs are to be seen as emergent states of continuous coworking, rather than performance. In relation to SA, Endsley (1995b, 2015) distinguished between the attainment of SA and eventual decision making, affecting performance. While the factors of SMM and SA are deemed important in the processes leading up to different forms of performance (Bolstad & Endsley, 1999; Endsley et al., 2003; Mathieu et al., 2000), they are not synonymous with them. It is possible that centralization hampers ERTs' task performance outcomes in other ways, that does not appear as associations with this study's measures of shared beliefs.

Density and shared beliefs.

Density expresses the actual distribution of interconnections in a network compared to the maximal possible amount of interconnections. In the current context, density indicates the extent to which flow of communication and reliance is distributed among team members, regardless of whether one member functions as a hub for the interconnections between other members. Therefore, density was deemed a suitable alternative measure for distribution of communication and reliance in the ERTs. This enabled us to explore the rationale behind H2a-d without focusing on individuals' positions in the networks, but rather the extent to which communication and reliance distribution in itself can be of predictive value for teams' shared beliefs. The correlations between density in both network types and shared beliefs, indicated a clear relationship between these variables, also directing further research towards the use of density as a predictor for shared beliefs. These results are in line with several previous findings. Various researchers (Balkundi & Harrison, 2006; Reagans, Zuckerman & McEvily, 2004; Lin, Yang, Arya, Huang & Li, 2005) have investigated team functions, such as effectiveness and performance, as outcomes for density and reported it to be a salient predictor. Wong (2008) measured knowledge density and found that increased density in knowledge networks also predicts team effectiveness.

Denser teams are often reported to have increased information exchange, collaboration, and general interaction between team members (Sparrowe, Liden, Wayne, & Kraimer, 2001; Wölfer, Faber & Hewstone, 2015). Team interaction patterns of this kind have been associated with increases in performance of the team as a whole, and for individual team members. Results of a meta-analysis of 72 independent studies on the 'hidden profile' paradigm (i.e. the social psychological phenomenon where individuals withhold relevant information known only to them in a group discussion, potentially leading to fallible group decisions) led the authors to conclude that "although moderators were identified, information sharing positively predicted team performance across all levels of moderators" (Mesmer-Magnus & DeChurch, 2009, p.535).

In a complimentary review and meta-analysis, Lu, Yuan and McLeod (2012) showed a strong main effect for in-group information sharing on the accuracy of a team's decision-making. In regards to SMM in particular, reviews of Kozlowski and Ilgen (2006), as well as Kozlowski and Bell (2012), suggest that establishing shared mental schema for joint task-activities supports task completion and coordination of team members. Further, Balkundi and Harrison's meta-analysis (2006) reported general positive associations between team density and team performance. Newer findings also support the notion that density can be a relevant factor in predicting team level processes (Mehra, Dixon, Brass, & Robertson, 2006; Roberson & Williamson, 2012: Henttonen, 2010). Given the general positive association of team level density and team functions, it was expected that ERTs with denser networks show greater degrees of shared mental models, and in extension, more accurate TSA. We consider our findings to be in line with the rationale behind above mentioned findings, where density in networks is associated with positive effects on team functions.

The density measures of communication and reliance were highly intercorrelated. This indicates that networks where communication was distributed and weighted evenly, reliance was distributed and weighted in an equal manner. The popularity values used to obtain the density measures were also intercorrelated (see Table 1.) The measures covary to such an extent that it is reasonable to question whether they are, in fact, separate constructs. The inherent meaning of 'reliance' and 'communication' cannot be regarded as the same, and one can argue that a closely collaborating team may communicate with and rely upon different people, depending on the context and nature of the team's tasks. Regardless, the measures did overlap in the current setting. We believe that this overlap may have been caused by the specific dynamics in these ERTs. The chief of staff's assigned responsibility for gathering and distributing information, and coordinating the team, can lead to that person being ranked in first place for both reliance and communication by the other team members. Furthermore, in these highly coordinated ERTs, communication is determined by the current situation, the tasks at hand and functional necessity. It is concise, brief and to the point. Thus, it is likely that the communication that does take place between team members is initiated to gain or give support, which in turn might be perceived and reported as reliance, resulting in convergence between communication and reliance measures.

Implications of the situation awareness measurement.

The similarity index used for calculating SA in the current analysis was developed with the intention of making a SA measure that can be applied and used in field settings (Sætrevik & Eid, 2014). As described in the introduction section, measuring SA has been found to be a demanding and controversial venture. Establishing a ground truth for comparison is time consuming and requires considerable resources in addition to expert knowledge about developing the measure, and the specific environment for which it is developed. SA measures have also been criticized for lack of ecological validity, as they have been tested and developed in controlled laboratory environments, not reflecting the complexity existing in field settings.

According to Sætrevik & Eid (2014, p. 121), “some level of intrusion into the task work seems to be inevitable in all SA measures, yet the amount of intrusion varies according to the approach used”. Their own approach was aimed at measuring SA in a non-invasive way, and at the same time, developing a measure that was highly resource-efficient and applicable to naturalistic settings. Sætrevik and Eid’s approach enables organizations to implement the measure to their routine operations, potentially generating insight in SA variation, within and between teams. We evaluate the benefits of this approach as greater than the limitations for the current analysis, as it provides highly naturalistic information about the investigated ERTs’ shared beliefs. Although the generalizability of this SA measure is relatively low, it does express the variability existing among teams and team members in these ERTs. Our goal was not to make inferences about teams in general but to explore whether SNA can be a useful tool for research regarding shared beliefs in this or similar settings. Using the best-informed team member as point of reference for team member’s SA is likely a more finely tuned measure than any general SA-measure, using a ground truth approach, for instance. Therefore, we consider it to be a fitting approach for our purpose, although the construct validity of this measure can be debated.

Possible Modifications for further Studies

Respondents were asked to indicate which other team members they communicated most with and whom they relied most upon to complete their tasks. However, exact definitions of how this was to be interpreted were not given. The resulting data is thus a function of what respondents themselves perceived and defined as communication with and reliance upon others. This implies that the content of ties may differ between team members. For instance, ‘reliance’ may connote the degree to which one team member trusts another member to share relevant information, to know which information is relevant to them, and when and how it is preferably transferred. Participants may give reliance ratings to other team members based on personal experience, and in accordance with subjective preferences for collaboration. ‘Communication’ can be interpreted as verbal communication, which may be unidirectional or bidirectional. Non-verbal communication could be a highly relevant form of communication for ERT members, as explicit commands and information exchange is minimized in such highly specialized teams (Espevik et al., 2016).

As mentioned in the Introduction, two common types of tie content studied in social networks are expressive and instrumental ties (Lincoln & Miller, 1979). However, inferring from the nature of the investigated ERTs work, the occurrence of strictly social (expressive) communication is likely minimal. In exploring whether the social dynamics that underlie the distribution of information and other team functions could predict variance in shared beliefs, it could nonetheless be useful to eliminate the possibility of participants ranking members they communicated most with in the expressive sense. One possible improvement for future research could therefore be to operationalize the communication ranking as ‘instrumental’ (e.g. asking participants to rank team members who provided relevant information).

The associations identified in the current analysis do not directly indicate the mechanisms through which the estimated relationships come to play. While we can assume that transfer of information and interdependence of team functions are the main explanatory factors in how communication and reliance networks are associated with team outcomes like shared beliefs, our measurements are not able to pinpoint the exact explanations. To approach this, one may apply direct measurement of the actual resources and information transferred throughout a network’s ties (Hansen, 1999) might mitigate this. Another possible approach would be to use audio recordings with subsequent coding of information to trace the paths of essential information, or hypothesizing patterns of functional dependence and then checking whether these patterns actually emerge, when tested in field settings. However, adjusting the data collection this way would require additional resources from the researcher in a context similar to our study, in the form of a more complicated experimental design, recording and storing equipment, or extended training for observers.

Since the combination of the SNA approach tested in this study and the similarity index for shared beliefs proposed in the original study from Sætrevik and Eid (2014) should be usable by an HRO on its own, it is important that adjustments made in the collection of data do not make appliance of the method too difficult for the organization. Not only the factor of raised resource use (e.g. in form of additional equipment or special expertise needed) is of concern, but also implications for the validity of measures, when additional data collection adds or prolongs freeze points in the scenario. When using freeze points in an ongoing scenario, one general concern is how the ‘stop and go’ between scenario training and assessment interruptions alters how the scenario develops in comparison to what the natural course of development would have been without the assessment (Salmon et al., 2009). Data collection has to be balanced between being sophisticated enough for the participants to give satisfactory information, and not being intrusive to the extent that it could compromise the experiment’s ecological validity. However, given that the density of social networks graphed out of two simple, time efficient rankings (only administered at the end of each scenario) showed strong correlations with shared beliefs, inclusion of such rankings at every freeze point seems like a reasonable approach. This would enable obtaining of longitudinal networks without impacting the scenario’s ecological validity too heavily.

One aspect the current experimental design is not able to answer is whether the predictive value of network density varies over time throughout the scenario. While the responses used to obtain the similarity indices were acquired through multiple freeze points - giving the possibility to present a temporal rendering of the development in shared beliefs - the questions for graphing the networks were asked when scenarios concluded. A future endeavour could be integrating the ranking of team members used to obtain the networks at each freeze point, enabling researchers to graph social interaction while scenario is ongoing. This could be used to assess whether density would be able to predict shared beliefs, which were shown to vary throughout training sessions (Sætrevik & Eid, 2014), equally at different points in time. Potential differences in predictive strength could point to eventual moderators.

Interpersonal relationships and group structural patterns are not static and have increasing influence on team members’ behavior as they are established, according to O’Neill and Salas (in press). For instance, team members will interact more with those they already know, and being part of an established team structure has an accelerating effect on the perceived importance of social norms (Lin et al., 2005). It could be argued that the approach applied in the current analysis would be fitting for uncovering temporal aspects of social dynamics, given some modifications. For future use of the same approach, a longitudinal design should be considered, where teams were probed at every training session over the course of a several months. This would especially be of interest when investigating newly established team structures, or before, during and after a training program aimed at developing collaborative skills had been implemented. This would give the organization insight into the development of reliance and communication patterns over time, and whether such fluctuations covary with shared beliefs, both on individual and team level. Comparing newer teams with established teams on these parameters would also be a potential direction for research using a longitudinal design.

In the data collection for the current experiment, participants were instructed to report only the top three candidates for communication and reliance, and to provide each reported team member with a rank value between 1-3. This entails that team members could also have additional ties that were rendered unreported. Thus, there may exist additional communication and reliance transactions that were not part of the analysis or the networks emerging from it. However, all networks have limitations, either in the form of methodological obstructions (e.g. limited resources or ethical concerns), or inherent properties (e.g. relevant individuals being unavailable or unknown to the researcher). The networks shown in the current analysis were products of an approach developed first and foremost to be applicable for naturalistic settings. This means that the goal of high usability was superior to achieving results loaded with theoretical nuances. While more detailed questionnaires (e.g. where participants were asked to rate all other team members for every freeze point) might have generated more extensive networks, they would also (since they would be more time-consuming) likely be a source of interference, fatigue, less compliance and more missing data.

It could have been beneficial to assess SA using several measures used in the current analysis. In an article reviewing the applicability of the then current measures for SA for C4i (command, control, communication, computers and intelligence) environments individual measurement techniques were deemed not sufficient by themselves to assess SA adequately for the environments in question (Salmon et al., 2006). According to the authors this methodological challenge could be attended to by use of several measurement approaches at once, since that would make testing for converging tendencies of SA possible. The employment of one technique is also the case in this study's design and future iterations (or similar study designs) should incorporate several SA measurement technique to assess the soundness of both individual measures, and the validity of the tendencies in SA scores for the whole study. Triangulation of methods has given human factors researchers confidence in SA being a valid and useful construct in human-system interaction (Parasuraman, Sheridan & Wickens, 2008), and, on a smaller scale, the same case can be made for use of confluencing assessment techniques in a single study. The inclusion of another SA measurement would have helped in this study in particular being a possible workaround to make use of the chief of staff's popularity-scores on the individual level.

Pre-registration of the Analysis

As mentioned in the introduction, the current analysis was pre-registered at Open science framework (osf.io). Pre-registering a research project involves determining which variables are to be examined, how they are operationalized and measured, and which analyses are to be conducted. This is all done before data collection, or, in this case, before accessing and reviewing the data. The purpose of pre-registering research projects is to enhance transparency. Predetermining and disclosing all methodological elements applied to a research project enable other researchers to replicate and falsify original findings using the exact same approach. Pre-registering research projects reduces the chance of hypothesizing after the results are known (so-called HARKing), or adjusting of hypotheses in accordance with findings. HARKing greatly increases the chance of type 1-errors to occur and may therefore be detrimental for the validity of results in question (Kerr, 1998). Predetermining which analyses and how many analyses are to be conducted also reduces the potential for post-hoc testing and subsequent '*p*-hacking' (Head, Holman, Lanfear, Kahn & Jennions, 2015). Pre-registration may therefore be one way of achieving more rigorous scientific publications.

The pre-registration process was a time consuming part of the current analysis. Identifying which concepts from the SNA literature would be appropriate for exploring the predicted associations, and whether they would be compatible with subsequent statistical analyses, required some preparation in itself, as the methodological framework of SNA was new to us. Making such decisions about the various stages of the analysis to be conducted without reviewing the data, required considerations about possible elements, such as how to handle self-rankings. As described in the Methods and results section, we also developed a new measure, based on relevant literature but tailored to our requirements. Formulating the pre-registration therefore called for evaluations that would not necessarily have come into play if we had reviewed the data beforehand. That said, the process required a deeper immersion into the methodology than would have been the case without a pre-registration, which proved advantageous throughout the process of conducting and interpreting this analysis.

Conclusion

ERTs work with critical situations, characterized by high stakes, ambiguous information and the need for swift and accurate decision making. Critical situations are inherently difficult to rehearse for, as unexpected elements will almost certainly emerge. Formalized knowledge and procedural training may only get operators so far in mitigating critical incidents. Underlying social or cognitive factors may be equally influential for team functioning. In interdependent teams, social dynamics affecting flow of information or who relies upon whom to perform their tasks could be a salient predictor for collaboration and team outcomes, such as productivity, effectivity and accident prevention. The results from the current analysis indicate that network density explain some of the similarity in ERT members' beliefs about their current situation. More importantly, the analysis as a whole indicate that measures of a team network's relational structure may be a valuable approach to investigate teams' degree of shared beliefs. This counts both in terms of team members' SMM of the tasks at hand, as well as the team's congruence in SA, when measured against the chief of staff. Based on previous findings and our own results, we believe that implementing SNA as a psychometric tool in team research has the potential for expanding knowledge in the field.

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